Project Report on

FractureVision

Submitted in partial fulfillment of the requirements for the award of the degree of

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in

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CERTIFICATE

This is to certify that the project report entitled ***"FractureVision"*** *is a bonafide record of the work done by* ***George Bibu (U2103094)****,* ***Jenil Biju (U2103109)****,* ***Justin George Soney (U2103120)****,* ***Kevin Benny Thukkuparambil (U2103125)*** *submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2024-2025.*

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Abstract

Fracture detection in complex anatomical regions, such as the spine and ribcage, presents significant challenges when using single imaging modalities like X-rays, which may lack sufficient detail for accurate diagnosis. To enhance diagnostic accuracy and overcome these limitations, this project proposes a multi-modal AI-based system that integrates X-ray and CT imaging for improved fracture detection. By leveraging Coupled Feature-Learning GAN (CFGAN) for medical image fusion, the system aims to retain critical structural and textural information from both imaging modalities, providing clinicians with a unified and comprehensive view of complex fractures. The system also addresses a critical issue in current AI applications in healthcare: the "black-box" nature of many models, which makes it difficult for radiologists to interpret AI predictions confidently. Therefore, this project incorporates Explainable AI (XAI) to ensure that AI-driven insights are transparent and interpretable, enhancing trust and adoption of AI in clinical settings. Using interpretable layers and visualization tools, the system will allow radiologists to understand the factors contributing to each prediction, facilitating better clinical decisions.

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Chapter 1

Introduction

1.1 Background

Fractures have been recognized for several millennia now, with early descriptions going back to ancient civilizations. Hippocrates, often regarded as the father of medicine, documented techniques for treating broken bones which were focused on immobilization. These early methods relied heavily on clinical observations and assumptions as no imaging tools were available to confirm the extent or location of fractures. In the centuries that followed, fracture detection gradually improved with advancements in surgical techniques and the development of orthopedic devices. However, the accurate diagnosis of fractures remained difficult due to the inability to visualize the internal structure of the body.

The advancement in fracture detection was marked in 1895 with the discovery of X-rays by Wilhel Conard Reontgen.This invention further facilitated the non-invasive examination of internal anatomical structures which resulted in the improvement of diagnostic radiology. The inaugural X-ray image captured was notable that of Roentgen's wife's hand, which distinctly revealed her bones along with her wedding ring. X-rays rapidly established themselves as one of the primary instrument for the fracture diagnosis which offered a swift and relatively economical method for the visualization of skeletal elements. Despite the transformation done by X-rays on fracture detection, they exhibited certain limitations particularity in the case of visualization of intricate fractures in the areas such as spine or pelvis. The introduction of the first CT scanner by Sir Godfrey Hounsfield in 1972 marked a significant evolution in the imaging technology which enabled three-dimensional visualization through the reconstruction of numerous cross-sectional images of the body.

The recent wave of artificial intelligence (AI) has added a new dimension to fracture diagnosis. AI algorithms, particularly deep learning models, can analyze X-rays and CT scans

to identify fractures with accuracy comparable to trained radiologists. The integration of Explainable AI (XAI) has further enhanced trust in these systems by allowing clinicians to understand the rationale behind AI predictions.
Medical imaging today integrates the advantages of conventional techniques, such as X-rays and CT scans, with advanced technologies including artificial intelligence and image processing. X-rays continue to be the most frequently utilized method for the preliminary identification of fractures, primarily due to their widespread availability and speed. CT scans, on the other hand, are used for more detailed assessments when precision is required.

1.2 Problem Definition

Accurate fracture detection, particularly for complex cases like spinal and rib fractures, remains challenging with single imaging modalities such as X-rays. Additionally, the black-box nature of current AI systems makes it difficult for radiologists to trust the results, leading to missed or delayed diagnoses and inadequate treatment plans. .

1.3 Scope and Motivation

1.3.1 Scope

This project focuses on developing a multi-modal AI system that integrates X-ray and CT imaging to improve fracture detection accuracy. Using publicly available datasets and using Coupled Feature Learning GAN (CFGAN) for fusing multimodal medical images, the objective of the system is to merge the structural info obtained during the x-rays with the textural depth offered by the CT scans. The incorporation of XAI within this framework significantly improves its utility by offering radilogists clarity regarding the Ai's decision-making process. This project encompasses the design,implementation and evaluation of the AI model in addition to its development of a user-friendly interface tailored for clinical use. This will be implemented through a website where users can register and upload the scans. Thus through this project, we aim to bridge the gap between advanced AI diagnostics and practical applicability in medical settings.

1.3.2 Motivation

When Wilhelm Conrad Roentgen discovered X-rays in 1895, it was a true innovation in fracture assessment. This groundbreaking discovery paved the way for the visualization of internal structures without invasion and ushered the dawn of modern-day diagnostic radiology. Interestingly, the very first photograph ever taken on X-ray was of Roentgen's wife's hand, and her bones and wedding ring were clearly depicted. X-rays soon became a staple for immediate diagnosis of fractures because of their relative speed and low cost visualization of bones. Crude and relying heavily on manual intervention great early Xray machines were nonetheless the earliest machines that did a lot to establish the course of understanding and managing skeletal injuries.Although X-rays revolutionized fracture detection, a limitation set them apart from other methods: they could not visualize complex fractures around the spine or pelvis. The first Computed Tomography (CT) scanner was invented by Sir Godfrey Hounsfield in 1972, a technology that made it possible to reconstruct several cross-sectional slices of the body for visualization, which is also known as 3D imaging.Artificial intelligence brought a new approach in the diagnosis of fractures through AI algorithms, such as deep learning, capable of analyzing X-rays and CT scans to detect fractures just like a trained radiologist would. The recent inclusion of XAI has allowed more belief in these systems as clinicians can sometimes understand the reasoning behind such predictions.Today, medical imaging really integrates together all the advantages from classic modalities, like X-rays and CT, into modern technology, mainly AI and image processors. X-rays are the most widely used method to detect fractures as they are rather accessible and quick, while detailed CT scans are used in cases where detail and accuracy are most important.

1.4 Objectives

- **Objective 1:** The design and the development of a multi-modal AI system that integrates X-ray and CT-images which improves the fracture detection accuracy mainly in comples cases.
- **Objective 2:** Implement a Coupled Feature-Learning GAN (CFGAN) for effective fusion of multimodal medical images, combining structural and textural details to create a comprehensive diagnostic view.
- **Objective 3:** Incorporate Explainable AI (XAI) components within the system to provide interpretable predictions, offering radiologists insights into the AI's decision-making process.
- **Objective 4:** Develop a user-friendly interface that allows clinicians to easily interact with AI-generated predictions and explanations, making the system accessible and practical for real-world clinical use.
- **Objective 5:** Evaluate the system's performance against traditional single-modality approaches by conducting qualitative and quantitative assessments on benchmark datasets to validate its accuracy and reliability in fracture detection.

1.5 Challenges

- **Challenge 1: Complex Multimodal Data Integration**
  Integration of X-ray and CT-images have challenges because of the difference in resolution, scale and various depth of info between the two types of images.
- **Challenge 2: Interpretability and Trust in AI Decisions**
  Making AI-generated predictions interpretable through Explainable AI (XAI) techniques is important for gaining the doctor's' belief and trust. However, developing interpretable models without sacrificing performance or accuracy remains a difficult balance, especially in complex cases like fractures.
- **Challenge 3: Ensuring Robustness Across Diverse Fracture Types**
  Fracture detection can vary widely based on the type and location of the fracture

(e.g., spinal, rib, or complex fractures). Ensuring that the model can handle this variety with high accuracy and consistency requires extensive data and fine-tuned model adaptability.

- **Challenge 4: Limited Availability of Annotated Medical Datasets**
  Acquiring sufficient and high-quality annotated datasets for training and validating the model is a major hurdle. Medical datasets are often sparse, restricted, or come with varying labeling standards, which can impact the system's generalization and accuracy.

- **Challenge 5: Real-Time Performance and Usability Constraints**
  Developing a system that can provide real-time or near-real-time predictions in a user-friendly interface is essential for clinical adoption. Balancing the computational complexity of the AI model with the need for efficient performance and a responsive, intuitive interface is a significant challenge.

1.6 Assumptions

- **Availability of Multimodal Data:** It is assumed that X-ray and CT scans for patients will be available for fusion. This may be the case because normally fractures are detected using 90 percent of fractures are detected with the primary first step which is X-Rays . If the fracture is not detected, the the person need to do a CT scan. The probability of a person taking both x-rays and ct is rare. It is also assumed that annotated datasets for training and validation are avaliable from reliable sources.

- **Computational Resources:** Sufficient computational resources are assumed to be available to handle complex AI and Explainable AI models, which require high processing power for training and inference.
  Creating a model requires high computational resources. This includes storage to store the dataset and high performance GPU that is used for training. The system also needs vram for the GPU to use and system ram to store the intermediate states while training the model.

- **Clinician Collaboration:** The project assumes collaboration with medical professionals to create a data set for training and validating the models predictions and interpretability features . Medical professionals can provide their inputs to validate the models decision

- **Consistent Data Quality:** Different hospitals use different machines which have different properties and features for taking images .It is assumed that the X-ray and CT scan images that we use are of the same resolution and of good quality . We also assume that the training and testing data have consistent labeling standards.
- **User Training and Familiarity:** It is assumed that clinicians using this system will receive adequate training on interpreting XAI generated explanations for accurate diagnosis. This include interpreting Heatmaps and understanding basic concepts in Machine learning

1.7 Societal/ Industrial Relevance

This project will improve diagnostic accuracy of fractures and ribs which can significantly improve patient management and outcomes. Detecting fractures early will ensure that serious complications do not arise in the future. Automating the fracture detection process also has the capability to increase accessibility to under-resourced or remote areas where access to experienced radiologists is limited. With respect to radiologists, automating fracture detection will reduce workloads of radiologists, increasing efficiency and reducing the chances for human errors. These are the various ways by which our project is relevant to society.
Industrially, the aims of this project align with the growing demand for AI integration in radiology, contributing to the development of automated detection methods for hospitals and clinics. Automating fracture detection also shows potential for telemedicine initiatives, enabling remote consultations with processed diagnostic images. Insights gained from such models can also be used for healthcare related research and can potentially help in various research areas such as post-fracture rehabilitation strategies.

1.8 Organization of the Report

Organization of the Report

1. **Chapter 1 - Introduction:** This chapter introduces the project, outlining the need for enhanced fracture detection through multimodal image fusion. It describes the motivation for integrating X-ray and CT images, explains the relevance of Coupled Feature-Learning GAN (CFGAN) in this context, and states the project objectives, including the goal of making AI predictions interpretable for radiologists.

2. **Chapter 2 - Literature Survey:** The literature survey highlights advancements in medical imaging techniques like TorchIO for efficient preprocessing, CFGAN for enhanced multimodal image fusion, Grad-CAM for explainable AI in fracture detection, and CNN-based frameworks for vertebral fracture analysis. These methods focus on improving diagnostic accuracy, clarity, and clinical relevance in medical imaging workflows.

3. **Chapter 3 - Requirements:** This chapter consists of all the hardware and software requirements for the successful development of the project. It also details all the functional requirements of the system

4. **Chapter 4 - System Architecture:** This chapter consists of a description of the core system components and system architecture. It delves into the various module divisions for each part of the project and Gantt chart for development.

5. **Chapter 5 - Results:** This chapter details the final results of the project. Results include metrics for training, validation and testing of UNET and ResNet models as well as the results of image fusion using CFGAN. This chapter also includes outputs of the fracture detection system along with screenshots of the different pages of the website.

6. **Chapter 6 - Conclusion and Future Scope:** The final chapter summarizes the project findings and discusses potential areas for future research and system improvements, suggesting how the system might evolve to tackle more complex diagnostic challenges.

Conclusion

This chapter has outlined the organization and purpose of each component of the project report, reflecting a structured approach to developing an advanced AI-driven fracture detection system. By leveraging multimodal image fusion through Coupled Feature-Learning GAN (CFGAN)[2] and integrating Explainable AI (XAI)[5], the project improves in cases where there is a need for improved diagnostic accuracy and also the interpretation in complex cases. Through a detailed design methodology, user-centered interface development, and rigorous performance evaluation, this report aims to validate the effectiveness and clinical relevance of the proposed system. The following chapters delve deeper into each aspect, providing a comprehensive understanding of the system's capabilities, design choices, and potential impact on medical imaging and diagnostic practices.

Chapter 2

Literature Survey

The literature survey provides an overview of state-of-the-art techniques and methodologies in data preprocessing, augmentation, and deep learning for medical imaging. It examines innovative tools and frameworks, such as TorchIO, CFGAN, and Grad-CAM, highlighting their contributions and limitations in addressing challenges like data heterogeneity, model interpretability, and computational efficiency.

2.1 TorchIO for Data Preprocessing and Augmentation for Medical Images[1]

2.1.1 Overview

TorchIO is a Python library created on top of PyTorch, especially focused on the use of medical image preprocessing and augmentation in deep learning. It fixes problems about maintaining metadata, the management of very large 3D datasets, and addresses the fact that medical image data augmentation often requires custom algorithms. It has input and output formats like NIfTI and DICOM compatible with standard workflows for imaging.

Key components are:

- **Data Component:** Structures such as `ScalarImage` (voxel intensities) and `LabelMap` (segmentation masks) handle metadata and spatial consistency for proper preprocessing.

- **Transforms Component:** Includes spatial and intensity transformations for preprocessing (resampling, histogram standardization) and augmentation (elastic deformation, random noise). These ensure uniformity across datasets while introducing variability for model generalization.

- **Patch-Based Training and Queue System:**Patch-based sampling breaks down 3D images into smaller manageable sub-volumes, which has a reduced memory footprint. Using multiprocessing queues for CPU-based preparation of data separated from GPU-based training ensures optimal workflow.

2.1.2 Methodology

TorchIO methodology is mainly about efficient, reproducible handling of data with deep learning, namely:

Preprocessing

- Spatial transforms for uniformly spacing and orienting voxels to make images compatible.
- Intensities are normalized using, for example min-max scaling that makes voxel distributions between scanners be the same augmentation

Augmentation

- Spatial augmentation (elastic deformation) represents anatomical variability for enhanced model robustness.
- Intensity augmentation (random noise, anisotropy) captures artifacts from the scanner for increased generalization.

Patch-Based Training

- Sampling techniques like `WeightedSampler` highlight areas of interest, such as abnormalities.
- Queue system, with preload and buffering of patches, randomly shuffled during training for different batch compositions.

Transforms Pipeline

- Metadata-aware transforms, like `RandomAffine` and `HistogramStandardization`, help ensure anatomical accuracy while making the images ready for neural networks.
- Augmentation transforms apply realistic distortions in such a way that models learn to recognize real-world variations in clinical imaging.

2.1.3 Conclusion

TorchIO is a complete tool to tackle the unique challenges of medical imaging in deep learning. It provides metadata-aware transformations, efficient patch-based sampling, and multiprocessing for preprocessing and augmentation. These capabilities enable researchers to handle large datasets with consistency and scalability, making sure that the medical imaging models are trained on anatomically accurate and diverse datasets, thereby enhancing robustness and clinical relevance. TorchIO's modular design, optimized for PyTorch workflows, is a reliable basis for medical image analysis in research and practical applications.

2.2 Coupled Feature-Learning GAN (CFGAN)[2]

2.2.1 Overview

CFGAN is designed to address the limitations of existing medical image fusion techniques, which often fail to fully integrate both structural and textural details from multimodal medical images like CT and MRI. By using a coupled adversarial framework, CFGAN ensures that fused images retain discriminative information across different medical imaging modalities.

2.2.2 Methodology

1. **Coupled Generators**: CFGAN incorporates two distinct generators, each dedicated to processing one of the input modalities—CT and MRI. Unlike conventional fusion methods that may merge images in a linear or simplistic manner, each generator in CFGAN learns a sophisticated representation of its respective modality, focusing on preserving crucial structural (CT) and textural (MRI) information.Through rigorous training the generators which will be refined in a recursive manner which produces fused images which shows the important features for assessment. The design encourages each generator to contribute unique, modality-specific information, enhancing the depth and detail of the final output.

2. **Coupled Discriminators**: In CFGAN, each generator is paired with a discriminator, creating two adversarial paths that make sure that both generated images

undergo vulgar quality evaluation. The discriminators are tasked with distinguishing between the real and fused images which makes the generator to produce closely resembling images. This setuo will provide a dual-layered control in quality mechanism in which each of the discriminator pushes the generator to retain the modality of specific attributes which ensures the overall realism of the fused output . This iterative adversarial training significantly enhances the perceptual and diagnostic quality of the fusion, as the discriminators act as specialized critics for each generator's output.

3. **Discriminative Feature Extraction (DFE) Block**: Tihs is used to improve the challenge of capturing the fine and coarse details, this block is embedded within each generator and due to that this block iterates over multiple dilation rates which enables the network to capture various details at multiple levels By the variation of the field the block is able to extract the detailed information like textures and edges from smaller regions, while also preserving larger structures such as anatomical shapes and contours. This multi-scale approach ensures that both high-frequency (texture) and low-frequency (structure) information are retained, making the fused image more informative and diagnostically valuable.

4. **Cross-Dimension Interaction Attention (CIA) Block**: This block enhances the fusion quality of the process by the process of modeling various dependencies across the spatial and channel dimensions. This block introduces various attention mechanisms whcih will dynamically weigh the importance of features based on their spatial location and channel intensity, ensuring that critical structural and textural features are prioritized. By promoting cross-dimensional interactions, this attention block allows the network to focus on clinically relevant areas which are crucial for perfect and accurate diagnosis. This modified representation will improve the contrast and clarity of the fused image.

2.2.3 Results

Important evaluations on the medical datasets demonstrated that CFGAN[2] achieves a more superior performance in medical image fusion when compared to traditional methods.Mainly :

- **Detail Preservation:** CFGAN exhibits outstanding performance in retaining fine details across multimodal inputs, which is critical for diagnostic accuracy.
- **Structural Similarity:** Quantitative SSIM scores show a significant improvement over other fusion techniques, indicating enhanced alignment with real structural features.
- **Peak Signal-to-Noise Ratio (PSNR):** The PSNR values of CFGAN[2] which surpasses those of old fusion methods which confirms the reduced noise and improved clarity in the output image.

2.2.4 Conclusion

The results demonstrate that CFGAN outperforms traditional fusion techniques across critical evaluation metrics, including detail preservation, structural similarity, and PSNR. Unlike conventional methods, which often struggle to fully capture and integrate the intricate structural and textural information from multimodal inputs like CT and MRI, CFGAN leverages its coupled adversarial framework and advanced feature extraction techniques to retain essential details and enhance image clarity. The architecture's focus on multi-scale feature learning and cross-dimension attention ensures a high-quality fusion outcome that aligns closely with the structural integrity of the original images. Consequently, CFGAN not only improves diagnostic value but also offers a robust, noise-resistant fusion method that surpasses existing methods in clarity and diagnostic reliability, making it a compelling choice for advanced medical image fusion.

2.3 Grad-CAM as XAI for Wrist and Elbow Fracture Detection

[5]

2.3.1 Overview

Wrist and elbow radiographs(X-Rays) are important images that will be used by professional to see abnormalities like fractures on wrist and elbow. The X-Ray images allow doctors and doctors to diagnose a multiple issues like dislocations,fractures and degenerative diseases. X-Rays can also be used check various metal artifacts which are from previous procedures done . Even after their use , analyzing and interpreting wrists and elbows X-rays can be a tough and complex task for multiple reasons . This is mainly because of the complex and intricate structure of the wrists and elbows. Therefore , there is an urgent need for better and more efficient methods or diagnostic tools that can help healthcare workers and doctors interpret the X-Rays more easily in order to detect fractures or other abnormalities over the past few decades, AI has had a significant impact in the case of radio processing improving diagnostic imaging. By using and implementing machine learning processes and Deep learning (DL) methods, AI was able to identify fractures, classify fractures, and predict various medical issues of various patients with accuracy values that may surpass those of expert doctors.6 Explainable Ai (XAI) is the AI systems in which their actions can be interpreted and understood by human beings. In the healthcare industry, more specifically, radiology and radiography, XAI can be an invaluable tool for improving readability and interpret ability. Explain-ability increases trust of doctor or healthcare workers in AI systems, as they are able to understand the reasoning behind the models decisions.

