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AI-Based Digital Twin for Orthopedic Surgery Planning and Recovery Prediction

AIML-PROJECT REPORT

Submitted by

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Certified that the project work titled "**AI-Based Digital Twin for Orthopedic Surgery Planning and Recovery Prediction**" is carried out by **Gauri G Singh (1RV23IS051)**, who is a bonafide student of R.V College of Engineering, Bangalore, in partial fulfillment for the award of degree of **Bachelor of Engineering in Information Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2025-26. It is certified that all corrections/suggestions indicated for the internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of project work as a part of the course "Artificial Intelligence and Machine Learning" prescribed by the institution for the said degree.

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I, Gauri G Singh student of fifth semester B.E., Department of Information Science and Engineering, RV College of Engineering, Bengaluru, hereby declare that the project titled "AI-Based Digital Twin for Orthopedic Surgery Planning and Recovery Prediction" has been carried out by me and submitted in partial fulfilment for the award of degree of **Bachelor of Engineering in Information Science and Engineering** during the year 2025-2026.

Further I declare that the content of the dissertation has not been submitted previously by anybody for the award of any degree or diploma to any other university.

I also declare that any Intellectual property rights generated out of this project carried out at RVCE will be the property of RV College of Engineering, Bengaluru and I will be among the authors of the same.

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ABSTRACT

This project presents an AI-inspired digital twin framework designed to support orthopedic surgery planning and post-operative recovery analysis for knee procedures. The proposed system creates a virtual representation of an orthopedic patient by integrating clinical input parameters, radiographic image visualization, and interactive three-dimensional anatomical models. Synthetic clinical datasets are used to simulate realistic patient recovery behavior while preserving data privacy and enabling controlled experimentation. The digital twin framework is designed to support the integration of machine learning–based recovery prediction models as modular components, enabling estimation of recovery duration based on patient-specific factors such as age and surgery type. The platform incorporates pre-operative and post-operative X-ray visualization alongside browser-based 3D anatomical rendering using glTF models, allowing intuitive inspection and exploratory "what-if" analysis. A lightweight web-based interface executed through a local HTTP server enables smooth interaction, visualization, and demonstration of digital twin concepts. The results demonstrate the feasibility of combining data-driven modeling concepts with interactive visualization to create an extensible and interpretable orthopedic digital twin prototype suitable for educational and demonstrative healthcare applications.

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LIST OF ABBREVIATIONS

- AI – Artificial Intelligence
- DT – Digital Twin
- CT – Computed Tomography
- MRI – Magnetic Resonance Imaging
- X-ray – X-Radiation Imaging Modality
- DICOM – Digital Imaging and Communications in Medicine
- ROI – Region of Interest
- 3D – Three-Dimensional
- GLB – Binary glTF (Graphics Library Transmission Format)
- glTF – Graphics Library Transmission Format
- WebGL – Web Graphics Library
- ML – Machine Learning
- RF – Random Forest
- XGBoost – Extreme Gradient Boosting
- MAE – Mean Absolute Error
- MSE – Mean Squared Error
- RMSE – Root Mean Squared Error
- R^2 – Coefficient of Determination
- BMI – Body Mass Index
- UI – User Interface
- HTTP – Hypertext Transfer Protocol

CHAPTER 1

INTRODUCTION

The AI-Based Orthopedic Digital Twin project aims to develop a patient-centric digital twin framework to support knee orthopedic surgery planning and recovery analysis. The system provides an interactive decision-support interface that integrates patient information, pre-operative and post-operative radiographic images, and three-dimensional anatomical visualization to improve clinical understanding and treatment evaluation.The digital twin represents a virtual counterpart of an orthopedic patient, enabling intuitive visualization of anatomical structures and comparison of surgical outcomes. Machine learning techniques for predicting patient-specific recovery duration using clinical and demographic parameters are explored as modular backend components, allowing future integration without altering the system architecture.By incorporating multimodal visualization through medical images and interactive 3D anatomical models rendered using WebGL-based technologies, the platform supports exploratory “what-if” analysis of treatment and rehabilitation factors. Overall, the project demonstrates the applicability of artificial intelligence and digital twin concepts in enhancing visualization, personalization, and interpretability in modern orthopedic healthcare.

1.1 Terminology

1.1.1 Digital Twin: A Digital Twin is a high-fidelity virtual replica of a physical system that uses real-world data and predictive models to simulate behavior, performance, and outcomes.

1.1.2. Multimodal Data Integration: Multimodal data integration refers to the fusion of heterogeneous data sources such as clinical parameters, medical images, and 3D anatomical models within a unified analytical framework.

1.1.3. Volumetric Rendering: Volumetric rendering is a 3D visualization technique that represents internal structures using voxel-based data rather than surface geometry, commonly used in CT and MRI visualization.

1.1.4. Explainable Artificial Intelligence (XAI): Explainable Artificial Intelligence comprises methods that make machine learning models transparent and interpretable to human users by revealing decision-driving factors.

1.2 Scope and Relevance

The scope of this work is restricted to postoperative recovery prediction and visual orthopedic planning for knee surgeries. The digital twin uses synthetic clinical data, machine-learning regression, radiograph upload, and anatomical three-dimensional models to create an interactive prediction environment. Diagnostic accuracy, medical judgement, and clinical prescription remain outside the project scope. Instead, the prototype demonstrates feasible computational techniques for estimating recovery duration and visualizing surgical anatomy as part of a research-oriented experimental setup.

The relevance of this work is significant for orthopedic decision support, physiotherapy planning, and personalized surgical assessment. By providing adjustable clinical parameters and instant recovery predictions, the system assists clinicians and students in exploring "what-if" treatment variations and understanding individual rehabilitation differences. In a broader context, this work highlights the potential of integrating Artificial Intelligence, lightweight imaging, and anatomical visualization into orthopedic workflows. The prototype also serves as a foundation for future clinical extension and integration with authentic medical datasets.

1.3 Motivation

Postoperative recovery is highly patient-dependent, and yet orthopedic clinical practice frequently applies uniform guidelines and rehabilitation timelines. Surgical outcome planning can benefit greatly from individualized predictions capable of accounting for specific patient characteristics such as age, musculoskeletal condition, and physiotherapy response. Motivated by this need, the present project explores how AI-based methods can construct simplified digital twin environments capable of modeling recovery while leveraging three-dimensional visualization for enhanced clinical interpretation.

1.4 Problem Statement

There is an absence of practical computational tools that support personalized orthopedic recovery prediction, simulate physiotherapy adjustments, and visually align anatomical models with diagnostic radiographs within a unified interface. Current systems rely on generalized estimations and lack interactive simulation capabilities essential for individualized orthopedic planning.

1.5 Objectives

- To develop a machine-learning-based digital twin that models postoperative recovery behavior in knee orthopedic cases.
- To integrate three-dimensional anatomical visualization and radiograph alignment capabilities into an interactive interface.
- To enable physiotherapy-based “what-if” simulation for clinical exploration.
- To design a Streamlit-based application for real-time orthopedic planning and recovery visualization.

1.6 Summary

This chapter introduced the motivation behind creating an AI-based orthopedic digital twin platform capable of predicting recovery duration and supporting surgery planning. We began by defining the concept of digital twins and highlighting their emerging significance in healthcare, particularly for personalized treatment planning. The problem was framed around the absence of systems that can simulate individualized recovery trajectories based on patient-specific clinical parameters. Objectives were stated in terms of prediction accuracy, interactive simulation, visualization capability and integration of machine learning with medical insight. Finally, the scope clarified that the project focuses only on knee orthopedic surgeries using clinical and patient-level features rather than medical imaging for primary prediction, while still supporting optional imaging-based interpretation. The chapter establishes a foundation for understanding how personalized recovery modeling can contribute to clinical decision support and modern digital healthcare workflows.

CHAPTER 2

LITERATURE SURVEY

2.1 Literature Review

One study in the area of orthopedic digital twins introduces a virtual reality–based platform that embeds users within a simulated surgical environment by reconstructing a three-dimensional operating room containing patient anatomy, surgical instruments, and procedural workflows [1]. The system enables immersive rehearsal, replay, and inspection of surgical steps, allowing clinicians to analyze spatial relationships and procedural outcomes in a controlled and risk-free setting. Unlike conventional static visualization tools, the digital twin evolves dynamically over time, supporting interactive learning and scenario-based exploration. This transition from static representations to time-dependent digital twins enhances surgical education and preoperative planning. The immersive nature of the platform improves spatial understanding and procedural confidence, demonstrating the value of realistic three-dimensional environments in orthopedic contexts. These concepts directly support the present project's emphasis on realistic 3D orthopedic visualization as a means of improving clinical understanding and decision support.

A comprehensive systematic literature review surveys the broader landscape of digital twin research in healthcare by categorizing existing studies according to application domains, data sources, modeling approaches, and architectural frameworks [2]. The review observes that most healthcare digital twins remain at prototype or experimental stages, with limited deployment in real clinical environments. Several critical challenges are identified, including data interoperability across heterogeneous systems, validation of simulation accuracy, cybersecurity risks, and ethical management of patient information. The lack of standardized frameworks and longitudinal data integration further restricts scalability and clinical adoption. These findings provide strong justification for adopting a modular and extensible system design. In the context of the present project, this review supports the use of a scalable architecture that can evolve from synthetic datasets toward real clinical integration in future implementations.