2.3.2 Algorithm and evaluation

A combination of 10 transfer-learning models was used with two different batch sizes. The batch sizes were 16 and 32. The models include VGG16, ResNet50V2, VGG19,ResNet101V2, DenseNet121,ResNet152V2, DenseNet169, InceptionV3,DenseNet201 and Xception. Running the models with two different batch sizes(16 and 32) allowed for a more clear evaluation of their performance and behaviour of the model under varying training conditions. Before the training was done, all the images were adjusted to a scale value of 1/255(1 represents black and 255 represents white). This was done to convert the images to grayscale. The images were also resized according to the input requirements of the specific models. Data augmentation was also done to increase the dataset and allow the model to analyze different variations in the input data. The augmentation parameters that were used include a zoom range of 0.2,shear range of 0.2, width shift range of 0.2,rotation range of 20,horizontal flipping and height shift range of 0.2.The Dice Similarity Coefficient (DSC) was used to evaluate the algorithm's efficiency in recognizing regions of interest.

$$Dice\ coefficient = \frac{2 \cdot |A \cap B|}{|A| + |B|} \tag{2.1}$$

Here A is the predicted points of pixel values from the area that model predicted and B is the Ground Truth.

2.3.3 Result analysis

The overall performance of the models was analyses by expert doctors using the generated heat maps from Grad-CAM.

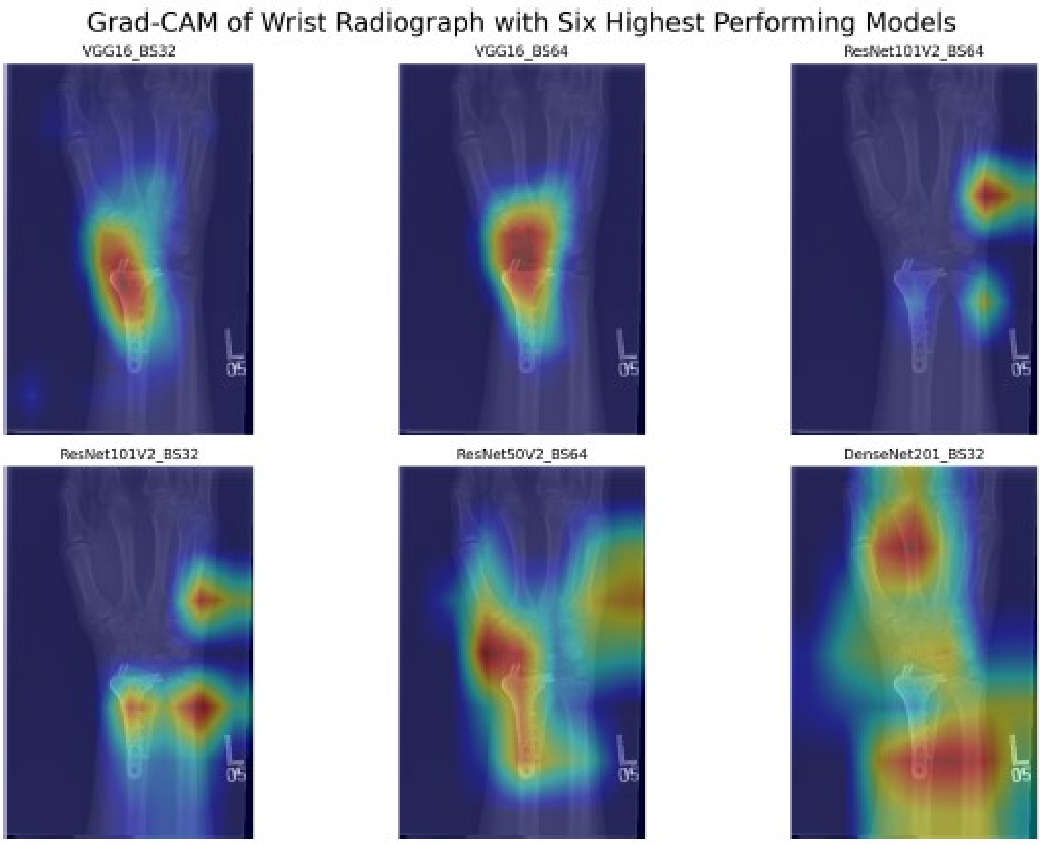


Figure 2.1: Wrist radiograph heat maps of highest models
[5]

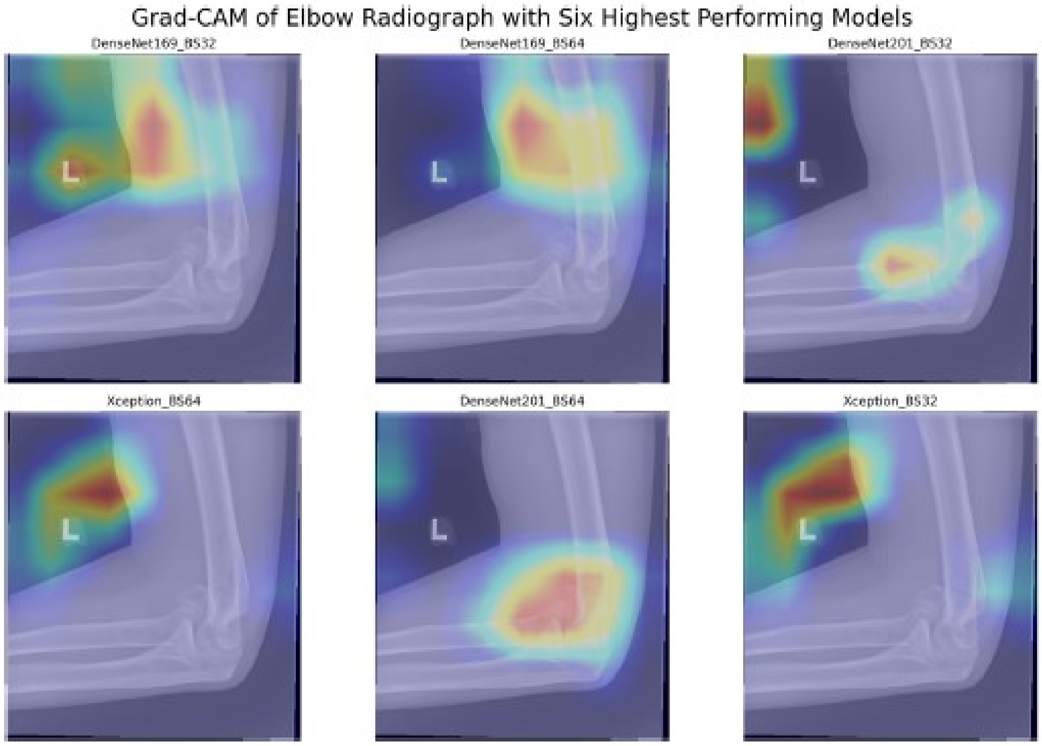


Figure 2.2: Elbow radiograph heat maps of highest models

[5]

From the heat maps generated it was clear to understand how each of the trained models focus on different part of the input X-Ray images. The models trained with wrist fractures were found to be more accurate than the same models trained using the elbow fractures. It was clear that even though the model predicted the fracture it was not focusing on the actual area of the fracture . This helped the developers to fine tune the model parameters so as to make a more accurate model.

2.4 Classification of Vertebral Body Fractures using a CNN[3]

2.4.1 Overview

This study presents a multistage deep learning framework for detecting and classifying vertebral fractures present in CT scans. The framework uses U-Net for vertebra localization, Graph Convolutional Networks (GCNs) to label vertebrae, and 3D-ResNet for fracture detection. In the final stage, a multi-branch classification network identifies the fracture type based on the AOSpine classification system. The model achieves high accuracy in detecting and classifying fractures, aiming to support radiologists by automating a time- intensive diagnostic process.

2.4.2 Results

1,217 CT images were analyzed in the study, comprising 760 female and 457 male patients with a mean age of 61.87 years. For fracture detection, the model showed 95.23the test dataset, achieving 97.93coefficient of 0.7014, indicating overlap with manual assessments. Fracture type classification showed AUCs for each type of fracture: 0.904 for A1, 0.945 for A2, 0.878 forA3, and 0.942 for A4, indicating strong discrimination between fracture subtypes.

Metric	**Training**	**Validation**	**Test**
Accuracy (Patient Level)	100.00%	95.87%	98.96%
AUC (Vertebrae Level)	1.000	0.990	0.993
Accuracy (Vertebrae Level)	99.50%	96.54%	97.93%
Specificity (Vertebrae Level)	99.41%	97.13%	98.35%
Sensitivity (Vertebrae Level)	100.00%	93.14%	95.23%

Table 2.1: Evaluation on patient and vertebrae levels

[3]

Metric	**A1**	**A2**	**A3**	**A4**
Accuracy	78.88%			
Balanced Accuracy	79.56%			
AUC	0.904	0.945	0.878	0.942
Specificity	89.30%	98.62%	84.70%	94.43%
Sensitivity	79.61%	81.82%	78.53%	78.26%
False Positives	29	5	28	17
False Negatives	21	2	41	15

Table 2.2: Classification of fracture in test evaluation on the test dataset

[3]

2.4.3 Improved Fusion Convolutional Neural Network: A General Fusion Network[4]

2.4.4 Overview

IFCNN (Improved Fusion Convolutional Neural Network) is a versatile and lightweight image fusion framework designed to address the limitations of traditional fusion methods. Unlike conventional approaches that rely on handcrafted features, IFCNN leverages convolutional neural networks (CNNs) to automatically learn and extract meaningful features from input images. It is widely applied in medical image fusion to integrate structural and textural details from multimodal images like CT and MRI, enhancing diagnostic accuracy and efficiency.

2.4.5 Methodology

- **Feature Extraction:** IFCNN employs a shallow CNN to extract structural and textural features from input images. The CNN is trained to focus on high-frequency details such as edges and fine textures.

- **Fusion Strategy:** The extracted features are processed through a fusion layer that combines them into a single representation, emphasizing essential details from both modalities.

- **Reconstruction:** The fused feature map is passed through reconstruction layers to generate the final fused image. This step ensures that the output image retains high resolution and meaningful diagnostic information.

Results

IFCNN demonstrates superior performance on benchmark medical datasets, including multimodal fusion of CT and MRI images. Key findings include:

- **Detail Preservation:** IFCNN effectively retains fine details and structural information from input images, making it ideal for clinical applications.
- **Quantitative Metrics:** The framework achieves higher structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR) scores compared to traditional fusion methods, indicating better image quality and reduced noise.
- **Computational Efficiency:** Unlike more complex methods such as CFGAN, IFCNN provides high-quality results with lower computational costs, making it suitable for real-time applications.

2.5 Summary Table and Gaps Identified

2.5.1 Summary Table

Title	Advantages	Disadvantages
TorchIO for Data Preprocessing and Augmentation for Medical Images	Metadata-aware transformations ensure anatomical accuracy. Patch-based training improves memory efficiency. Seamless PyTorch integration supports efficient workflows.	Limited to preprocessing and augmentation tasks. Limited real-time support.
Coupled Feature-Learning GAN (CFGAN)	Effectively preserves both structural and textural features, Incorporates multi-scale feature learning and cross-dimension attention.	High computational complexity. Modality-specific training requirements increase implementation complexity.
Grad-CAM in Wrist and Elbow Fracture Detection	It helps visualize the specific regions in an image that contribute most to a model's prediction. It can be applied to various CNNs without needing architectural modifications.	They are limited by the resolution of the last convolutional layer, which may miss minute fractures. Grad-CAM cannot influence model training and only explains already-trained models.

Table 2.3: Summary of Advantages and Disadvantages of Reviewed Techniques (Part 1)

Title	Advantages	Disadvantages
Detection and Classification of Vertebral Body Fractures Using Convolutional Networks	High sensitivity and specificity in fracture detection. Multi-stage framework ensures precise vertebra localization and classification.	Relies on extensive datasets. Classification accuracy for certain fracture types (e.g., A3) remains suboptimal.
IFCNN: A General Image Fusion Framework Based on Convolutional Neural Network	Computationally lightweight compared to advanced methods like CFGAN. The framework excels in retaining structural and textural details.	IFCNN does not incorporate advanced attention mechanisms or multi-scale feature learning. Performance relies on the pre-training of CNN models, which can lead to suboptimal results if training data is insufficient or not diverse.

Table 2.4: Summary of Advantages and Disadvantages of Reviewed Techniques (Part 2)

2.5.2 Gaps Identified

1. **Limited Generalizability Across Modalities:** Existing methods often lack the ability to generalize across multiple modalities (e.g., CT, MRI, and X-rays) due to modality-specific optimizations.

2. **Computational Overhead:** Approaches like CFGAN require significant computational resources, making them less feasible for real-time clinical applications or settings with limited hardware.

3. **Inconsistent Interpretability:** While Grad-CAM provides visual explanations, it may fail to accurately highlight the correct fracture regions, reducing reliability for clinicians.

4. **Dependence on Large Datasets:** Many methodologies, especially deep learning-

based ones, require large annotated datasets, which are often difficult to obtain due to privacy and cost concerns.

5. **Variable Performance Across Fracture Types:** Methods such as vertebrae fracture classification frameworks show disparities in performance between different fracture types (e.g., lower AUC for A3 fractures), indicating a need for more robust classification techniques.

2.6 Conclusion

The literature survey highlights the advancements in data preprocessing, augmentation, and deep learning methodologies applied to medical imaging. Techniques such as TorchIO's metadata-aware transformations, CFGAN's feature-preserving fusion, Grad-CAM's explainable AI approach, and vertebral fracture detection frameworks demonstrate significant progress in addressing domain-specific challenges. However, critical gaps such as generalizability across modalities, computational efficiency, and dependence on large datasets emphasize the need for continued innovation to enhance accuracy, interpretability, and scalability in medical imaging applications.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

1. Processor
   - Minimum: Intel Core i5 / AMD Ryzen 5 (5000 series)
   - Recommended: Intel Core i7(12th) / AMD Ryzen 7 (7000 series)
2. GPU: (For Model Development)
   - Minimum: Nvidia GTX 2060
   - Recommended: Nvidia RTX 3050 or later versions is recommended due its CUDA support which accelerates deep learning tasks.
3. Storage
   - Minimum: 256 GB for storage of software and part of dataset.
   - Recommended: 1 TB which can be split between external storage devices to store large datasets.
4. Memory
   - Minimum: 16 GB
   - Recommended: 32 GB for handling large datasets and complex neural systems
5. Python Environment
   - Python 3.9 or later is recommended.
   - CuDNN (CUDA Deep Neural Network) version 9.0 is recommended

3.2 Functional Requirements

1. Input Data Handling: The System must accept 3D medical images in NifTi (.nii) or DICOM (.dcm) format.

2. Image Slicing & conversion: The system must extract 2D slices from 3D images along the axial, coronal and sagittal planes.

3. Pre-processing: Images should undergo preprocessing (resizing, normalization, and noise reduction) for consistency

4. Classification Model (ResNet-18): Predicts fracture categories among No Fracture, Displaced Fracture, Non-Displaced Fracture, Segmented Fracture and Buckle Fracture and outputs the classification results with probability scores.

5. Segmentation Model (U-Net): It highlights fracture regions by performing pixel-wise segmentation

6. CFGAN-Model: CFGAN needs to pick structural information from CT scans and contrast data from X-rays to fuse more effectively

7. Grad-CAM Model: It generates heatmaps, which indicate the regions affecting the model's prediction.

8. User Management: Consists of seperate data tables for Doctors and Patients ensuring secure record management.

9. CT Scan Upload & Visualization: The user should be able to browse through the CT slices using a slider-based viewer.

10. Frature Detection and Analysis: The model must processes uploaded scans in real time and display classification results, probability scores and provide heatmap visualizations from the Grad-CAM model.

Chapter 4

System Architecture

In this chapter, we present a general description of our fracture detection system including its design, structure, module separation, and project planning visualization by Gantt Chart.

4.1 System Overview

Through the application of deep learning models, explainable AI, and medical image fusion algorithms, the system facilitates high accuracy with interpretability in medical image analysis. The system scans CT images through segmentation models, classification net-techniques, and image fusion methods to improve diagnostic accuracy. The process starts with preprocessing of the dataset, i.e., decompression, augmentation, and CT slicing into axial, coronal, and sagittal images. This organized input is then fed to multiple models for fracture detection.

To demonstrate an interactive and user-friendly experience, the system employs a Flask-based web application to make it easy for users to upload medical images, visualize segmentation overlays, and merge results for analysis seamlessly. For better transparency and explainability, Grad-CAM is incorporated in a manner that radiologists are able to interpret model predictions by identifying important regions of the images.

The final output of the system is dynamically generated medical reports, which combine segmentation masks, fusion results, classification predictions, and visual findings from Grad-CAM analysis. The reports provide structured, data-driven diagnostic assistance, enabling efficient and accurate diagnosis of fractures.

4.2 Architectural Design

The system architecture is optimized to provide effective medical image processing, fracture detection, and image fusion with accuracy and interpretability. The process starts with the acquisition of input data, where CT and X-ray images are acquired and then processed using preprocessing methods like noise reduction, normalization, and enhancement. As CT images store volumetric data, they are processed further using CT slicing, in which every scan is segmented into three anatomical planes: axial, coronal, and sagittal. These slices are essential for structural analysis and are subsequently utilized for classification and segmentation processes.

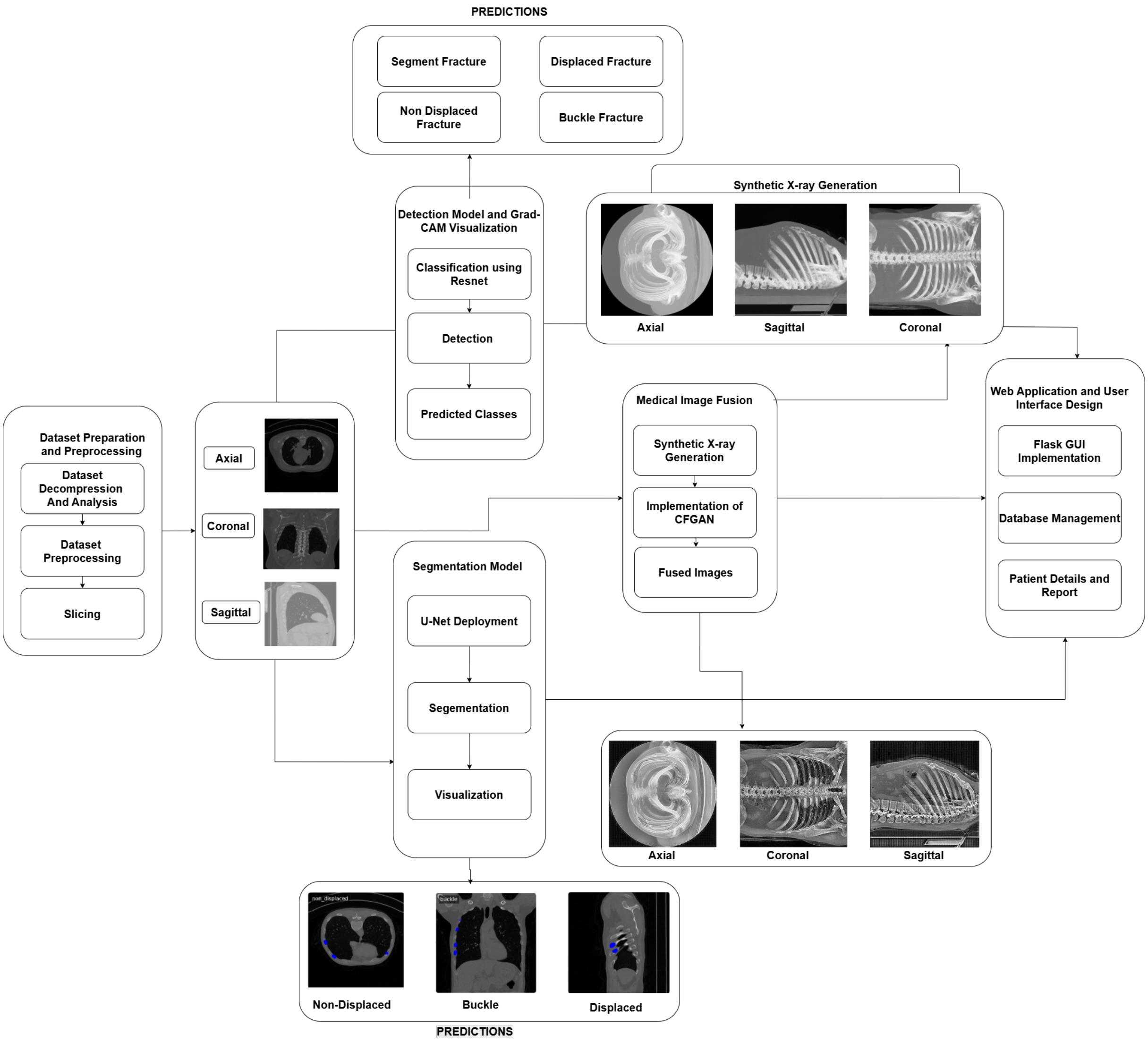


Figure 4.1: System Architecture

Once preprocessing is done, the images are used as input for various deep learning models. The ResNet-based classification models (ResNet18, ResNet50, and ResNet101) analyze the CT slices to determine the presence of fractures, leveraging their deep feature extraction capabilities. Simultaneously, the U-Net segmentation model processes these slices to generate precise fracture masks, helping in identifying the exact fracture location. To improve interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) is incorporated into these models so that medical experts can see the important areas that impacted the decision-making of the AI.

Meanwhile, the system uses CFGAN (Coupled Fusion Generative Adversarial Network) to enhance diagnostic certainty through the fusion of X-ray and CT images. The CFGAN model receives CT slices and produces X-ray look-alike images, which are subsequently blended with actual X-ray images to produce a fused image. The fusion method enhances the visibility of fractures while maintaining fine details from both modalities so that radiologists are provided with a complete diagnostic image.

Dynamic web-based interaction and report generation complete the last level of the architecture. The model outputs from fusion, segmentation, and classification are assembled into an organized medical report, which also contains segmented images, fused data, classification information, and visualizations of Grad-CAM. This report assists in medical decision-making through the data-driven diagnosis summary. The whole system is made accessible via a web application based on Flask, making it possible for users to upload images, get results, and download reports to analyze further. The backend database manages patient data storage and retrieval efficiently, giving healthcare professionals an uninterrupted experience.

Through the use of several deep learning models, medical image fusion, and explainable AI methods, the architecture provides a strong, accurate, and understandable method of fracture detection. The modularity in its design allows for adaptability, facilitating continuous improvement and optimization in subsequent versions.

4.2.1 Phase 1: Preprocessing, Deteection and Classification

a. Preprocessing:

CT data is by virtue of its design a 3 D data type that can only be viewed in hospitals with special equipment and specialized software. In hospitals CT Scans are primarily stored , retrieved and viewed using specialized and industry standard systems like PACS (Picture Archiving and Communication System) that stores the high-resolution CT scans in a format called DICOM(Digital Imaging and Communications in Medicine). Different companies that manufacture CT Scanners have their own version of PACS but they are essentially the same at the core. The PACS allow the CT scan to be viewed on a DICOM monitor where it can be traversed through all three axes(Axial, Coronal and Sagittal). A traditional computer system cannot access a CT scan with softwares like DICOM viewer or 3D Slicer. Moreover an AI model cannot be given an Entire CT Scan as an input because of technical limitations. To combat this limitation we need to convert the 3D Scans into 2 dimensions . This is achieved by slicing along the 3 axis and getting a 2D image. This 2D image is stored as a PNG/JPEG image. Different axes have different 2D resolutions so all the slices are saved with their original resolution which are resized later either by the model or separately and saved in a folder.

Slicing a single scan can result in an image count of anywhere between 700 to 1500 images and saving these to a specific folder cannot be useful for the task of classification. The images need to be put into a specific directory separated into the 4 classes for classification. The 4 classes are Displaced fractures, Non-Displaced Fractures , Segmented fractures and Buckle fractures. For identifying the type of fracture the data set consisted of a label file that corresponds to the CT Scan. The same slicing method was used in the case of the label files. But in this method, each slice is not saved. Instead each slice is analyzed and converted into a numpy array. It is a 2D array where each line represents a pixel row in the image. The numpy array consists of multiple numbers ranging from 0 to 4, where 0 is the background ,1 is Displaced rib fracture, 2 is non-displaced rib fracture, 3 is buckle rib fracture and 4 is segmented rib fractures. After the image is converted to a numpy array the array is analysed from top to bottom and based on the labels the corresponding images in the CT scan are segregated into specific groups. These images are put into their specific folders with the correct directory path that is specified in the code.

The slicing module for the UNET model has a few changes as for UNET we need both the label image and the CT image. UNET cannot be used for classification tasks so we can ignore teh numpy conversion and completely save the label image into the labels folder and CT image into the image folder under a single for main folder for a particular CT Scan.

b. Image classification:

1. Model selection:

For fracture detection in CT scans, both segmentation and classification are required. Classification can be performed using a multi-class model. A few of the models that were tried include , YOLOv11, CNN8, HybridCnn and Resnet. For a preliminary assessment the models were trained on the axial axis and accuracy was only taken for a quick overview.

Model	**Accuracy**
CNN-8	32%
YOLOv11	54%
Hybrid-CNN	23%
ResNet-18	97%
ResNet-50	73%

Table 4.1: Preliminary Accuracy of Different Models

From this we selected Resnet as the model for classification as it was the most accurate and readily available to import.

2. Image classification in ResNet:

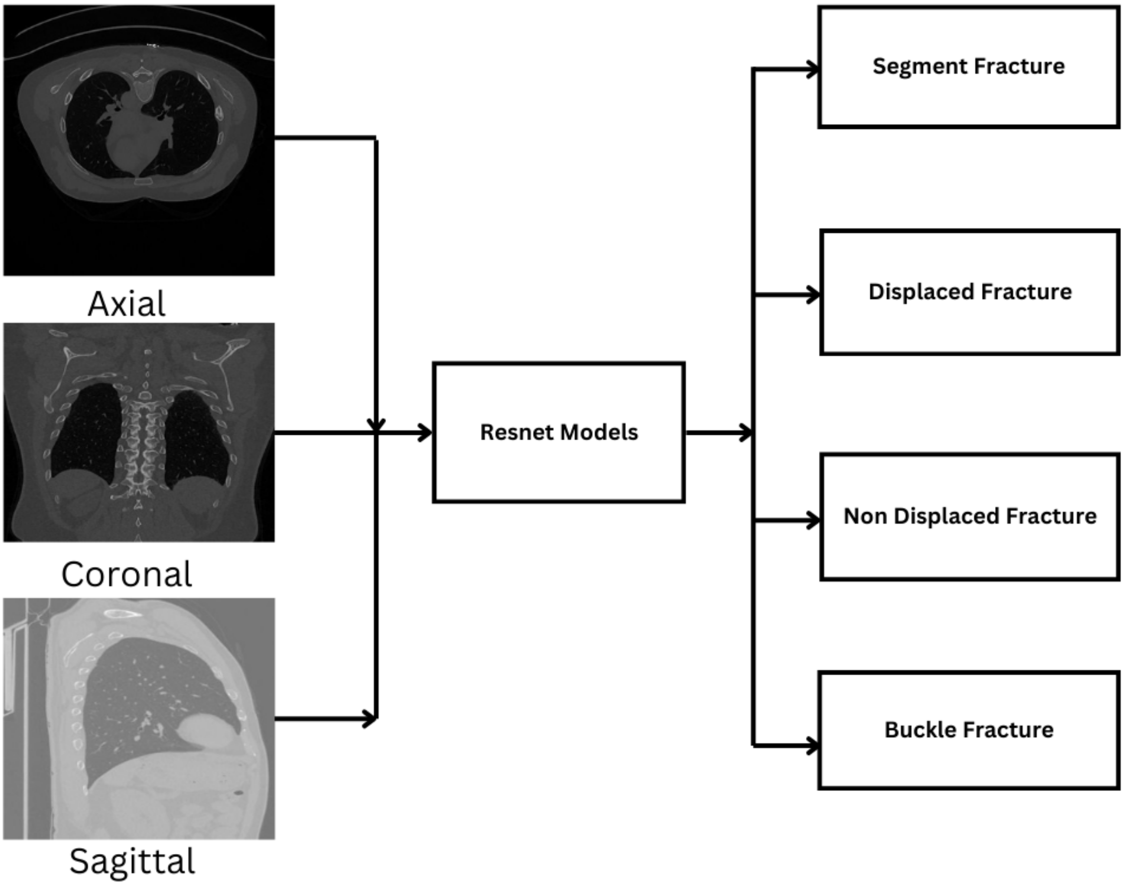


Figure 4.2: Fracture classification on ResNet

c. Image segmentation:

1. Model Selection:

   For the purpose of segmentation we needed a model that can be trained using supervised learning. This called for the need of a model that takes both images and labels as an input image for the purpose of training. In the paper [6] a comparison was made between U-Net,VGG16, VGG19, Resnet50,Xception for segmentation for detection of esophageal mucosa and squamous cell neoplasm. The results from the study are given below

Models	IoU (%)	Accuracy (%)	PPV (%)	TPR (%)	Specificity (%)	DSC (%)	AUC (%)	F1-Score (%)
U-Net	91.95	95.90	95.62	95.71	97.88	95.81	94.92	95.67
VGG16	51.01	65.71	51.75	69.51	73.81	67.56	62.41	59.33
VGG19	51.05	65.72	51.73	69.58	73.79	67.59	62.42	59.34
ResNet50	51.16	65.80	51.80	69.69	73.84	67.69	62.50	59.43
Xception	51.11	65.71	51.76	69.70	73.75	67.65	62.43	59.41

Table 4.2: Performance comparison of different models

2. UNET was selected as it was originally developed for medical image segmentation. It works well with limited data, can do precise Pixel-Level segmentation, it has no fully connected layer and can skip connections to help retain finer and smaller details

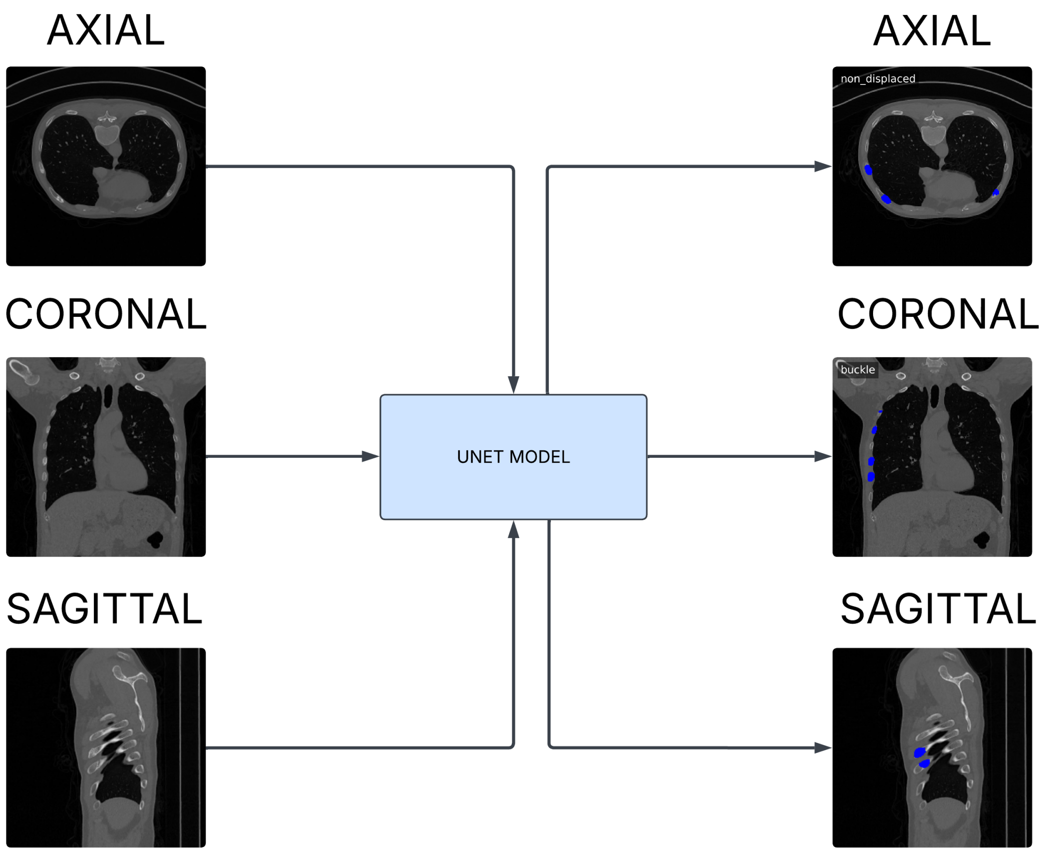


Figure 4.3: UNET Segmentation of fractures

For the accurate prediction and classification of fractures in our model we employed 2 Models , one being ResNet18 and the other being UNET. Resnet was chosen as it was the most accurate for finding fractures in medical images and works well with binary images and grayscale images like CT Scans. Moreover it has multiple versions with different internal structures like ResNet8, ResNet18, ResNet50, ResNet101 with 8, 18, 50 and 101 convolution layers respectively . For our applications RexsNet18 was selected for its ease of implementation and moderate load on our systems during training.The data was augmented and resized to a resolution of 256x256 for uniformity. The model was trained for 100 epochs and a batch size of 8.

d. Fracture Detection:

AI models in general give us results that we have to blindly trust if we have no background knowledge of the data that we are using. This gives us the interpretation that an AI model is a black box model, whose internal workings are hidden. To combat this issue we are using Explainable AI(XAI) to make the model more of a white box model. The XAI technique we are using is Heatmaps. It provides a visual representation of the area of interest of the model. For the heat map implementation we used Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM works by computing the gradient of the model's output by analyzing the final convolutional layer.This creates an activation map which is then overlaid onto the original CT scan to produce a heatmap. This allows for more transparency in our models results.

The results are saved into a specific patient directory after the slicing process and passing it to the model . This includes the result as well as the heat maps of the specific image. The user can download the consolidated result that consists of the details like patient details , doctor details, diagnosis and the model results which shows the outputs of the model. To implement this we used the reportgeneration model , which is a built-in module in python to make the reports. The first page is made to pull details from the database to get basic details like patient details and doctor details while the pages after that are made using a function that executes to build report pages as long as there are images in the result folder of the patient. The report also includes a dynamic element at the bottom where the date and time at which the report is made is placed.

4.2.2 Phase 2: Medical Image Fusion

a. Synthetic X-Ray generation

1. Need for Synthetic X-ray:

   Although X-rays are commonly employed for fracture detection, they do not provide the depth and structural information inherent in CT scans. In most situations, obtaining both CT and X-ray scans from the same patient is cost-prohibitive, either through radiation exposure or lack of availability. Synthetic X-ray generation compensates by generating X-ray-like images from CT scans directly so that the fusion process has higher-quality inputs for better diagnosis.

   Through the use of deep learning-based transformation methods, synthetic X-ray creation not only mimics the contrast and definition of actual X-rays but also preserves significant structural information from CT scans. This guarantees that radiologists and AI algorithms gain advantages through a more diverse dataset that blends the strengths of both imaging systems. Furthermore, routine X-ray imaging tends to have difficulty with overlapping structures and thus may cause misinterpretation, while synthetic X-rays based on CT scans enable more detailed visualization of fractures with clearer presentation and fewer occlusions.

   The second important advantage of synthetic X-ray generation is reduction in patient load. Instead of exposing patients to a series of scans, clinics and hospitals are able to derive synthetic X-rays from already performed CT scans with lower doses of radiation, saving on diagnostic quality. In regions where the presence of X-ray machines is lesser, synthetic models of X-rays can enable clinicians to make first fracture diagnoses by utilizing only CT scans, improving diagnostics accessibility for patients in poverty-stricken surroundings.

   The incorporation of GAN-based models for synthetic X-ray generation also helps enhance AI-assisted diagnosis, as fusion models learned with real and synthetic data sets enjoy increased variability and generalization. This results in more reliable and effective fracture detection, eliminating false negatives and false positives in medical image-based AI. In the end, synthetic X-ray generation is essential for augmenting medical image fusion, streamlining clinical workflows, and enhancing patient outcomes in fracture diagnosis.

2. Purpose:
   Synthetic X-ray generation from CT scans is based on a well-defined pipeline intended to provide real representation of the bone structures along with improved diagnostic clarity. It starts with preprocessing of CT images where axial, coronal, and sagittal slices are obtained from the raw 3D CT scan.In order to ensure uniformity and enhance contrast, intensity normalization and histogram equalization are carried out, thereby reducing pixel intensity variations as much as possible and minimizing noise that can affect the fusion process.

   Depth-to-projection transformation is then performed after preprocessing, which is a significant process projecting 3D depth data of CT scans into 2D projection views. This process is designed to simulate transmission of X-rays through bone tissues such that the synthetic X-ray so produced retains detection of fractures and closely approximates real radiographic images.