Research focused on musculoskeletal digital twins proposes a framework that models bones, joints, and soft tissues to simulate motion, loading conditions, and biomechanical behavior [3]. By integrating anatomical geometry with kinematic and kinetic data, the system enables realistic representation of joint function under varying physical conditions. This approach supports functional assessment, rehabilitation planning, and treatment evaluation by capturing both structural and behavioral characteristics of the musculoskeletal system. The study demonstrates that effective digital twins must represent dynamic interactions rather than static anatomy alone. This perspective provides conceptual support for modeling knee structures as realistic and functional digital entities in the present project, reinforcing the importance of dynamic representation even when the immediate focus is visualization and recovery prediction.

An alternative approach to healthcare digital twins is presented through a precision medicine platform developed using a service-oriented architecture [4]. The platform supports modular services for data ingestion, patient profiling, model execution, and personalized recommendation generation. By decoupling system components, the architecture enables flexibility, scalability, and interoperability with existing healthcare information systems. The web-based design facilitates integration with analytical tools and clinical data repositories. These architectural principles offer valuable guidance for orthopedic digital twin development, particularly in designing systems that can evolve incrementally. While the current project focuses on visualization and recovery prediction, the modular structure allows future expansion into clinical integration and telemedicine support.

A layered architectural model for healthcare digital twins is explored through a framework consisting of data acquisition, processing, simulation, analytics, and visualization layers [5]. The separation of concerns across layers enhances maintainability, security, and adaptability. Through a social distancing case study, the authors demonstrate how digital twins can operate at both individual and population levels. Although the application domain differs from orthopedics, the architectural principles remain directly applicable. The present project benefits from a similar layered design, where visualization and prediction modules function independently of data sources. This approach supports scalability and future integration of real-world patient data.

Focused attention on arthroscopic knee surgery reveals that digital twin applications remain limited despite advances in enabling technologies such as patient-specific imaging, biomechanical modeling, and real-time tracking systems [6]. A systematic review of existing work highlights that most solutions address isolated phases of surgical care rather than offering continuous modeling across the treatment lifecycle. Postoperative recovery, in particular, is identified as an underexplored area with significant potential. This gap is often attributed to challenges in collecting longitudinal rehabilitation data, validating predictive models across diverse patient populations, and integrating digital systems into physiotherapy workflows. Additionally, clinical adoption is hindered by the lack of standardized recovery metrics and real-time feedback mechanisms. These limitations reinforce the relevance of the present project's emphasis on recovery prediction and three-dimensional visualization, which targets a practical and impactful segment of orthopedic care. By focusing on postoperative outcomes, the project contributes toward bridging the gap between surgical intervention and long-term functional recovery.

Beyond clinical settings, a human digital twin framework for fitness management demonstrates how wearable sensor data, self-reported inputs, and behavioral patterns can be fused to support personalized health monitoring [7]. The system emphasizes continuous data integration, allowing the digital twin to evolve dynamically over time and reflect real-world behavioral and physiological changes. Such adaptability enables personalized feedback and long-term trend analysis, which are critical for sustained health management. Although the application focuses on fitness rather than rehabilitation, the underlying principles are directly applicable to orthopedic recovery. This work illustrates how future extensions of the present project could incorporate physiotherapy adherence, mobility metrics, pain progression, and patient-reported outcomes. Additionally, the framework highlights the importance of data quality, temporal consistency, and user engagement in maintaining an accurate digital representation. These considerations are particularly relevant in postoperative recovery, where patient compliance and daily activity variations significantly influence outcomes. Incorporating these insights would enable more responsive, personalized, and clinically meaningful recovery modeling.

The evolution of computer-assisted orthopedic surgery is examined through a review of navigation systems, image-guided tools, robotics, and tracking technologies [8]. While these systems have significantly improved surgical accuracy and reproducibility, challenges related to workflow complexity, high system costs, and seamless integration into routine clinical practice persist. Many technologies require specialized infrastructure and training, limiting their widespread adoption. The review argues that future advancements must move beyond intraoperative assistance toward patient-specific simulation and longitudinal outcome analysis. Orthopedic digital twins are positioned as a natural progression beyond conventional computer-assisted systems, as they enable personalized modeling, continuous monitoring, and predictive analysis across the entire treatment lifecycle. This perspective directly supports the present project’s emphasis on patient-centered recovery modeling rather than procedure-centric assistance.

Clinical decision-support systems in orthopedics have also been explored through computer-assisted diagnosis and preoperative planning platforms integrated with electronic patient records [9]. These systems enhance diagnostic consistency and workflow efficiency by consolidating imaging data, clinical notes, and visualization tools into unified interfaces. However, they largely operate as static support tools, providing snapshot-based insights rather than continuous patient modeling. The absence of predictive analytics, adaptive learning mechanisms, and longitudinal data integration limits their effectiveness in monitoring postoperative progress and anticipating complications. These constraints highlight the need for systems that evolve alongside the patient’s recovery trajectory. Furthermore, reliance on retrospective data restricts the ability to generate proactive recommendations. The present project addresses these gaps by integrating recovery prediction with interactive visualization, enabling forward-looking analysis and personalized outcome assessment. This shift supports more informed clinical decisions throughout the rehabilitation phase.

Finally, work on musculoskeletal digital twins emphasizing modular skeletal modeling demonstrates how detailed anatomical structures can be combined with simulation tools to explore dynamic biomechanical responses under varying conditions [10]. The study underscores the importance of separating structural modeling from analytical and predictive components to support extensibility and system longevity. Such modularity allows new functionalities, including recovery analytics, patient-specific simulations, and machine-learning models, to be incorporated without redesigning the core framework. This design philosophy aligns with the present project's strategy of treating anatomical visualization as a foundational layer. In addition, modular digital twins facilitate validation and incremental testing, which are essential in healthcare contexts. By enabling gradual enhancement and targeted refinement, this approach supports the long-term evolution of orthopedic digital twins toward clinically reliable and scalable systems.

2.2 Functional Requirements

2.2.1 Patient Clinical Input Interface

The system shall provide a user-friendly interface to capture basic patient and clinical details such as age, gender, and surgery type (knee). These inputs shall be used to personalize the digital twin visualization and serve as parameters for future integration of predictive analytics modules.

2.2.2 Predictive Analytics Module (Conceptual Integration)

The system shall support the integration of machine learning–based regression models for estimating post-operative recovery duration using clinical and demographic parameters. In the current implementation, the architecture is designed to accommodate prediction outputs, enabling seamless future deployment of real-time recovery estimation.

2.2.3 X-ray Visualization Module

The system shall allow the display of pre-operative and post-operative knee radiographic images for visual comparison and educational purposes. These images provide contextual understanding of surgical outcomes and are intended for demonstration and visualization rather than clinical diagnosis.

2.2.4 3D Anatomical Model Viewer

The system shall render interactive three-dimensional knee anatomical models using standard .glb mesh formats. The viewer shall support basic interactions such as rotation and zooming to enable intuitive exploration of anatomical structures as part of the digital twin representation.

2.2.5 Interactive Digital Twin Simulation

The system shall support exploratory "what-if" analysis by allowing users to conceptually assess the impact of different clinical and rehabilitation parameters on recovery outcomes. This functionality demonstrates how digital twins can be used for simulation and treatment planning in orthopedic scenarios.

2.2.6 Result Interpretation and Educational Insight

The system shall present interpretable outputs and visual indicators that explain the influence of patient parameters on recovery outcomes. This feature supports learning, demonstration, and exploratory analysis for students and clinicians, rather than serving as a replacement for expert medical judgment.

2.3 Hardware Requirements

2.3.1 Windows Laptop or Desktop System

The system must operate on a standard Windows 10 or higher laptop or desktop computer. No specialized gaming or high-end graphical hardware is mandatory; however, sufficient computing capability is required to support local execution of Python scripts, browser-based visualization, and interactive digital twin rendering.

2.3.2 Minimum 8 GB RAM

The execution of Python-based processing, visualization libraries, browser-based 3D rendering, and image handling requires a minimum of 8 GB RAM.

2.3.3 Dual-Core Processor or Above

The system is designed to run efficiently on personal computing devices; however, processors such as Intel i5 provide improved performance when handling visualization rendering, image display, and multi-stage interface execution.

2.3.4 Stable Internet Connectivity

Although the core system execution can operate locally, stable internet connectivity is required for installing dependencies, loading web-based visualization components, and supporting future extensions such as cloud deployment or remote demonstrations.

2.3.5 Graphics Capability (Integrated Sufficient)

Three-dimensional anatomical visualization is performed through browser-based WebGL rendering, which is supported by standard integrated graphics hardware. Dedicated graphics cards are optional and may enhance rendering smoothness for complex anatomical meshes.

2.4 Software Requirements

2.4.1 Windows 10/11 Operating System

The project is developed and executed on a Windows-based operating system. Windows PowerShell or Command Prompt is used for running Python scripts, managing dependencies, and launching local web-based interfaces.

2.4.2 Python 3.9 or Above

Python serves as the primary development language for data handling, preprocessing, modular machine learning integration, and system orchestration. The project is compatible with Python version 3.9 or higher.

2.4.3 Required Libraries (scikit-learn, Pandas, NumPy, Pillow)

The system utilizes standard Python libraries for data processing, numerical computation, and image handling. These libraries support regression modeling experiments, preprocessing workflows, and radiographic image preparation for visualization purposes.