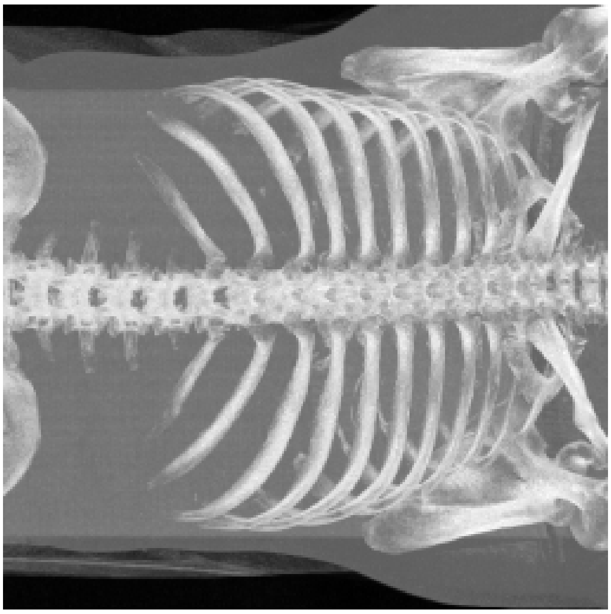


Figure 4.4: Synthetic fracture 1

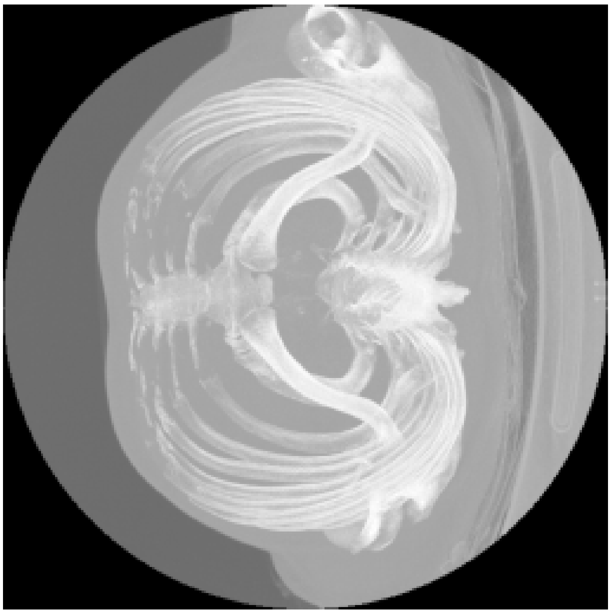


Figure 4.5: Synthetic fracture 2

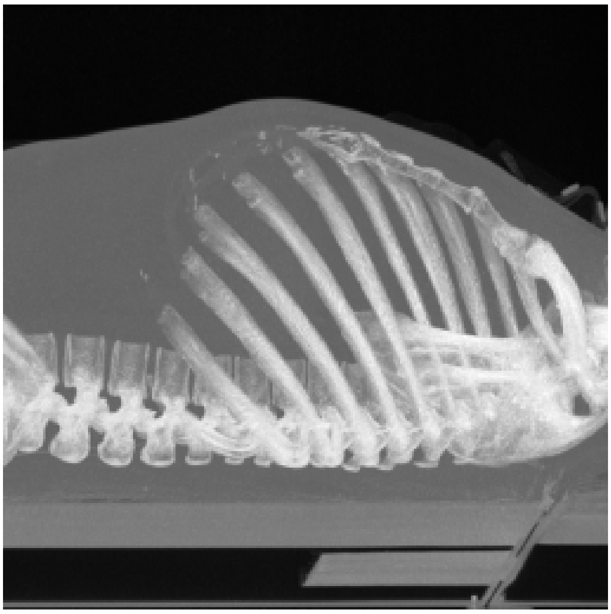


Figure 4.6: Synthetic fracture 3

Final processing and image quality improvement is the last operation, where high-end techniques like adaptive histogram equalization and filtering denoisers are used in order to refine the synthetic X-ray images one step further.These procedures help in the removal of noise, enhancement of contrast, and overall clarity so that the produced images not only structurally compare with real X-rays but also are optimized to fuse with real X-ray scans. This process allows high-quality synthetic X-rays to be created, which act as good inputs for medical image fusion, and thus enhance the diagnostic performance of fracture detection

b. Fusion

1. Diagram and Processes

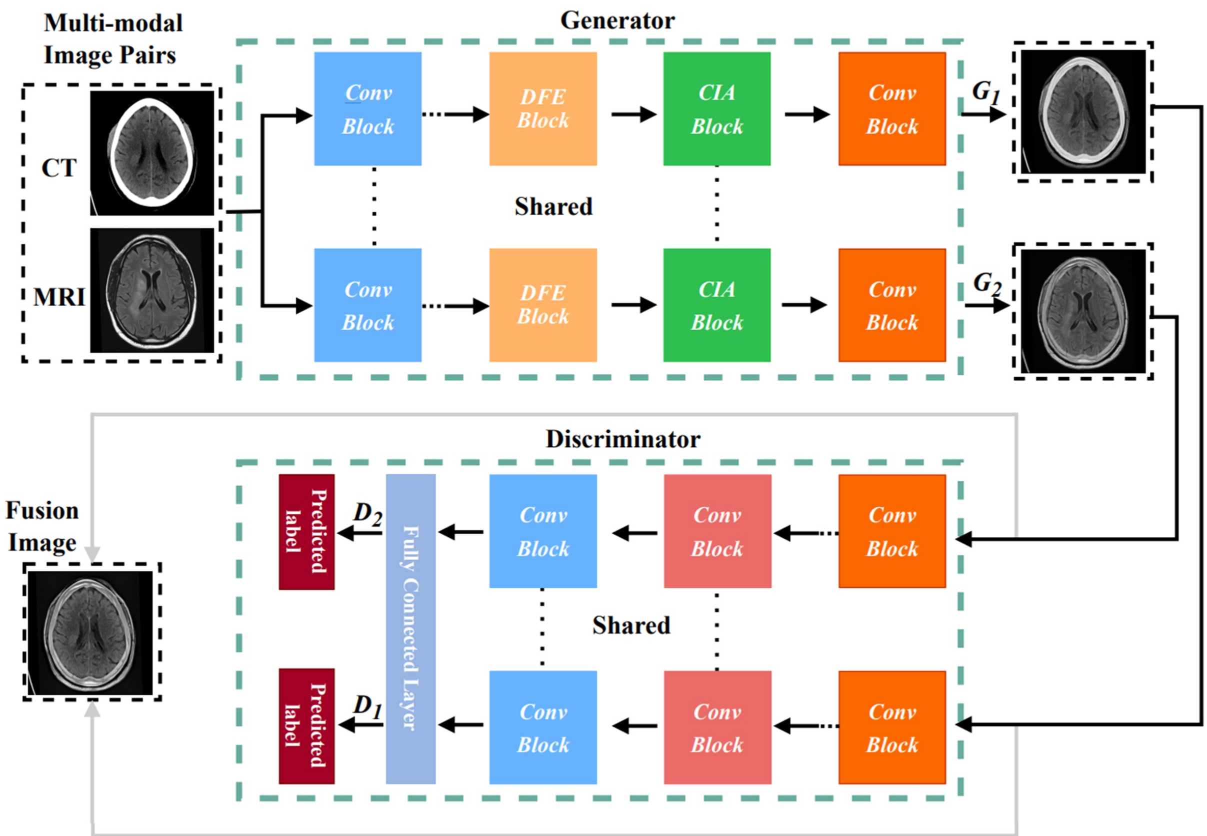


Figure 4.7: CFGAN Architecture

The medical image fusion technique with CFGAN includes the intelligent combination of synthetic X-rays and CT slices to generate an improved and more detailed medical image. The technique starts with the selection of input images, where slices of CT scans from axial, coronal, and sagittal planes are combined with their respective synthetic X-rays.These images are feature-extracted by deep networks, in which the generator model extracts important features from both modalities.Whereas the CT scans give structure depth, the synthetic X-rays highlight bone contrast so that the merged image retains the most vital diagnostic information.

After feature extraction, CFGAN-based fusion follows. The generator network forms a better image from the best CT and simulated X-ray image features. The discriminator network verifies the combined images so that they are medically realistic as well as agree with expert radiologist readings.The combined images are boosted for higher contrast, clarity, and diagnostic use through several iterations of adversarial learning.

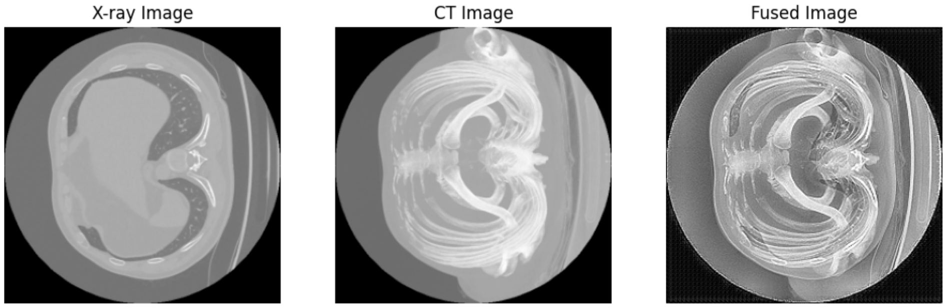


Figure 4.8: Fusion of Axial Slice

Finally, output enhancement and Grad-CAM visualization are used to refine image quality and emphasize fracture-vulnerable areas. Heatmaps based on Grad-CAM enable visualization of AI model reasoning with higher transparency and confidence in computer-aided diagnosis. This integration process greatly enhances detectability of fractures, minimizes diagnostic errors, and provides clinically informative outputs, thus allowing radiologists to make more accurate decisions.

2. Analysis

   In order to evaluate the performance of our CFGAN-based medical image fusion algorithm, we compare the visual quality of resulting fused images and the quantitative performance metrics that measure structural similarity and image fidelity. The testing is conducted in a number of fusion situations with CT slices (axial, coronal, sagittal) and synthetic X-rays to provide thorough testing of our model's performance.

   Quantitative Metrics Evaluation The performance of CFGAN is measured using well-standardized image quality metrics:

   - Structural Similarity Index (SSIM): – SSIM measures the degree up to which the output fused image maintains structural detail from the input modalities. Higher SSIM value indicates better fusion, in which anatomical information necessary for diagnosis is preserved.

- Peak Signal-to-Noise Ratio (PSNR): – PSNR estimates how well the image reconstruction is done by relating signal strength to noise. Higher PSNR value indicates that the fused image contains high fidelity and has minimum distortions.
- Recall: – The ability of the model to effectively identify fractures in fused images. A high value for recall would indicate that the model effectively identifies most fractures without missing important cases.
- Test Accuracy – The total accuracy of CFGAN in correct classification of fused images into fractured or non-fractured groups. The metric provides an indication of the effectiveness of the fusion process in improving diagnostic consistency.

Metric	Value
SSIM (X-ray vs Fused)	0.6865
PSNR (X-ray vs Fused)	21.08 dB
SSIM (CT vs Fused)	0.7656
PSNR (CT vs Fused)	25.79 dB

Figure 4.9: Metrics For Axial

Our results table yields a comparative analysis of SSIM and PSNR values for various fusion methods, pointing out the superiority of CFGAN over conventional fusion approaches. Comparison proves that CFGAN produces higher SSIM and PSNR values in all cases such that the fusion images preserve structural depth from CT scans but improve contrast through synthesized X-rays.

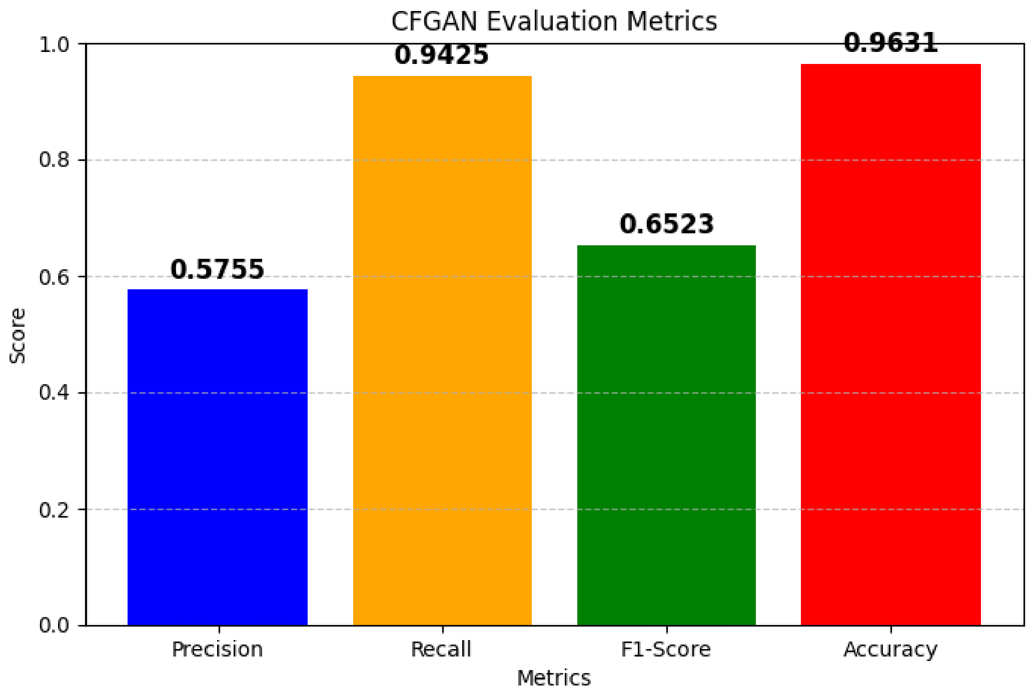


Figure 4.10: Results Of CFGAN

Visual Inspection & Fractale Clarity

- In addition to quantitative assessments, the visual quality of the fused images is also checked to evaluate fracture detectability, noise reduction, and anatomical harmony. Fused images produced by CFGAN demonstrate:
- More clear-cut fracture boundaries, providing better fracture detection of subtle fractures.
- Improved bone contrast, which enhances the diagnostic performance of the fused images.

  Low artifacts, minimizing distortions associated with traditional fusion methods.

4.2.3 Phase 3: Web Interface for Medical Emergencies

a. Features

1. Design Overview:

   The system is designed as an interactive web application to assist doctors in managing fracture detection and patient records efficiently. The frontend, built using HTML, CSS, and JavaScript, allows users to upload CT scans, navigate through slices, and view model-generated results seamlessly. This interface interacts with a Flask backend, which handles image processing, model inference, and data retrieval. To ensure structured data management, the backend communicates with a relational database, built on Flask SQLAlchemy, organized with two primary tables: Doctor and Patient. The database schema is provided in Table 4.3.

2. Explanation of Each Section:

   i. User Authentication & Access Control

      - Doctors must log in with their credentials to access the system.
      - New users can register, and their details are stored in the Doctor table of the database.
      - The system validates credentials before granting access, ensuring security and restricted access.

   ii. Home Page & Navigation

      - Upon login, the doctor is redirected to a personalized home page displaying a welcome message and usage instructions.
      - The interface provides options to add a new patient or view existing patient records.

   iii. Adding a New Patient

      - Doctors can enter patient details such as name, gender, date of birth (DOB), and diagnosis.
      - The system allows CT scan uploads, which are stored in the database and linked to the respective patient.
      - Once added, the patient's details are permanently stored, ensuring easy retrieval.

   iv. Viewing Patient Records & Performing Fracture Detection

- The View Patients page presents all registered patients in a tabular format.
- Doctors can browse a list of patients, view their details, and access uploaded CT scans.
- The system provides an interactive image slider to navigate through CT slices.
- Doctors can run fracture detection models, and results are displayed alongside the scan.

v. Report Generation & Download

- The system can automatically generate diagnostic reports summarizing the model's findings.
- These reports are formatted into PDFs for easy sharing and storage.

b. GUI, Database, Expected Output

(a) GUI (Graphical User Interface)

- Built using HTML, CSS, JavaScript for a responsive and user-friendly design.
- Features include file uploads, patient management, interactive CT scan viewing, and model result visualization.

(b) Database Structure

- The Doctor table stores login credentials and user details.
- The Patient table contains demographic data, diagnosis, and CT scan references, ensuring structured data storage.
- The system implements a one-to-many relationship, where each doctor can manage multiple patients.

Column	Data Type	Constraints	Description
		Doctor Table	
id	Integer	Primary Key	Unique doctor ID
doctor_id	String(5)	Unique, Not Null	Assigned doctor identifier
doctor_name	String(80)	Unique, Not Null	Doctor's full name
username	String(80)	Unique, Not Null	Login username
password	String(80)	Not Null	Hashed password
		Patient Table	
id	Integer	Primary Key	Unique patient ID
first_name	String(80)	Not Null	Patient's first name
middle_name	String(80)	Nullable	Patient's middle name
last_name	String(80)	Not Null	Patient's last name
gender	String(80)	Not Null	Patient's gender
dob	Date	Not Null	Date of birth
age	Integer	Not Null	Patient's age
diagnosis	String(200)	Not Null	Diagnosis details
ct_scan	String(120)	Not Null	Path to CT scan file
doctor_id	String(5)	Foreign Key	Links to Doctor(doctor_id)

Table 4.3: Database Schema for Doctor and Patient Tables

(c) Expected Output

- Doctors can log in securely and manage patient data efficiently.
- The system will process CT scans, displaying fracture detection results using machine learning models.
- Generated reports will be stored and downloadable as PDFs, providing structured diagnostic insights.

4.3 Work Schedule - Gantt Chart

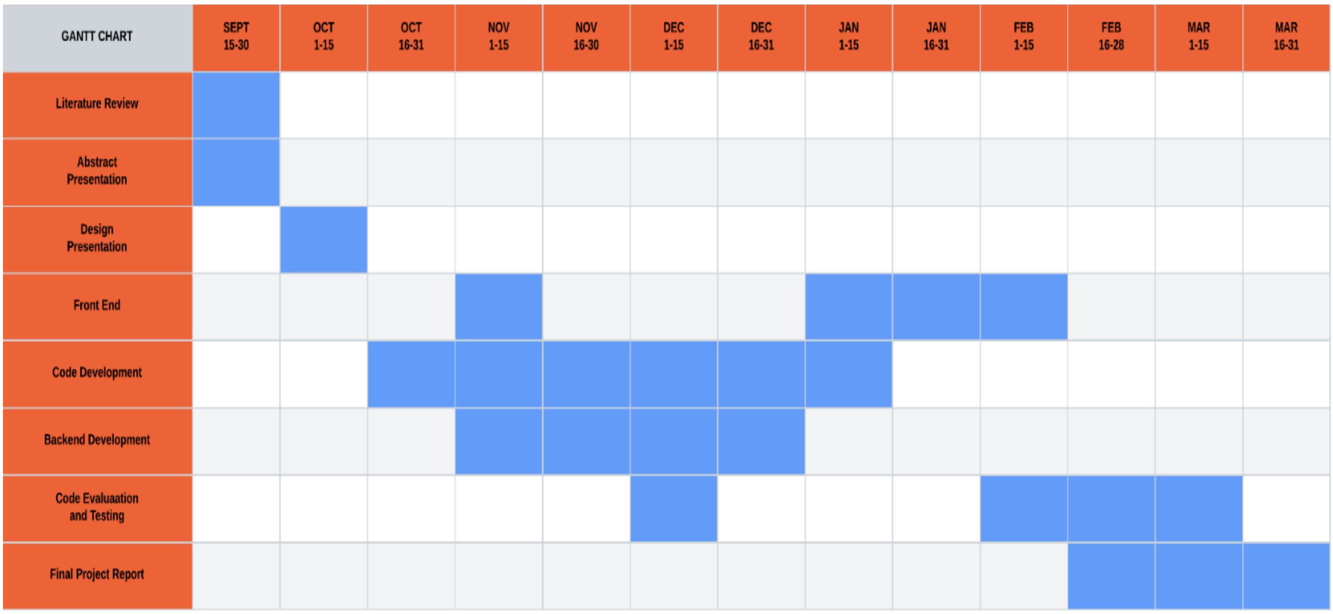


Figure 4.11: Gantt Chart

Chapter 5

Results and Discussions

This chapter includes the thorough findings from our fracture detection system, which was designed to assist radiologists diagnose chest CT scans quickly and efficiently in order to reduce workloads and to reduce the chances of missing fractures due to human error. With the help of an intuitive, user-friendly interface, users of the system can add patient details along with their CT scan and X-Ray to detect and classify fractures within them. The system uses CFGAN to fuse the CT scan and X-Ray. The CT scan can be viewed in 3 different axes seamlessly. The system also automatically generates a report containing patient details and fracture detection results along with their corresponding heat maps generated with XAI, further enhancing understandability and trust. We evaluate our system's overall effectiveness, accuracy, and efficiency in helping medical professionals diagnose fractures in chest CT scans.

5.1 System as a whole

Our artificial intelligence-powered medical imaging system presents a simple, easy-to-use interface to aid in smooth management of patient information and CT scan analysis to support an intuitive, hassle-free user experience. User login or system sign-up can be done while adding multiple records of patients, uploading CT scans in an orderly fashion to assist in easy browsing of each slice and result. The uploaded scans are then processed by the system's backend. The backend incorporates deep learning models to identify and classify fractures in the CT scans efficiently and CFGAN to fuse X-Rays and CT scans. After a scan is uploaded, the X-ray and the CT scan are fused using CFGAN. Then the system applies the UNET model for segmentation to detect possible fracture areas with coloured blobs for visibility. After the predictions of the UNET, the ResNet18 model is applied to classify fractures into four classes: Displaced fractures, Non-Displaced fractures, Segmented fractures, and Buckle fractures. ResNet has high performance in medical image classification. It classifies fractures correctly with a combination of convolutional layers for feature extraction. Upon processing by the UNET and ResNet18 models, the system provides a detailed result set containing the classified type of fracture, confidence scores, and visual heatmaps generated using Grad-CAM. The heatmaps indicate significant areas in the scan that contributed to the model's decision, providing improved interpretability and facilitating radiologists to confirm results. Furthermore, the system also automates the creation of structured reports about patients. These patient reports integrate patient information, fracture classifications identified, confidence, and heatmaps into an orderly document that can be easily viewed. The reports are downloadable and can be shared for additional medical assessment to support continuity of care and efficient clinical decision-making. By combining deep learning models with an easy-to-access web interface, our AI-enabled medical imaging technology improves diagnostic speed and accuracy in detecting fractures via CT scans. The use of UNET to segment, ResNet18 for classifying, and Grad-CAM for interpretability provides for an easy, user-friendly system to aid radiologists in diagnosis of CT scans.