2.4.4 Web-Based Interface Technologies

The user interface is implemented using lightweight web technologies executed through a local HTTP server. This approach enables reliable rendering of images and interactive components while maintaining compatibility with browser-based 3D visualization frameworks.

2.4.5 Model-Viewer and WebGL-Based Visualization

Google Model-Viewer is used to load and render .glb anatomical models within the browser, enabling rotation, zooming, and interactive exploration. WebGL-based rendering ensures efficient and hardware-accelerated visualization of three-dimensional orthopedic structures.

2.4.6 Virtual Environment and Package Manager (pip / venv)

The project requires an isolated Python virtual environment to manage dependencies and library versions. Package installation and environment management are handled using pip and venv to ensure system stability and reproducibility.

2.5 Summary

The literature review showed that most existing works focus on either clinical data modelling or medical image classification, but very few combine both into a unified digital twin environment. Several studies have examined rehabilitation estimation, post-operative complication prediction and orthopedic imaging analytics, but datasets remain limited and mostly disease-specific. A review of 10 papers enabled identification of common features influencing orthopedic outcomes such as patient fitness, age and physiotherapy duration while also revealing gaps in comparative recovery simulations. Requirements analysis demonstrated that minimal hardware is sufficient while software depends primarily on machine learning and visualization libraries. Collectively, the literature survey justifies the relevance of a multi-modal orthopedic digital twin which integrates interactive dashboards, ML prediction and 3-D visualization to provide a more comprehensive view than conventional clinical assessment tools.

CHAPTER 3

DESIGN OF THE SYSTEM

3.1 Theory and Concepts

The proposed system is based on the concept of a **Digital Twin**, which represents a virtual counterpart of a physical entity used for analysis, visualization, and simulation. In orthopedic healthcare, a digital twin enables the representation of patient-specific parameters and anatomical structures in a computational environment. The system also draws from **supervised machine learning principles**, where historical data is used to model relationships between clinical inputs and recovery outcomes. Additionally, **medical visualization theory** and **web-based 3D rendering** concepts are applied to enhance interpretability and user interaction. Together, these theories support a unified framework for orthopedic recovery analysis and visualization.

Core Concepts Used

- **Digital Twin Concept** – Creation of a virtual orthopedic patient using clinical parameters and anatomical visualization.
- **Regression-Based Learning** – Modeling continuous recovery duration using supervised learning techniques.
- **Synthetic Data Modeling** – Use of artificially generated clinical data to preserve privacy while enabling experimentation.
- **Medical Image Processing** – Basic grayscale conversion and preprocessing of X-ray images for visualization and demonstration.
- **3D Visualization and WebGL Rendering** – Use of mesh geometry, transformations, and browser-based rendering for interactive anatomy exploration.

3.2 Dataset Description

The dataset used in this project is a **Synthetic Orthopedic Recovery Dataset** designed to simulate realistic patient profiles undergoing knee replacement surgery. Each data instance represents a single patient case and includes numerical attributes such as age, body mass index (BMI), pre-operative pain score, normalized bone density value, duration of surgery, and physiotherapy frequency assumptions. Categorical attributes include patient gender and surgery type (knee replacement).

The target variable represents estimated post-operative recovery duration measured in days, generated based on clinically reasonable relationships between input parameters. Synthetic data generation enables controlled experimentation without exposing sensitive patient information, while still capturing realistic variability across orthopedic conditions. Feature engineering techniques such as age-squared terms, BMI thresholds, and interaction effects were applied to better represent non-linear recovery behavior. Additionally, a small set of sample radiographic images was used separately for demonstrating image visualization and basic classification functionality within the digital twin framework.

3.3 Design and Methodology

1. Data Preprocessing

Clinical parameters were organized into numerical and categorical variables, followed by missing-value handling, normalization, and encoding. Feature engineering functions were applied to capture non-linear and interaction effects influencing recovery patterns.

2. Machine Learning Model Development (Conceptual)

Regression models were explored during experimentation to understand recovery prediction behavior. Model selection was guided by standard error metrics, and the architecture was designed to support future integration of trained models.

3. X-ray Processing and Visualization

Orthopedic radiographs were preprocessed using grayscale conversion and resizing. These images were displayed within the interface to support visual comparison and contextual understanding rather than clinical diagnosis.

4. 3D Anatomy Visualization

Knee anatomical models in glTF (`.glb`) format were rendered using browser-based 3D visualization tools. Users can rotate and inspect anatomical structures to enhance understanding of surgical outcomes.

5. Interface Integration

All components—patient input, image visualization, and 3D anatomy rendering—were integrated into a unified web-based interface executed through a local HTTP server, enabling smooth interaction and demonstrative digital twin functionality.

3.4 System Architecture

The system architecture is organized into four primary layers: data input, processing, visualization, and user interaction. Patient-related clinical values are captured through a web-based input interface and prepared for downstream processing using structured handling mechanisms. Predictive modeling components are designed as modular elements, allowing recovery estimation logic to be integrated as backend services in future extensions.

The visualization layer handles multimodal outputs, including the display of pre-operative and post-operative radiographic images and interactive three-dimensional anatomical models. The 3D visualization module loads glTF (.glb) files and supports user-driven interaction such as rotation and zooming to facilitate anatomical inspection. The application is executed in a local browser environment using a lightweight HTTP server, which enables seamless integration of visual components and interactive functionality within a unified and responsive digital twin interface.

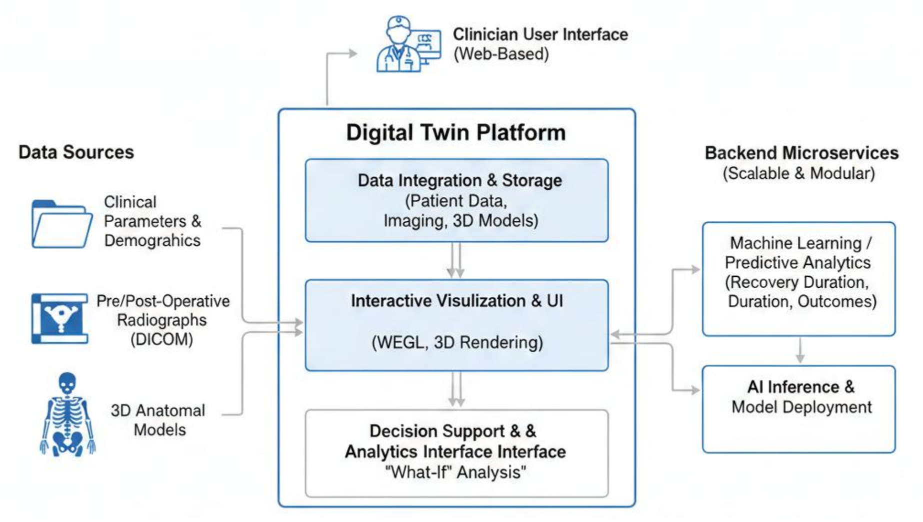

Figure 3.1 System Architecture

Module	Description	Output
Patient Input	Collects patient ID, age, gender and case selection	Validated patient details
Case Selection	Allows selection of different orthopedic cases	Selected case
Pre-operative View	Displays pre-surgery orthopedic image	Pre-operative image
Post-operative View	Displays predicted post-surgery image	Post-operative image
Recovery Prediction	Predicts recovery time and risk level	Recovery duration and risk
3D Digital Twin	Displays rotating 3D knee model	Interactive 3D visualization
Results Dashboard	Shows predictions and patient information	Case analysis results

Table 3.1 Functional Modules of the Orthopedic Digital Twin System

3.5 Tools and APIs

3.5.1 Python and Virtual Environment

Python serves as the core programming language for data handling, application logic, and visualization orchestration. A virtual environment is used to isolate project dependencies, ensuring consistent execution without affecting system-wide Python installations.

3.5.2 scikit-learn

The scikit-learn library is utilized during experimentation for data preprocessing, feature transformation, and regression-based recovery modeling. Model evaluation and serialization techniques support reproducible experimentation and future integration of predictive components.

3.5.3 Web-Based Interface Technologies

The user interface is implemented using lightweight web technologies executed within a browser environment. A local HTTP server is used to host the application files, enabling reliable rendering of images and interactive components without requiring complex backend frameworks.

3.5.4 Plotly Visualization Library

Plotly is used for generating interactive visual representations, including exploratory plots and synthetic three-dimensional visual summaries. Browser-based rendering enables responsive interaction and clear presentation of recovery-related trends and anatomical context.

3.5.5 Google Model-Viewer and glTF Mesh Support

Google Model-Viewer is employed to load and render `.glb` anatomical models directly within the browser. It supports interactive rotation, zooming, and transformation of orthopedic structures, enabling intuitive exploration without the need for external graphics engines.

3.6 Summary

This chapter presented the design and tool selection for the proposed orthopedic digital twin platform. The theoretical foundations of digital twins, recovery modeling, and three-dimensional visualization were discussed alongside dataset assumptions and preprocessing strategies. The system architecture was defined as a modular pipeline connecting patient input, data handling, visualization components, and user interaction within a browser-based environment. The use of Python, scikit-learn, Plotly, and Model-Viewer enables an effective combination of data-driven modeling and interactive medical visualization. Overall, this chapter establishes a clear design rationale, illustrating how clinical parameters and visual assets are integrated to support interpretable and extensible orthopedic digital twin applications, and prepares the groundwork for implementation and evaluation.