5.2 UNET Model

The UNET model plays a crucial role in the system by performing precise segmentation of rib fractures from CT scan images. As an advanced deep learning architecture designed for medical image segmentation, UNET effectively delineates fractured regions. UNET follows an encoder-decoder structure with skip connections that help retain fine details. The encoder consists of multiple convolutional layers that extract hierarchical features, while the decoder reconstructs the segmented image with high spatial accuracy. Skip connections link corresponding encoder and decoder layers to preserve spatial context, which is critical for identifying fractures in CT scans. Since CT scans can be viewed through three different axes: axial, coronal and sagittal, we trained three UNET models for each axis.

5.2.1 UNET Metrics

Model	Epoch	Dice Coefficient	Loss	Precision	Recall
Axial	43	0.7708	0.2292	0.8500	0.7250
Coronal	49	0.6193	0.3807	0.7370	0.5728
Sagittal	68	0.8242	0.1758	0.9035	0.7901

Table 5.1: Training Metrics

Model	Epoch	Dice Coefficient	Loss	Precision	Recall
Axial	43	0.5688	0.4309	0.8107	0.7404
Coronal	49	0.3101	0.6898	0.7393	0.5656
Sagittal	68	0.4732	0.5266	0.8957	0.7429

Table 5.2: Validation Metrics

Model	Accuracy	F1	Jaccard	Precision	Recall
Axial	0.9997	0.7859	0.7708	0.9346	0.8165
Coronal	0.9997	0.8054	0.7961	0.9522	0.8277
Sagittal	0.9997	0.8135	0.8054	0.9750	0.8210

Table 5.3: Test Metrics

5.3 ResNet18

Our fracture classification system leverages ResNet18, a deep convolutional neural network, to classify fractures into distinct categories. ResNet (Residual Network) is widely used for medical imaging tasks due to its ability to learn deep hierarchical features while addressing the vanishing gradient problem through residual connections.

5.3.1 ResNet18 Metrics

Model	Epoch	Training Accuracy	Training Loss	Training Precision	Training Recall
Axial	100	92.49	11.34	91.38	90.24
Coronal	100	91.28	7.54	94.55	92.20

Table 5.4: Training Metrics

Model	Epoch	Loss	Validation Accuracy	Validation Loss	Validation Precision	Validation Recall
Axial	100	41.17	83.84	41.17	83.45	85.78
Coronal	100	10.11	90.22	10.11	92.15	84.25

Table 5.5: Validation Metrics

Class	Accuracy
Buckle Rib Fracture	93.35
Displaced Rib Fracture	82.65
Non-Displaced Rib Fracture	86.86
Segmented Rib Fracture	99.71

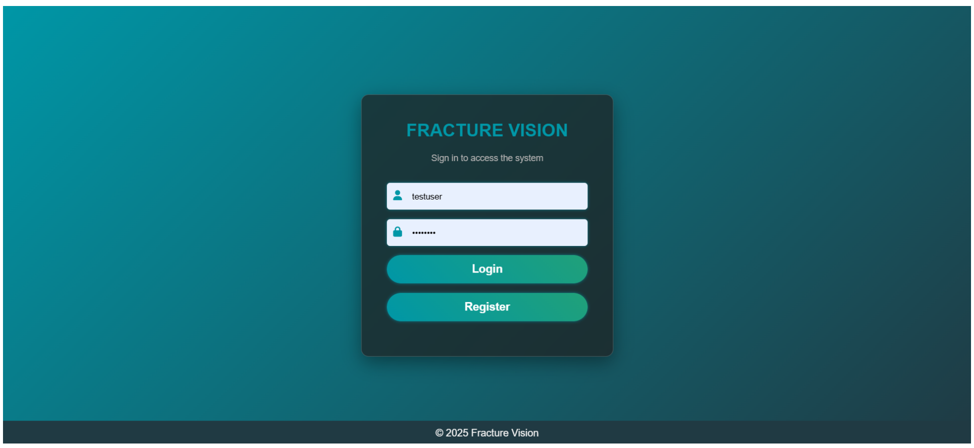
Table 5.6: Test Metrics

The sagittal axis presents images where multiple rib fracture classes appear together within one slice that results in confusion for the model when training. Fractures appear more distinctly separated in axial and coronal views compared to sagittal slices which show overlapping or adjacent fractures from multiple categories. The model frequently misclassificies fractures and results in low accuracy level of 22% . Because of these reasons the sagittal model was not implemented.

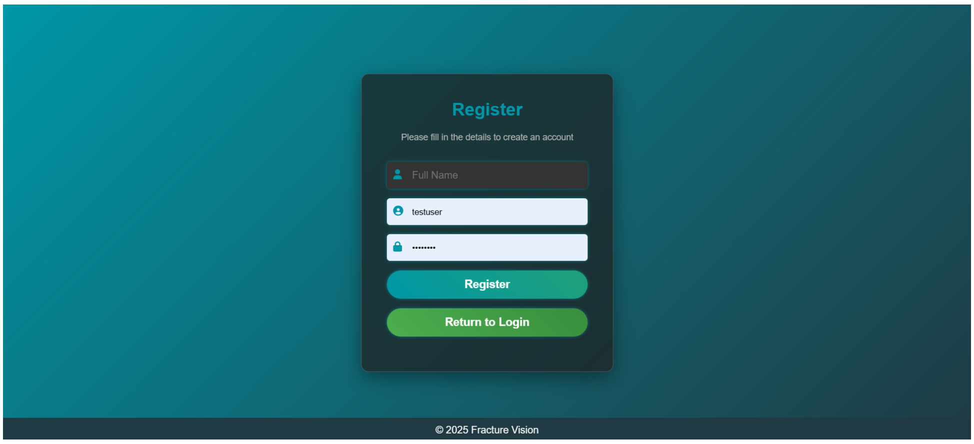
5.4 User Interface

Our system features a structured and intuitive user interface that allows seamless interaction for healthcare professionals. Upon accessing the system, users are first presented with a login and signup page, where they can authenticate their credentials to enter the platform. The homepage provides two primary options: viewing existing patient records or adding a new patient. When adding a patient, the user enters relevant details and uploads a .nii CT scan file. The system then automatically processes this file, slicing it into a series of 2D PNG images, which are stored in a dedicated directory for that patient. Once patients are added, they are displayed in a structured list on the "View Patients" page, where users can access individual patient profiles. Each profile provides options to visualize the CT scan across three anatomical axes: axial, coronal, and sagittal. The detection process can be initiated directly from the patient's profile. Once started, the system sends the preprocessed CT slices to the UNET model for segmentation and the ResNet model for fracture classification. After processing, the results are stored and made available for review. Users can navigate to the results section to examine model outputs, including segmentation masks and heatmaps generated via explainability techniques. Additionally, the system provides an option to generate a structured report summarizing the findings, which can be downloaded for further reference.

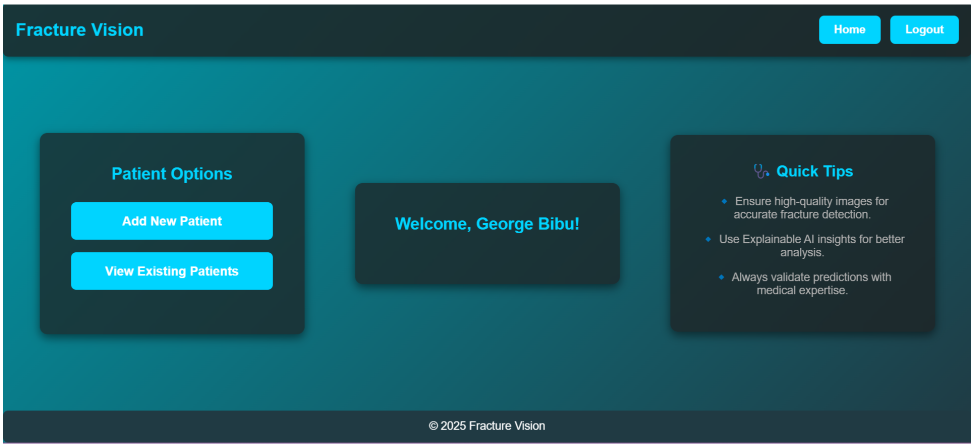
5.4.1 Login Page



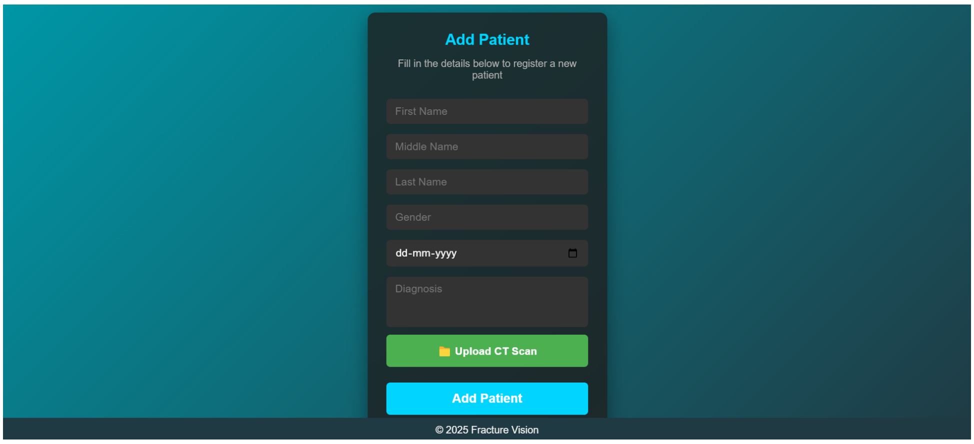
5.4.2 Sign-Up Page



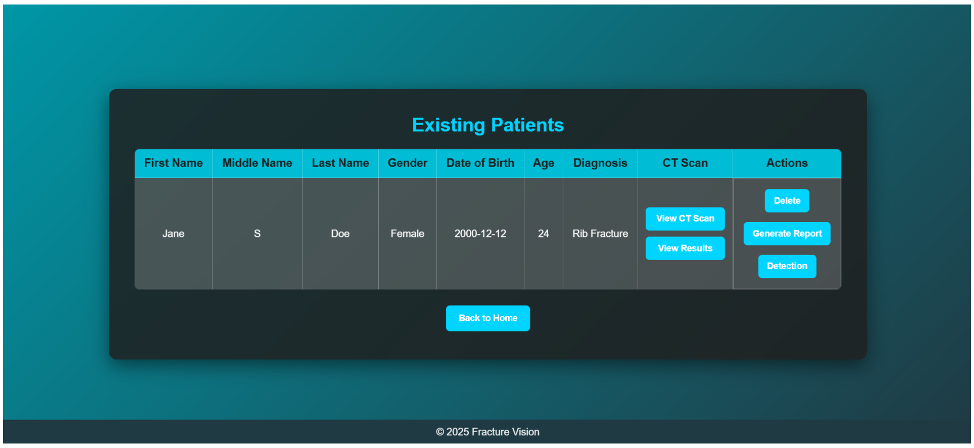
5.4.3 Home Page



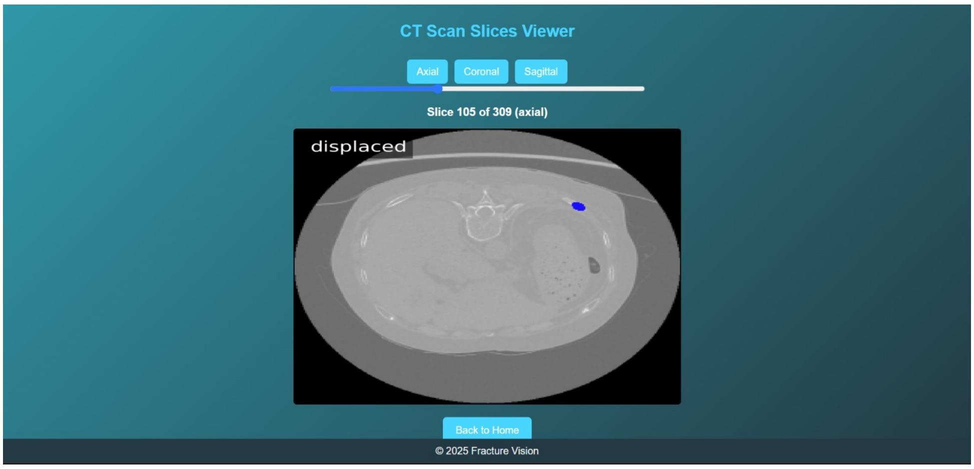
5.4.4 Add Patient Page



5.4.5 View Patients Page



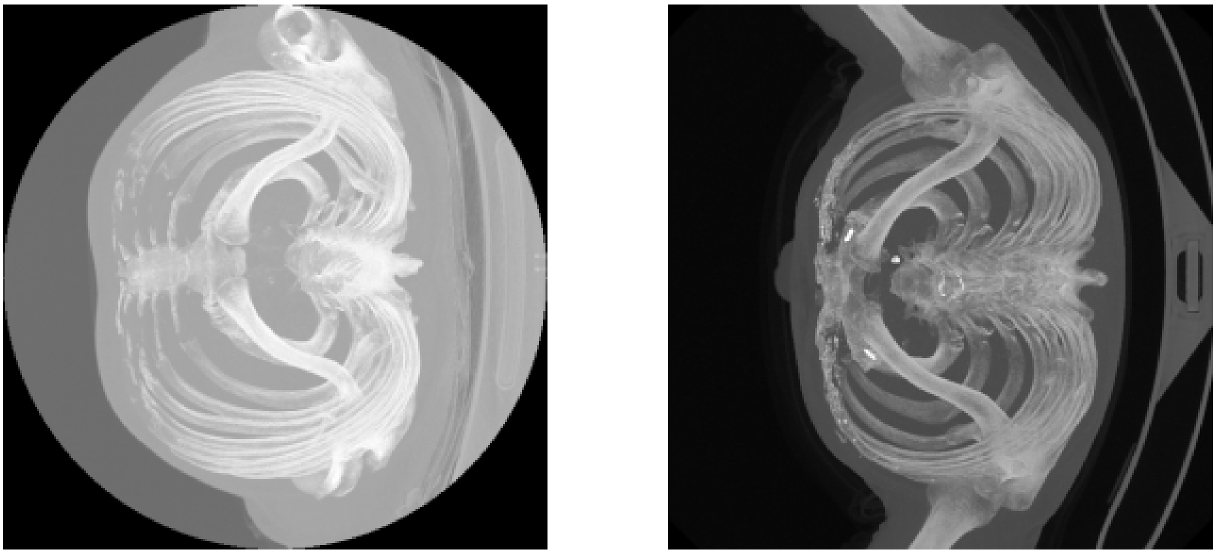
5.4.6 Results Display Page



5.5 Synthetic X-ray and Medical Image Fusion

The efficacy of the synthetic X-ray generation procedure is measured with respect to structural similarity of generated images to real X-rays. The synthetic X-rays preserve dominant anatomical characteristics and improve bone contrast, yet are amenable to fusion with CT scans. Synthetic X-ray intensity distribution follows real X-rays closely, which ensures that the synthetic X-rays yield diagnostically relevant inputs for the process of fusion.

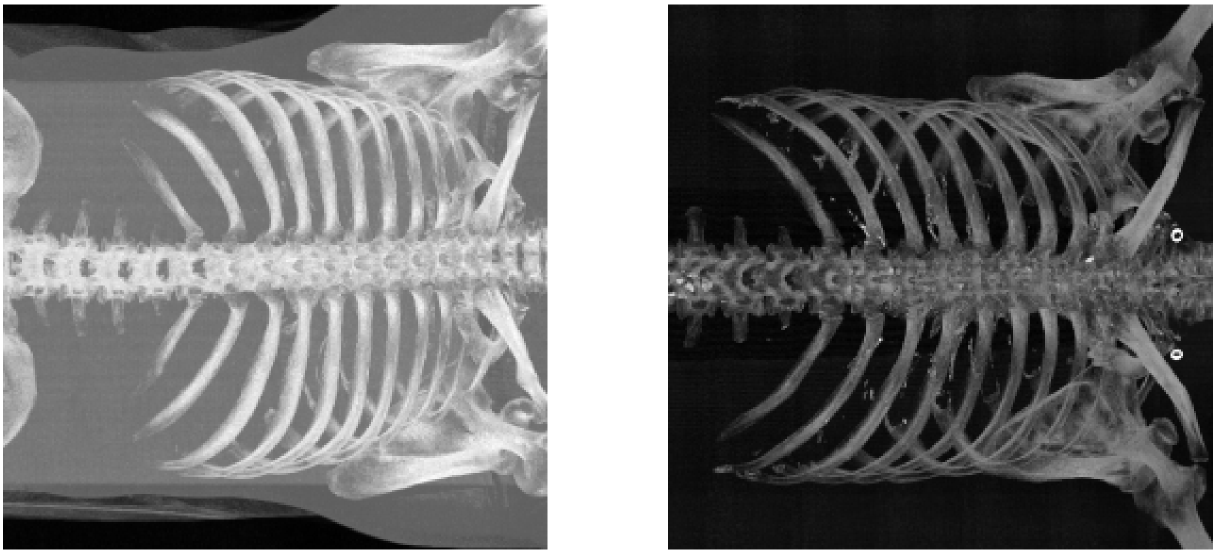
To evaluate synthetically generated X-ray quality quantitatively, we measure SSIM and PSNR scores between synthetic and actual X-rays. The values reflect high structural similarity, establishing that the synthetic images accurately reproduce actual X-rays with



(a) Synthetic X-ray (b) Real X-ray

Figure 5.1: Comparison between Synthetic and Real X-ray images.

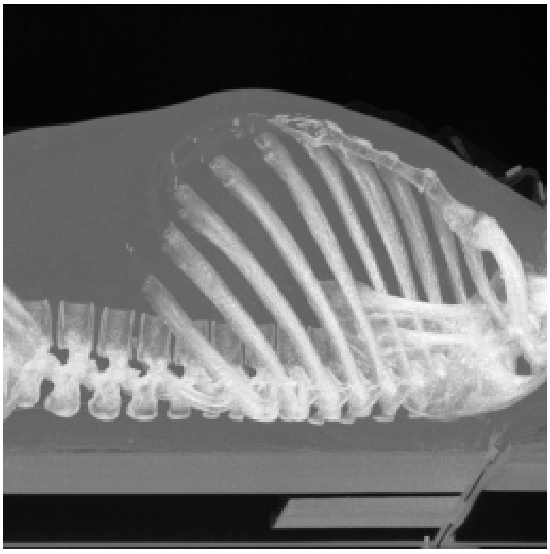
essential fracture details intact. The adversarial learning method ensures that the produced X-rays are free from unwanted artifacts and have high visual sharpness.



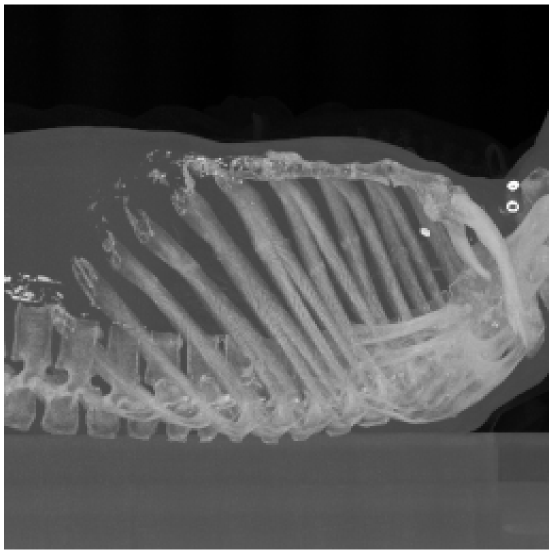
(a) Synthetic X-ray (b) Real X-ray

Figure 5.3: Comparison between Synthetic and Real X-ray images.

Visual inspection also certifies the proficiency of synthetic X-ray creation with better bone contour and higher contrast in areas of interest. It greatly enhances the fusion pipeline through the validation of input images fused for higher diagnostic value, culmi-



(a) Synthetic X-ray



(b) Real X-ray

Figure 5.2: Comparison between Synthetic and Real X-ray images.

nating in system performance enhancement overall.

The proposed CFGAN-based image fusion system for medical images was evaluated using axial, sagittal, and coronal CT slices and their corresponding X-ray images. The resulting fusions were compared on their structural integrity, clarity, and capacity to outline fractures. Qualitative assessment found that in the majority of cases, the fusion process maintained salient anatomical details effectively such that fractures were made more apparent that were less obvious in stand-alone CT or X-ray images. The merged images were able to combine the depth information of CT scans and X-ray's high contrast, making it easy to analyze the bone structures.

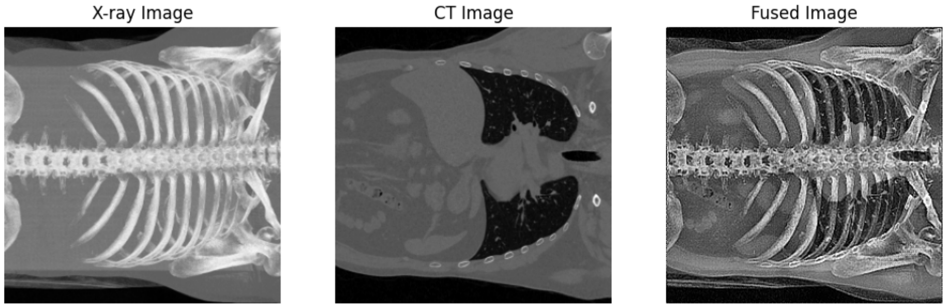


Figure 5.4: Fused Image of the Coronal Slice

Metric	Value
SSIM (X-ray vs Fused)	0.6525
PSNR (X-ray vs Fused)	12.47 dB
SSIM (CT vs Fused)	0.6014
PSNR (CT vs Fused)	20.90 dB

Figure 5.5: SSIM and PSNR

However, there are some limitations. Due to the limited size of the dataset, at certain times the model was unable to generalize fracture types. A few of the blended outputs also showed blurriness to an extent that reduced the overall sharpness of the image by making the fracture lines of smaller magnitude less apparent. In addition to this, fusion artifacts also occurred in a few instances when the registration of the CT and X-ray images was not perfect, causing some distortions in certain areas of the fused images. Overcoming these disadvantages, the overall improvement of diagnostic interpretability shows that CFGAN has excellent potential to improve medical image fusion techniques.

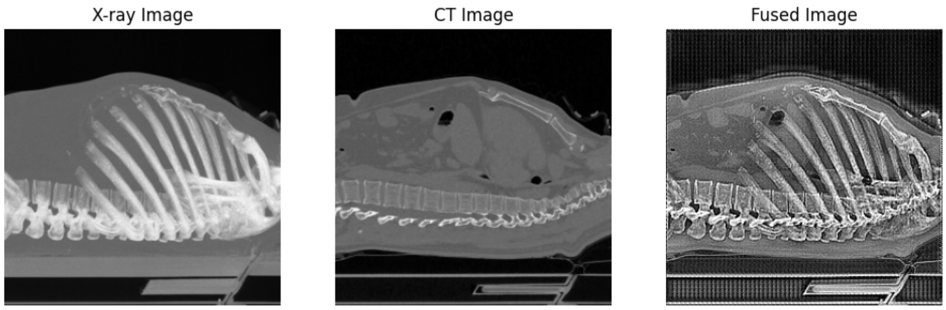


Figure 5.6: Fused Image of the Sagittal Slice

Metric	Value
SSIM (X-ray vs Fused)	0.6394
PSNR (X-ray vs Fused)	15.37 dB
SSIM (CT vs Fused)	0.5767
PSNR (CT vs Fused)	22.65 dB

Figure 5.7: SSIM and PSNR

To provide qualitative analysis of the performance of fused images, other quantitative metrics such as Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) were used. SSIM values revealed that the fused images retained fundamental structural information so that critical diagnostic data was minimally lost. PSNR values reflected that image quality was adequately sustained by fusion with no abnormal noise enhancement. A comparison with common fusion techniques indicated that CFGAN performed better in maintaining fine-grained details at the expense of eliminating unwanted artifacts compared to classical approaches.

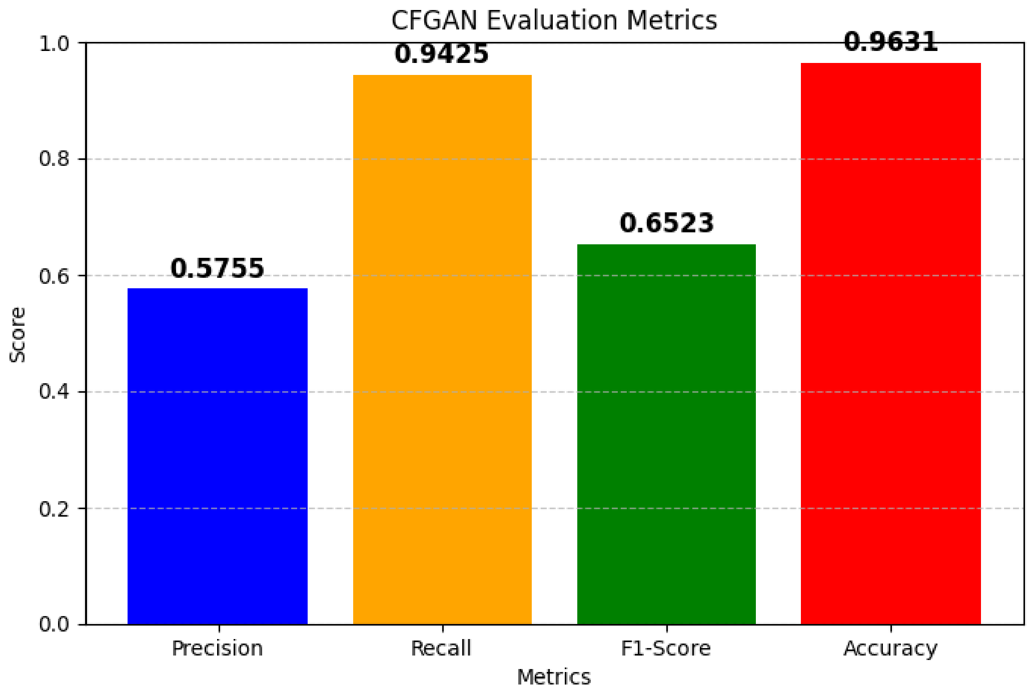
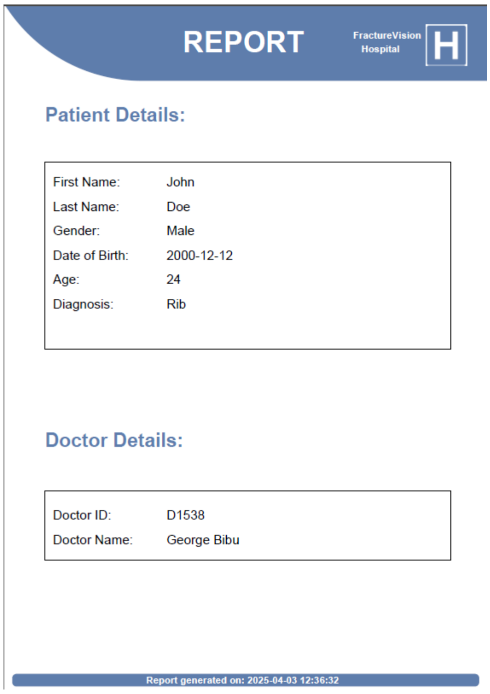


Figure 5.8: Evaluation Metrics

Overall, the findings suggest that CFGAN-based medical image fusion introduces a new way forward for enhancing fracture visibility and diagnostic clarity.

5.6 Report Generation

The report generation module is responsible for compiling patient details, model predictions, and visual outputs into a structured document. Each report begins with an overview of the patient's information, including their name, age, gender, date of birth and diagnosis along with the corresponding doctor's details. Following this, the results obtained from both the UNET and ResNet models are presented in a structured format. The UNET model's segmentation masks are displayed alongside the ResNet model's fracture classification outputs, which include confidence scores and heatmaps.



REPORT

FractureVision Hospital

Patient Details:

First Name:	John
Last Name:	Doe
Gender:	Male
Date of Birth:	2000-12-12
Age:	24
Diagnosis:	Rib

Doctor Details:

Doctor ID:	D1538
Doctor Name:	George Bibu

Report generated on: 2025-04-03 12:36:32

Figure 5.9: Report Front Page

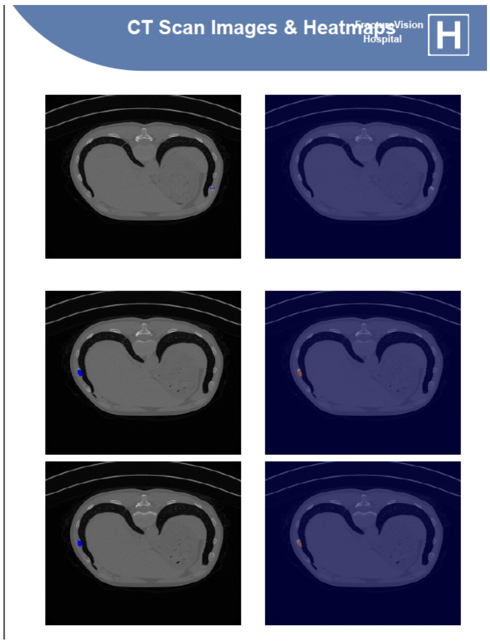


Figure 5.10: Report Results

5.7 Chapter Summary

The outcomes highlight the effective deployment of our AI-based fracture detection system, combining UNET for segmentation and ResNet for classification and CFGAN for

X-Ray and CT image fusion. The system effectively processes CT scans, isolates meaningful slices, and detects fractures, presenting users with a clear visual representation of the abnormalities identified. Heuristics generated using XAI methods further boost interpretability through highlighting severe regions of interest. Structured reporting facilitates the ease of recording of all findings such as patient information and model responses for quick reading by medical doctors. In totality, the system proves worthy as an aide for radiologists in that the process of detection of fractures becomes simplified and is more efficient from a diagnostic viewpoint.

Chapter 6

Conclusions & Future Scope

6.1 Conclusion

FractureVision provides a comprehensive system for rib fracture detection and classification using deep learning and Explainable AI(XAI) and gives a complete solution for analyzing fractures in CT Scans. By using ResNet 18 and UNET for classification and segmentation , the overall system can identify fractures and highlight the regions of fractures with high accuracy. Through the use of slicing we also overcome the challenges associated with high dimensional data. The use and incorporation of XAI technique Grad-Cam ensures that the model is focusing on the correct area , aiding both the developers and the doctors making more informed decisions. Finally the inclusion of an interactive Web-based interface allows medical professionals to easily interact with the models, visualize results and generate automated results.

6.2 Future Scope

The current project with the trained models has very promising results, but there are several areas where improvements can be made. A few of the possible future enhancements are:

1. **Implementing a Multi-Modal System:** The system can be made more versatile by incorporating X-Rays and MRI scans along with CT Scans for broader application and improved diagnosis.

2. **Improving Segmentation:** The system's U-Net model can be enhanced by adopting advanced architectures like Attention U-Net or Swin U-Net, which provide higher accuracy in fracture localization.

3. **Fracture Severity Assessment:** A grading system can be integrated into the project to classify fractures based on severity, assisting medical professionals in making informed decisions.

4. **Optimization for Low-Power Systems:** Currently, the project relies on powerful hardware with a dedicated GPU. Since many hospitals lack such resources, optimizing the system to run efficiently on edge devices (e.g., NVIDIA Jetson) and utilizing frameworks like TensorRT or ONNX can improve inference speed and accessibility.

5. **Enhancing Explainable AI (XAI) Techniques:** At present, Grad-CAM is used for heatmap generation on 2D images. However, there is no straightforward implementation for 3D CT scans. Ongoing research in this area may enable future integration of explainability techniques for 3D medical data.

6. **Enhancing Fusion Techniques:** The Coupled Fusion Generative Adversarial Network is mainly used for fusion process but as improvement the fused images can be fed to models like various resnet which fill further improve the detection and classification purpose and improve the whole project.

References

[1] F. Pérez-García, R. Sparks, and S. Ourselin, "Torchio: A python library for efficient loading, preprocessing, augmentation, and patch-based sampling of medical images in deep learning," *Computer Methods and Programs in Biomedicine*, vol. 208, p. 106236, 2021.

[2] Q. Mao, W. Zhai, X. Lei, Z. Wang, and Y. Liang, "Ct and mri image fusion via coupled feature-learning gan," *Frontiers in Endocrinology*, vol. 14, pp. 1–11, March 2024.

[3] J. Zhang, F. Liu, J. Xu, Q. Zhao, C. Huang, Y. Yu, and H. Yuan, "Automated detection and classification of acute vertebral body fractures using a convolutional neural network on computed tomography," *Frontiers in Endocrinology*, vol. 14, pp. 1–11, March 2023.

[4] Y. Li, X. Kang, and L. Fang, "Ifcnn: A general image fusion framework based on convolutional neural networks," *Information Fusion*, vol. 54, pp. 1–15, 2020.

[5] J. Smith, R. Brown, and T. Green, "Utilizing heat maps as explainable artificial intelligence for detecting abnormalities on wrist and elbow radiographs," in *Proceedings of the International Conference on Medical Imaging*. IEEE, 2023, pp. 45–50.

[6] F. Su, W. Zhang, Y. Liu, S. Chen, M. Lin, M. Feng, J. Yin, L. Tan, and Y. Shen, "The development and validation of pathological sections based u-net deep learning segmentation model for the detection of esophageal mucosa and squamous cell neoplasm," *Journal of Gastrointestinal Oncology*, vol. n/a, p. n/a, n/a 2024.

Appendix A: Presentation

FRACTUREVISION

GUIDED BY

DR. JISHA G.

BY

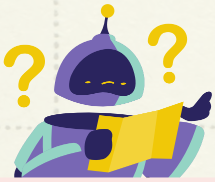
GEORGE BIBU
JENIL BIJU
JUSTIN GEORGE
KEVIN BENNY

INTRODUCTION

FractureVision is an advanced medical imaging solution designed to assist healthcare professionals in detecting and diagnosing bone fractures. Using computer vision techniques and XAI, FractureVision analyzes CT scan images to identify fractures across body regions with high accuracy. We also address the challenge of explainability by integrating explainable AI (XAI) methods Grad-CAM, as it provides interpretable visual insights into the model's decision-making process. This tool aims to support radiologists and improve patient outcomes through faster, more precise fracture detection.

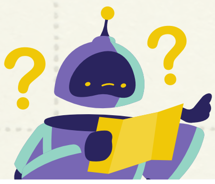
PROBLEM DEFINITION

Accurate fracture detection, particularly for complex cases like rib fractures, remains challenging with single imaging modalities such as X-rays. Additionally, the black-box nature of current AI systems makes it difficult for radiologists to trust the results, leading to missed or delayed diagnoses and inadequate treatment plans.



OBJECTIVES

- To design an AI-based system that integrates X-ray and CT imaging for more accurate fracture detection.
- Implement Explainable AI (XAI) to provide interpretable predictions.
- Develop a user-friendly interface for clinicians to interact with the AI predictions and explanations.



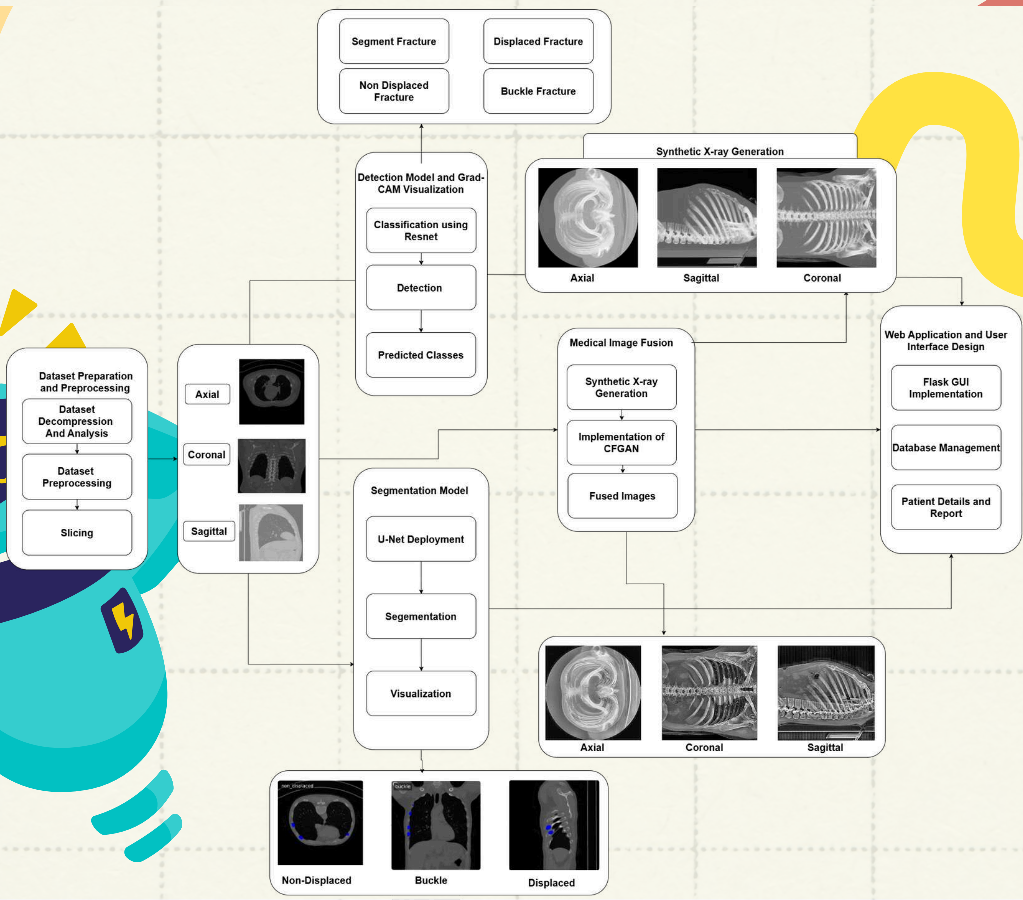
WORK DIVISION

George: Dataset decompression and analysis ,U -Net development

Jenil: Flask GUI Implementation, Database Management, patient scan form and dynamic report integration.

Kevin: Grad-CAM generation, CT slicing and directory structure , Report generation .

Justin: Hybrid model design and development , Data augmentation using GAN's and Front end development.



MODULES

1.Dataset Preparation and Preprocessing

2.Model Development and Grad-CAM Visualization

3.Medical Image Fusion

4.Web Application and User Interface Design

5.Report Generation and Patient Data Handling

1 DATASET PREPARATION AND PREPROCESSING

- <u>DECOMPRESSION OF .NII.GZ FILES</u>: HANDLING LARGE ZIP FILES CONTAINING CT SCAN IMAGES, ENSURING NO DATA LOSS DURING DECOMPRESSION.