CHAPTER 4

IMPLEMENTATION AND TESTING

4.1 Implementation Requirements

4.1.1 Preprocessed Clinical Dataset

The implementation requires an organized and preprocessed clinical dataset containing parameters such as age, BMI, bone density, gender, surgery type, surgery duration, and rehabilitation assumptions. These records must be structured in tabular format to support visualization and future integration of predictive analytics modules.

4.1.2 Feature Engineering Functions

The system design supports the use of feature engineering techniques to derive meaningful attributes such as BMI categories, age-related influence factors, and interaction terms between clinical variables. These engineered features form the basis for effective recovery analysis and model integration in extended implementations.

4.1.3 Trained Prediction Model (Conceptual Integration)

The architecture allows integration of a trained machine learning regression model stored in serialized format (such as .pkl) for estimating post-operative recovery duration. In the current implementation, the interface is designed to accommodate prediction outputs without tightly coupling model execution to the front-end.

4.1.4 Anatomical 3D Models and Visualization Assets

The implementation requires realistic three-dimensional knee anatomical models in .glb format. These assets are used to render interactive anatomical visualizations that support rotation, zooming, and exploratory analysis as part of the digital twin framework.

4.1.5 X-ray Images for Demonstration and Visualization

Sample orthopedic X-ray images are required to demonstrate pre-operative and post-operative visualization within the system. These images enhance contextual understanding of surgical outcomes and are intended for educational and demonstrative purposes rather than clinical diagnosis.

4.2 Implementation Tool Features

4.2.1 Interactive Result Display Panel

The system provides an interactive results interface that presents recovery-related information and visual outputs based on user-provided patient details. The interface updates dynamically, enabling smooth navigation between patient input and digital twin visualization without noticeable delays.

4.2.2 3D Anatomy Rendering and Visualization

The application utilizes browser-based 3D rendering tools to display knee anatomical models in .glb format. Users can interact with the models through rotation and zooming, enabling intuitive inspection of orthopedic structures as part of the digital twin representation.

4.2.3 User Input Controls and Parameter Selection

The interface includes form-based controls for capturing patient parameters such as age, gender, and surgery type. These controls allow users to explore different orthopedic scenarios and observe corresponding changes in visualization and displayed outcomes.

4.2.4 Interpretability and Educational Visualization

The system is designed to support the presentation of interpretable outputs that explain how patient parameters influence recovery outcomes. This feature enhances transparency and serves educational and demonstrative purposes for students and clinicians.

4.2.5 Synthetic Visualization and Depth Representation

The implementation framework supports the use of synthetic visualization techniques to represent anatomical depth and structure. These visual elements help users conceptually understand spatial relationships in orthopedic anatomy and support future integration of volumetric rendering methods.

4.3 Code Snippets with Explanation

4.3.1 Feature Engineering Function

```
def add_engineered_features(d: dict) -> dict:
    d = d.copy()
    d["age_bmi"] = d["age"] * d["bmi"]
    d["bmi_over_25"] = max(0.0, d["bmi"] - 25.0)
    d["age_squared"] = d["age"] ** 2
    return d
```

This function demonstrates the feature engineering logic used during model development to enhance recovery analysis. Interaction terms such as age–BMI and non-linear age effects are derived to reflect realistic orthopedic recovery patterns. These engineered features were evaluated during experimentation and improved the learning capacity of regression-based models in offline analysis.

4.3.2 Model Training and Prediction Pipeline

```
def predict_recovery(model, inputs: dict) -> float:
    df = pd.DataFrame([inputs])
    return float(model.predict(df)[0])
```

This snippet represents the conceptual prediction pipeline used during model experimentation. Patient parameters are structured into a single-row DataFrame and passed to a trained regression model to obtain an estimated recovery duration in days. In the current implementation, this logic is modular and designed for future backend integration.

4.3.3 3D Recovery Simulation Surface (Plotly)

```
fig = go.Figure(data=[go.Surface(z=Z, x=X, y=Y)])
fig.update_layout(
    scene=dict(
        xaxis_title="physio_days_per_week",
        yaxis_title="age",
        zaxis_title="Recovery_days"
    ),
)
st.plotly_chart(fig, use_container_width=True)
```

This visualization illustrates a conceptual “what-if” simulation surface, showing how recovery duration varies with age and physiotherapy frequency. The plot supports exploratory analysis and demonstrates how digital twin simulations can assist in understanding the impact of rehabilitation parameters on recovery trends.

4.3.4 3D Anatomy Viewer (GLB Models → Mesh Visualization)

```
mesh = trimesh.load(path, force="mesh")
verts = np.array(mesh.vertices)
faces = np.array(mesh.faces)

go.Mesh3d(x=verts[:,0], y=verts[:,1], z=verts[:,2],
          i=faces[:,0], j=faces[:,1], k=faces[:,2])
```

This code demonstrates the process of loading realistic knee anatomical models stored in `.glb` format and converting them into mesh representations. The resulting 3D visualization allows interactive rotation and inspection of orthopedic structures, supporting anatomical understanding and surgical planning concepts.