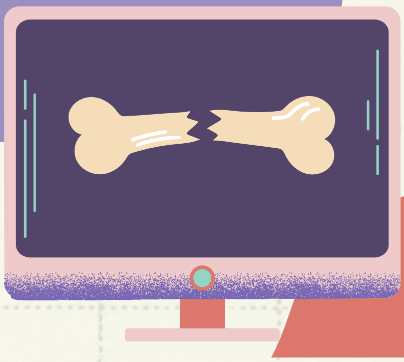
- <u>CT IMAGE EXTRACTION</u>: TRAVERSING THROUGH CT SCANS, ISOLATING IMAGES WITH FRACTURES, AND SAVING THESE AS INDIVIDUAL JPG FILES FOR TRAINING.

- <u>IMAGE DIRECTORY STRUCTURE</u>: CREATING A FILE STRUCTURE TO STORE EXTRACTED IMAGES INTO LABELS FOLDERS FOR EASY ACCESS.

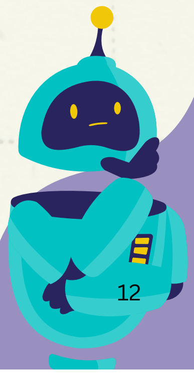
- CREATING CUSTOM SUB-DATASETS TO WORK WITH A VARIETY OF CNN MODELS.
- TRAINING CNN MODELS : TO FIND OUT WHICH MODEL TO USE, WE DID AN ANALYSIS OF A FEW MODELS AND THEY WERE JUDGED BASED ON ACCURACY AS A PRERLIMINARY STEP.
  - CNN (8 C LAYERS AND ONE F LAYER)(40%)
  - DENSENET18(88%)
  - RESNET18(90%)
  - RESNET50(85%)
  - RESNET101(75%)
  - UNET(95%)
- FROM THE ABOVE WE CONCLUDED RESNET18 WAS THE BEST FOR CLASSIFICATIONA AND UNET WAS SELECTED FOR SEGREGATIONS.

2

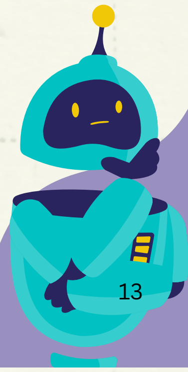
MODEL DEVELOPMENT AND GRAD-CAM VISUALIZATION



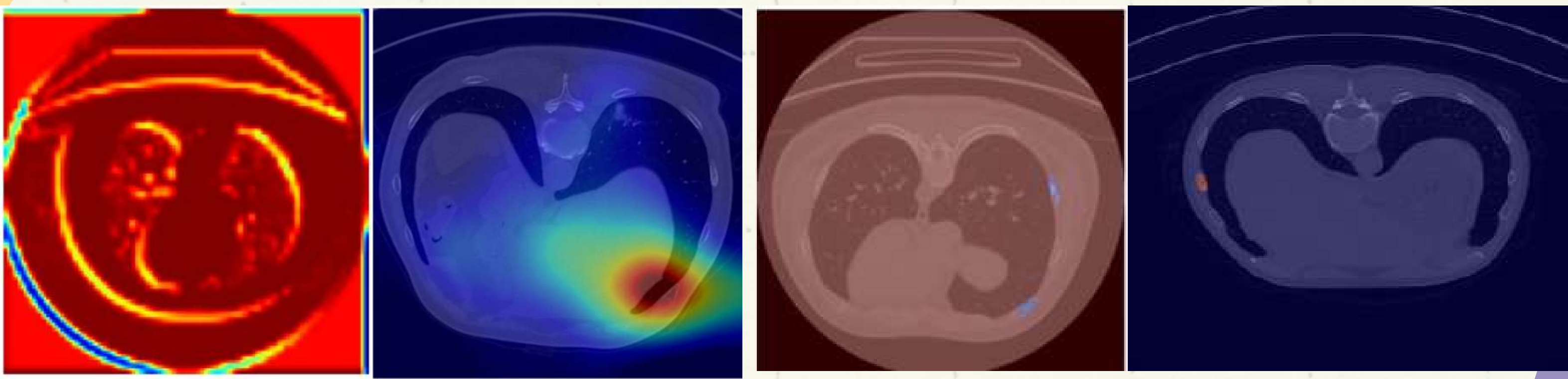
- <u>CNN MODEL DEVELOPMENT</u>: THE RESNET118 MODEL WAS TRAINED FOR 100 EPOCHS WITH A BATCH SIZE OF 16 .
- <u>UNET MODEL DEVELOPMENT</u>:THE UNET MODEL FOR SEGREGATION WAS TRAINED WITH A BATCH SIZE OF 32 AND EARLY STOPPING WAS USED TO END THE MODELS TRAINING. FOR THE MODEL TO END ITS TRAINING WE ALSO SET A PATIENCE VALUE OF 10.



- **<u>GRAD-CAM IMPLEMENTATION</u>: WE ADDING GRAD-CAM VISUALIZATION TO THE MODEL TO HIGHLIGHT THE WHERE THE MODELS IS FOCUSING . THIS HEPS DEVELOPERS TO UNDERSTAND IF THE MODEL TRAINING IS CORRECT . IT ALSO HELPING DOCTORS UNDERSTAND THE MODEL'S FOCUS AND IMPROVE TRUST IN THE PREDICTIONS.**



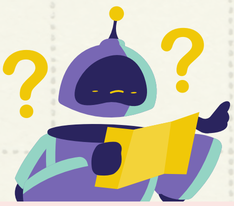
Comparison Between 30% ,60%, 75% and 100%



3 MEDICAL IMAGE FUSION

- MEDICAL IMAGE FUSION COMBINES MULTIPLE IMAGING MODALITIES (X-RAY + CT) FOR ENHANCED VISUALIZATION.
- HELPS IN IMPROVING DIAGNOSTIC ACCURACY BY PRESERVING CRITICAL DETAILS FROM BOTH IMAGES.
- ESSENTIAL FOR FRACTURE DETECTION WHERE DIFFERENT IMAGING MODALITIES PROVIDE COMPLEMENTARY INFORMATION.

- X-RAYS PROVIDE A 2D SKELETAL STRUCTURE BUT LACK DEPTH.
- CT SCANS GIVE 3D ANATOMICAL DETAILS BUT MAY HAVE NOISE OR ARTIFACTS.
- FUSION ENSURES BETTER CONTRAST, EDGE PRESERVATION, AND DETAIL ENHANCEMENT FOR ACCURATE DIAGNOSIS.



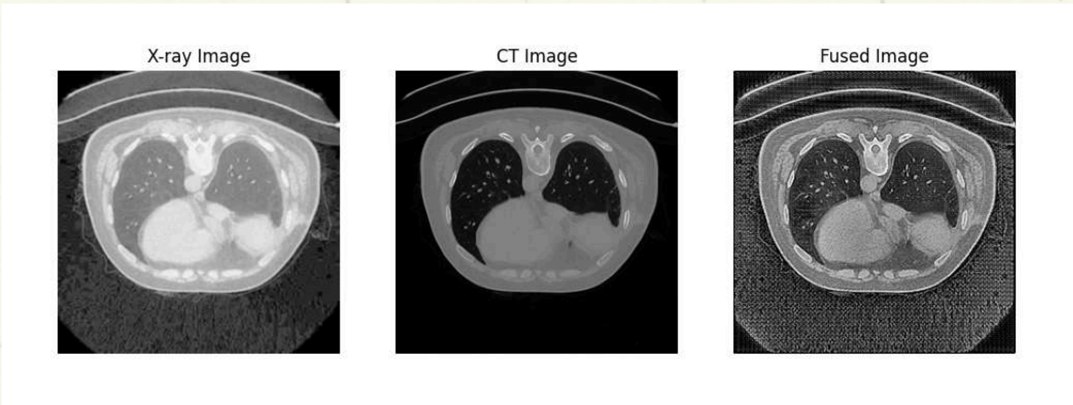
SYNTHETIC X-RAY GENERATION

- INSTEAD OF USING GANS, WE EMPLOYED MIT-BASED METHODS FOR SLICE-WISE TRANSFORMATION.
- THIS APPROACH SELECTIVELY EXTRACTS BONE STRUCTURES WHILE FILTERING OUT SOFT TISSUE, ENSURING X-RAY-LIKE CONTRAST AND INTENSITY.
- POST-PROCESSING TECHNIQUES SUCH AS ADAPTIVE HISTOGRAM EQUALIZATION AND NOISE REDUCTION FURTHER REFINE THE SYNTHETIC X-RAYS, MAKING THEM SUITABLE FOR MEDICAL ANALYSIS.

FUSION PROCESS

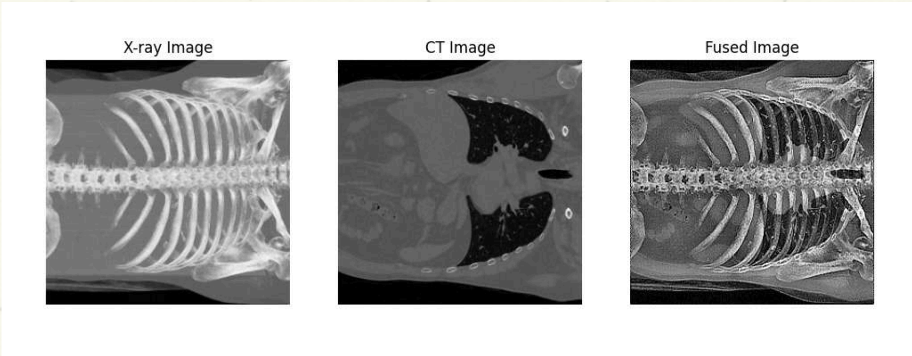
- CFGAN INTELLIGENTLY INTEGRATES FEATURES FROM BOTH MODALITIES, ENSURING CLEAR FRACTURE VISUALIZATION AND HIGH-FIDELITY FUSION.
- THE MODEL FOCUSES ON STRUCTURAL PRESERVATION AND CONTRAST ENHANCEMENT, IMPROVING INTERPRETABILITY FOR RADIOLOGISTS.
- ADVERSARIAL LEARNING ENSURES THAT THE FUSED IMAGES ACHIEVE HIGHER SSIM (STRUCTURAL SIMILARITY) AND PSNR (IMAGE CLARITY) COMPARED TO CONVENTIONAL METHODS.

FUSED IMAGES IN THE AXIAL PLANE



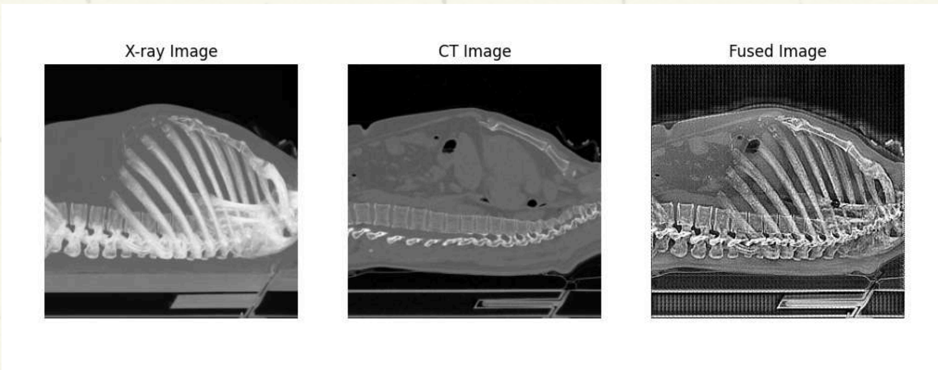
Metric	Value
SSIM (X-ray vs Fused)	0.7366
PSNR (X-ray vs Fused)	15.23 dB
SSIM (CT vs Fused)	0.5502
PSNR (CT vs Fused)	19.31 dB

FUSED IMAGES IN THE CORONAL PLANE



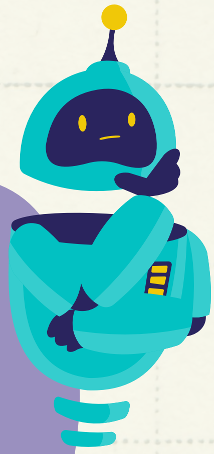
Metric	Value
SSIM (X-ray vs Fused)	0.7398
PSNR (X-ray vs Fused)	15.51 dB
SSIM (CT vs Fused)	0.8224
PSNR (CT vs Fused)	22.52 dB

FUSED IMAGES IN THE SAGITTAL PLANE



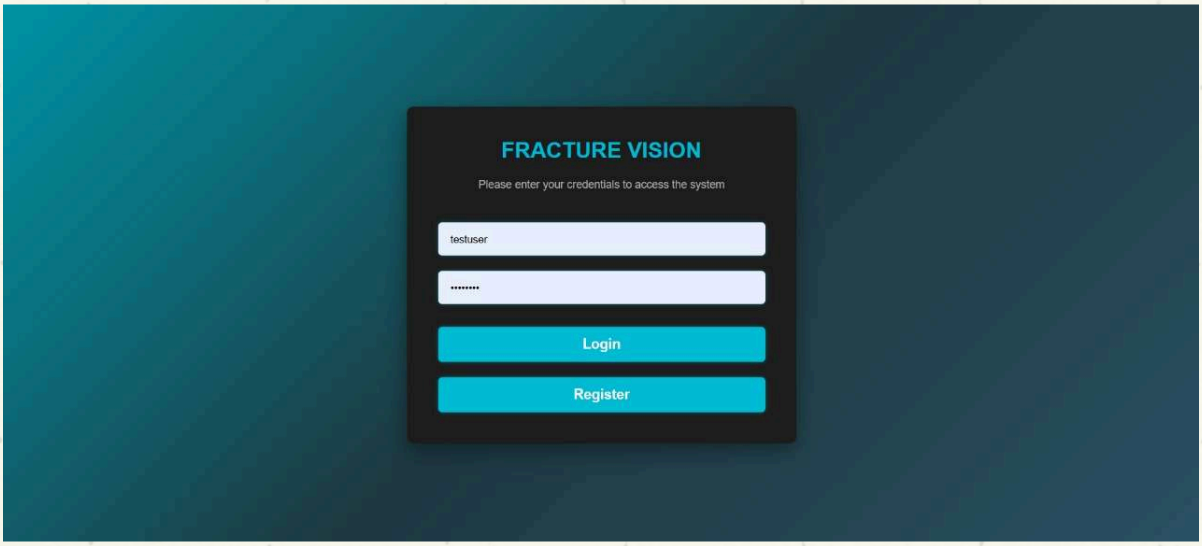
Metric	Value
SSIM (X-ray vs Fused)	0.6940
PSNR (X-ray vs Fused)	13.49 dB
SSIM (CT vs Fused)	0.5536
PSNR (CT vs Fused)	18.57 dB

4 WEB APPLICATION AND USER INTERFACE DESIGN

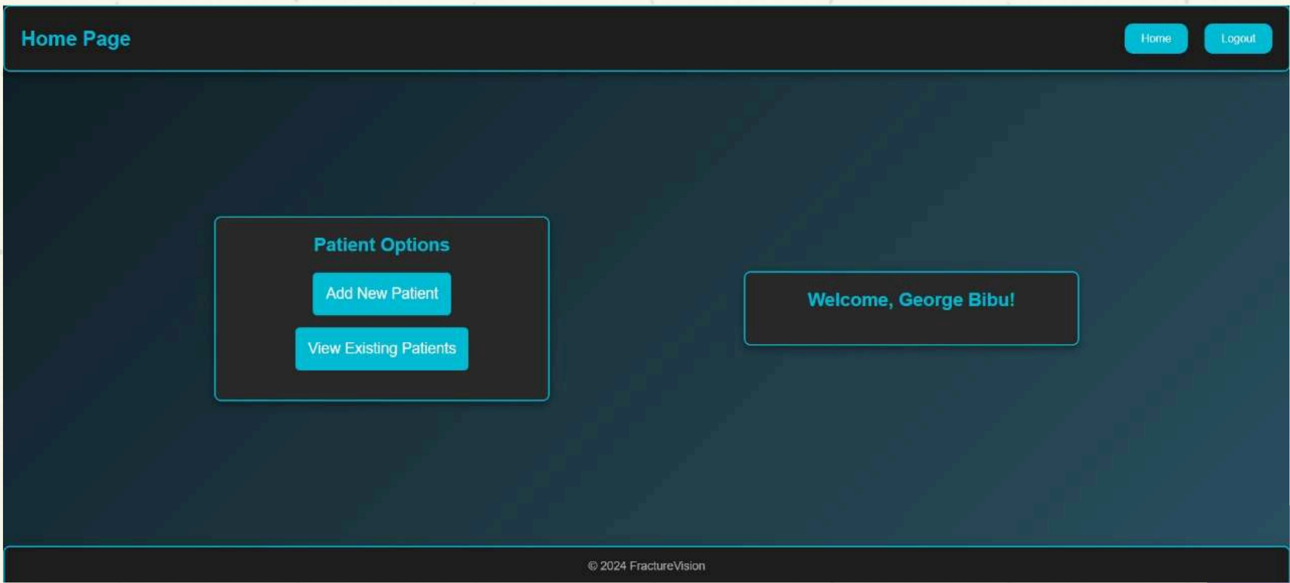


- FLASK GUI IMPLEMENTATION: DEVELOPING THE BACK-END GUI WITH FLASK, INCLUDING LOGIN, REGISTRATION, AND A HOME PAGE.
- DATABASE MANAGEMENT: SETTING UP SEPARATE DATABASES FOR DOCTORS AND PATIENTS TO STORE USER DETAILS SECURELY.
- FRONTEND HTML PAGES: DESIGNING THE LAYOUT AND STRUCTURE OF THE WEB PAGES TO ENSURE A SEAMLESS USER EXPERIENCE.

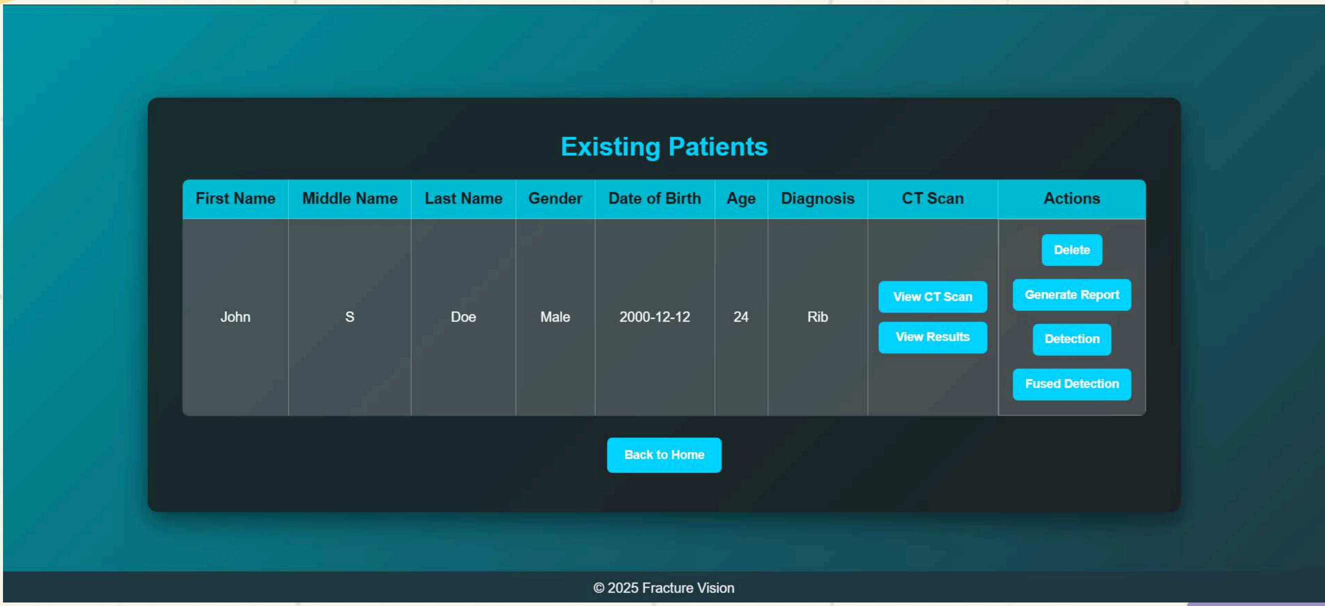
Login Screen



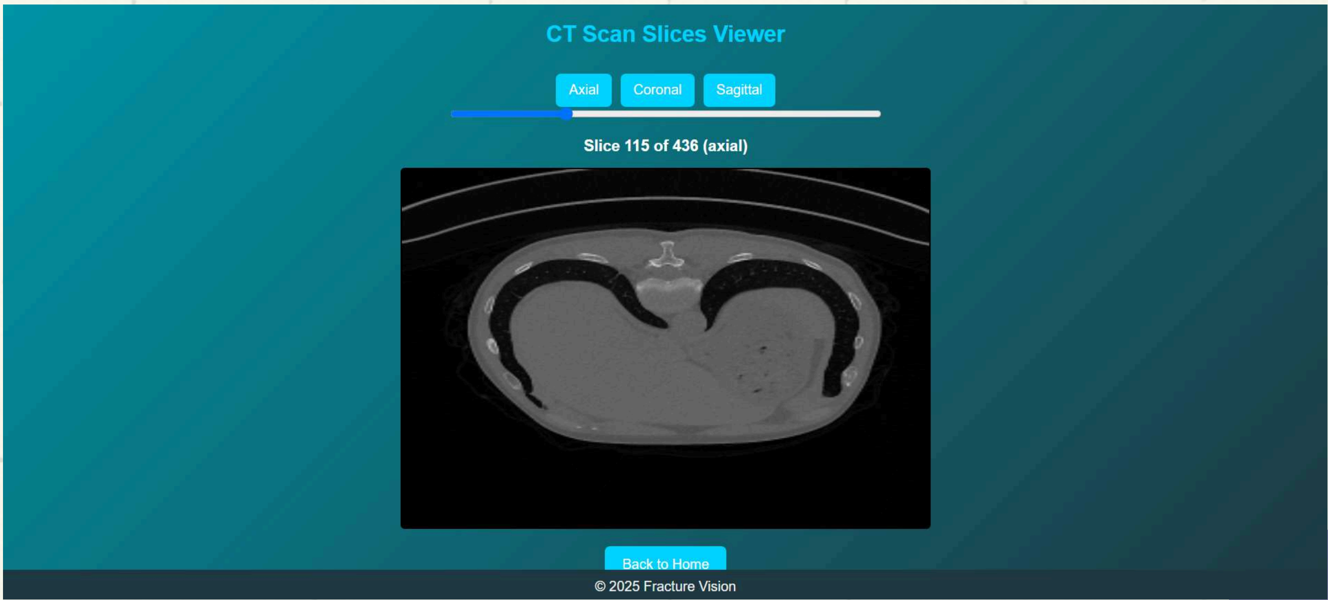
Main Screen



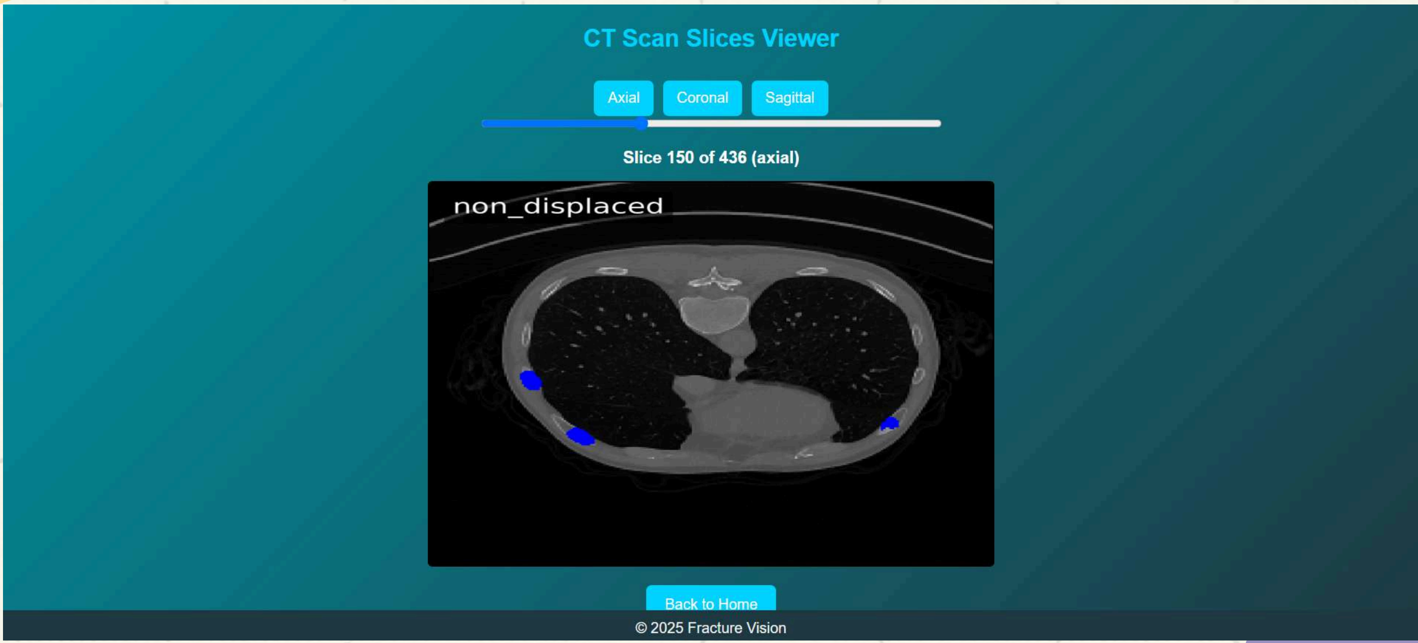
Patient List



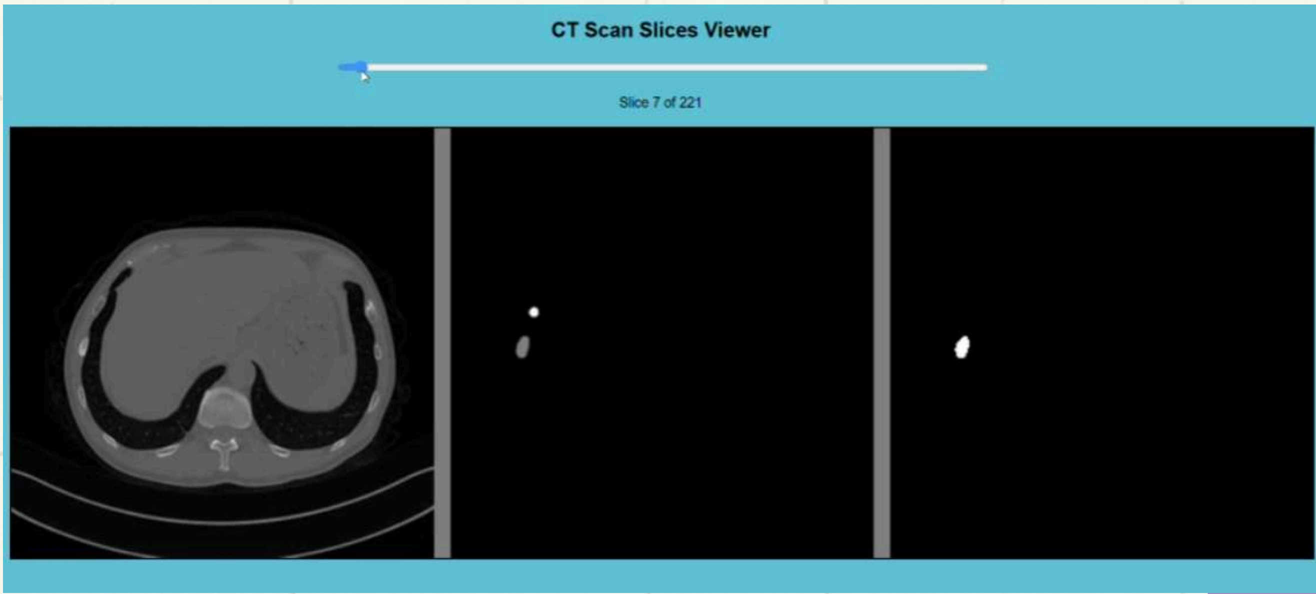
CT Slicing Web View



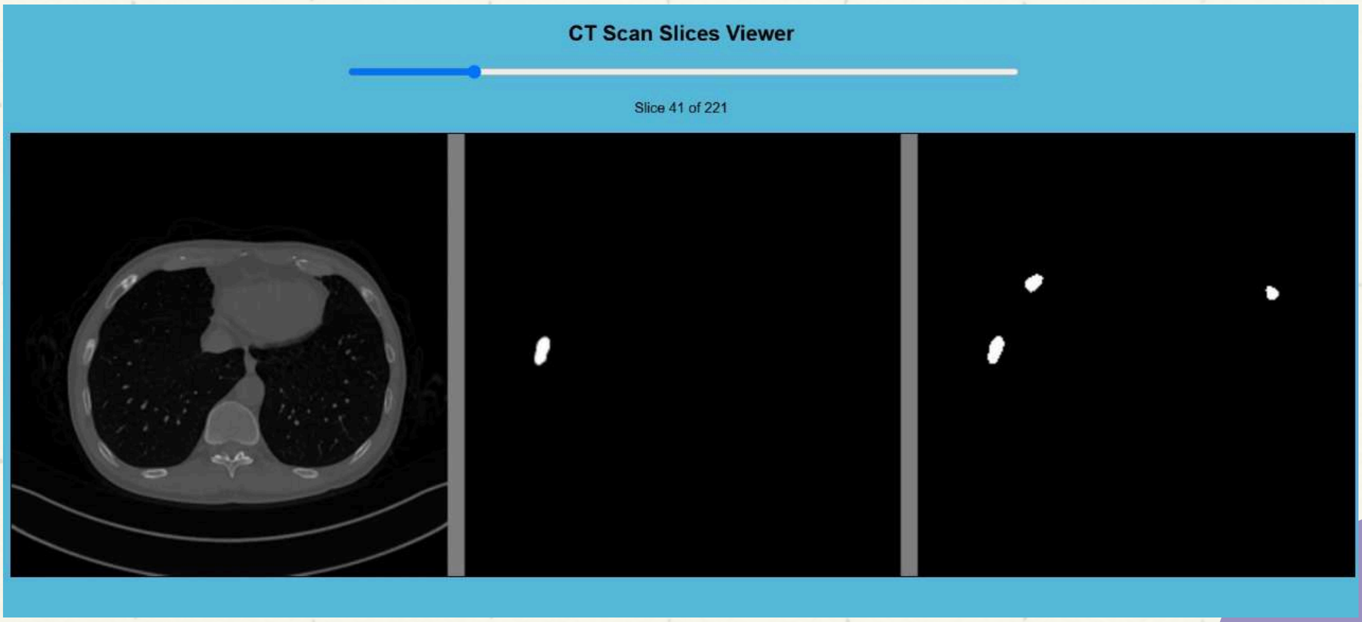
Detection Results Display



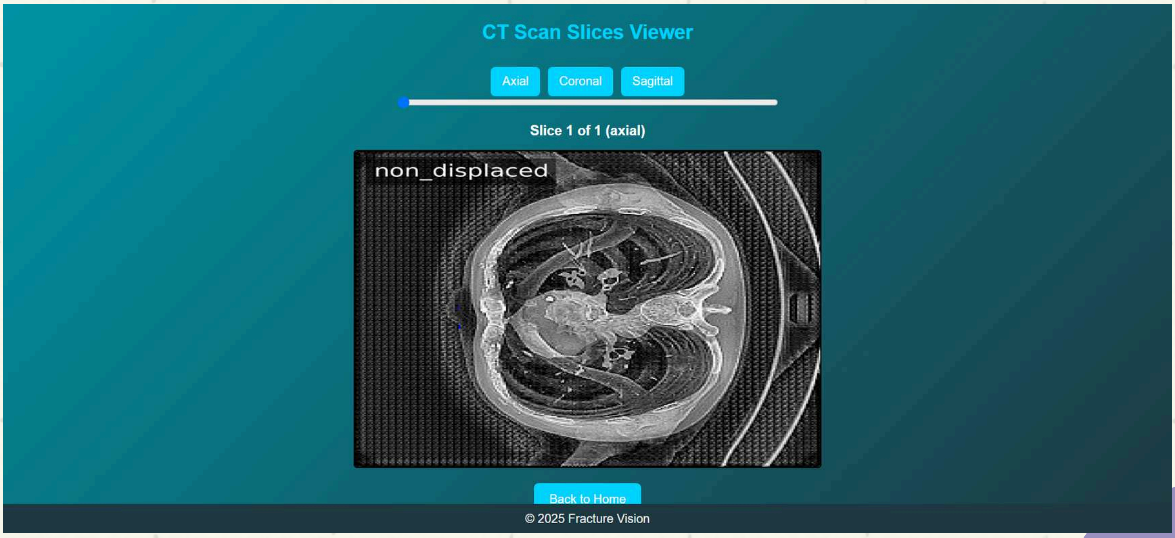
CT Slicing Web View with output



CT Slicing Web View with output



Fused Image Detection



4 REPORT GENERATION AND PATIENT DATA HANDLING

- REPORT GENERATION WITH REPORTLAB: GENERATING PDF REPORTS THAT SUMMARIZE SCAN DETAILS, RESULTS, AND PATIENT INFORMATION USING PYTHON'S REPORTLAB LIBRARY.

- PATIENT SCAN SUBMISSION: IMPLEMENTING A FORM FOR PATIENT SCAN UPLOADS AND CONNECTING IT TO THE BACKEND FOR STORAGE AND PROCESSING.

- DYNAMIC REPORT DISPLAY: DISPLAYING PATIENT DETAILS DYNAMICALLY IN THE GENERATED REPORT FOR EASY REFERENCE AND USE BY MEDICAL PROFESSIONALS.

REPORT

FractureVision Hospital

Patient Details:

First Name:	Jacob
Middle Name:	M
Last Name:	Markose
Gender:	Male
Date of Birth:	1999-01-04
Age:	26
Diagnosis:	Rib Fracture

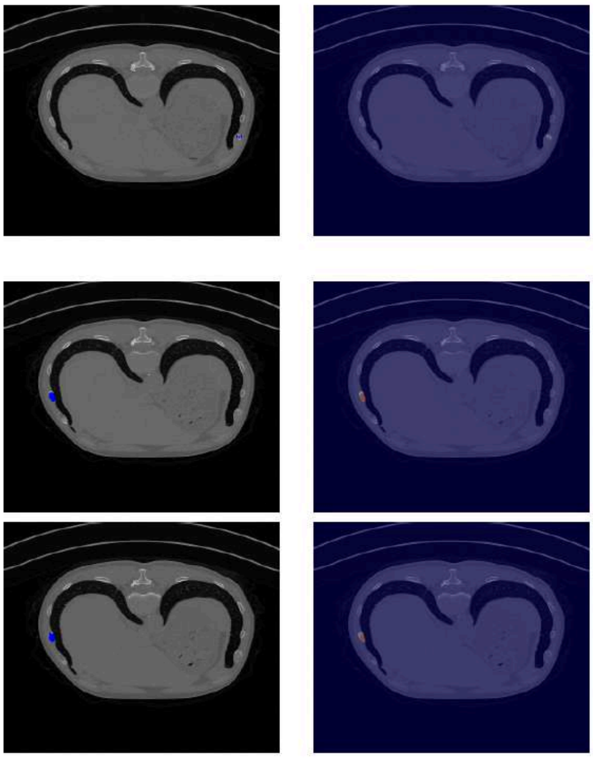
Doctor Details:

Doctor ID:	D4842
Doctor Name:	Dr. Jenil Biju

Report generated on: 2025-01-15 12:50:03

CT Scan Images & Heatmaps

FractureVision Hospital



RESULTS

UNET METRICES

Training metrics

Model	Epoch	Dice Coefficient	Loss	Precision	Recall
Axial	43	0.7708	0.2292	0.8500	0.7250
Coronal	49	0.6193	0.3807	0.7370	0.5728
Sagittal	68	0.8242	0.1758	0.9035	0.7901

UNET METRICES

Validation metrics

Model	Epoch	Dice Coefficient	Loss	Precision	Recall
Axial	43	0.5688	0.4309	0.8107	0.7404
Coronal	49	0.3101	0.6898	0.7393	0.5656
Sagittal	68	0.4732	0.5266	0.8957	0.7429

UNET METRICES

Test metrics

Model	Accuracy	F1	Jaccard	Precision	Recall
Axial	0.9997	0.7859	0.7708	0.9346	0.8165
Coronal	0.9997	0.8054	0.79619	0.95223	0.8277
Sagittal	0.9997	0.8135	0.8054	09750	0.8210

ResNet METRICES

Training metrics

Model	Epoch	Training Accuracy	Training Loss	Training Precision	Training Recall
Axial	100	92.49	11.34	91.38	90.24
Coronal	100	91.28	7.54	94.55	92.20

ResNet METRICES

Validation metrics

Model	Epoch	Training Accuracy	Training Loss	Training Precision	Training Recall
Axial	100	83.84	41.17	83.45	85.78
Coronal	100	90.22	10.11	92.15	84.25

ResNet METRICES

Perclass Accuracy

Class	Accuracy
Buckle Rib Fracture	93.35
Displaced Rib Fracture	82.65
Non-Displaced Rib Fracture	86.86
Segmented Rib Fracture	99.71

Fusion Metrices

Axial Plane

Matric	Value
SSIM (X-ray vs Fused)	0.7366
PSNR (X-ray vs Fused)	15.23 dB
SSIM (CT vs Fused)	0.5502
PSNR (CT vs Fused)	19.31 dB

Fusion Metrices

Coronal Plane

Matric	Value
SSIM (X-ray vs Fused)	0.7398
PSNR (X-ray vs Fused)	15.51 dB
SSIM (CT vs Fused)	0.8224
PSNR (CT vs Fused)	22.52 dB

Fusion Metrices

Sagittal Plane

Matric	Value
SSIM (X-ray vs Fused)	0.6940
PSNR (X-ray vs Fused)	13.49 dB
SSIM (CT vs Fused)	0.5536
PSNR (CT vs Fused)	18.57 dB

THANK YOU!

Appendix B: Vision, Mission, Program Outcomes and Course Outcomes

Vision, Mission, Program Outcomes and Course Outcomes

Vision: To become a Centre of Excellence in Computer Science Engineering, moulding professionals catering to the research and professional needs of national and international organizations..

Mission: To inspire and nurture students, with up-to-date knowledge in Computer Science Engineering, Ethics, Team Spirit, Leadership Abilities, Innovation and Creativity to come out with solutions meeting the societal needs.

Program Outcomes (PO)

PO1: Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

PO2: Problem analysis: Identify, formulate, research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Program Specific Outcomes (PSO)

PSO1: Computer Science Specific Skills: The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills: The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills: The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

CO1: Model and solve real world problems by applying knowledge across domains.
CO2: Develop products, processes, or technologies for sustainable and socially relevant applications.
CO3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks.
CO4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms.
CO5: Identify technology/research gaps and propose innovative/creative solutions.
CO6: Organize and communicate technical and scientific findings effectively in written and oral forms.

article graphicx

Appendix C

CO-PO and CO-PSO Mapping

	PO 1	**PO 2**	**PO 3**	**PO 4**	**PO 5**	**PO 6**	**PO 7**	**PO 8**	**PO 9**	**PO 10**	**PO 11**	**PO 12**	**PSO 1**	**PSO 2**	**PSO 3**
CO1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO2	2	2	2		1	3	3	1	1		1	1		2	
CO3									3	2	2	1			3
CO4					2			3	2	2	3	2			3
CO5	2	3	3	1	2							1	3		
CO6					2			2	2	3	1	1			3

3/2/1: high/medium/low