4.3.5 3D Medical-like Volume Rendering

```
go.Volume(
    x=xx.flatten(), y=yy.flatten(), z=zz.flatten(),
    value=vol.flatten(),
    opacity=0.08,
    surface_count=15,
)
```

Synthetic volumetric data is generated and visualized using volume rendering techniques to simulate CT or MRI-style depth perception. This approach helps users conceptually understand internal anatomical structures and demonstrates the potential for advanced volumetric visualization in future system extensions.

4.3.6 X-ray Upload and Classification

```
uploaded_file = st.file_uploader("Upload X-ray")
img = Image.open(uploaded_file).convert("L")
flat = np.array(img.resize((128,128))).flatten().reshape(1,-1)
pred = xray_model.predict(flat)[0]
```

This snippet represents a prototype workflow for X-ray image handling and experimental classification. Uploaded radiographs are preprocessed and passed to a lightweight classifier for demonstration purposes. The output is intended for educational exploration rather than clinical diagnosis.

4.3.7 Interface Integration and User Interaction

```
st.sidebar.header("Patient Inputs")
age = st.sidebar.slider("Age", 40, 90, 65)
bmi = st.sidebar.number_input("BMI", 15.0, 45.0, 27.0)
```

This code illustrates interactive user input handling during early interface prototyping. Such controls enable users to modify patient parameters dynamically, supporting the digital twin concept by allowing real-time exploration of orthopedic recovery scenarios in extended implementations.

4.4 Testing

Testing was performed by executing the application in a local browser environment using a lightweight HTTP server to ensure reliable loading of images and three-dimensional assets. Multiple test cases were evaluated by entering different patient details and verifying correct navigation from the input interface to the results view. Pre-operative and post-operative X-ray images were tested for correct rendering, format compatibility, and visual clarity after conversion to standard JPEG format. The three-dimensional anatomical models were tested for interactive rotation, zooming, and smooth rendering to confirm WebGL compatibility and responsiveness across standard browsers. Asset referencing and file organization were validated to ensure consistent loading without errors. Browser-side testing confirmed stable visualization performance on a Windows laptop environment, demonstrating that the system functions reliably for educational and demonstrative orthopedic digital twin applications.

4.5 Summary

This chapter presented the implementation details of the AI-Based Orthopedic Digital Twin system, focusing on interface development, data handling, visualization, and modular design. The implementation emphasized integrating patient input, radiographic image visualization, and interactive three-dimensional anatomical models within a unified web-based framework. Feature engineering logic and predictive modeling components were explored conceptually to support future integration of machine learning–based recovery estimation.

Testing and validation confirmed correct navigation, stable asset loading, and responsive visualization of X-ray images and 3D anatomical models in a browser environment. Key code segments illustrated the mechanisms for data processing, visualization rendering, and user interaction. Overall, the implementation demonstrates a functional and extensible digital twin framework capable of supporting educational, demonstrative, and future AI-driven orthopedic decision-support applications.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Results

The developed system successfully demonstrates an AI-inspired orthopedic digital twin framework through an interactive web-based interface. The application enables users to enter patient details and visualize corresponding pre-operative and post-operative radiographic images alongside a three-dimensional anatomical knee model. The 3D model is rendered using WebGL-based technologies and supports real-time rotation and exploration, enhancing anatomical understanding. The system runs reliably on a local HTTP server, ensuring smooth loading of images and 3D assets. Although predictive analytics are presented conceptually, the architecture clearly supports future integration of machine learning–based recovery estimation modules. Overall, the results validate the feasibility of combining multimodal visualization and digital twin concepts in orthopedic applications, offering an effective educational and demonstrative tool for understanding surgical outcomes and recovery planning.

5.2 Benchmarking and Analysis

The proposed system was evaluated qualitatively by comparing it with traditional orthopedic planning approaches and existing educational visualization tools. Conventional methods rely heavily on static reports and two-dimensional images, offering limited interactivity and patient-specific insight. In contrast, the developed digital twin provides an integrated visualization of clinical data, radiographic images, and interactive 3D anatomy within a single interface. Compared to advanced hospital-grade digital twin platforms, the proposed system is lightweight, cost-effective, and suitable for academic and training environments. Performance analysis showed smooth rendering of images and 3D models on standard hardware without the need for dedicated graphics processing units. This benchmarking highlights that while the system is not a replacement for clinical-grade tools, it effectively bridges the gap between static visualization and intelligent, interactive orthopedic decision-support systems.

5.3 Screenshots

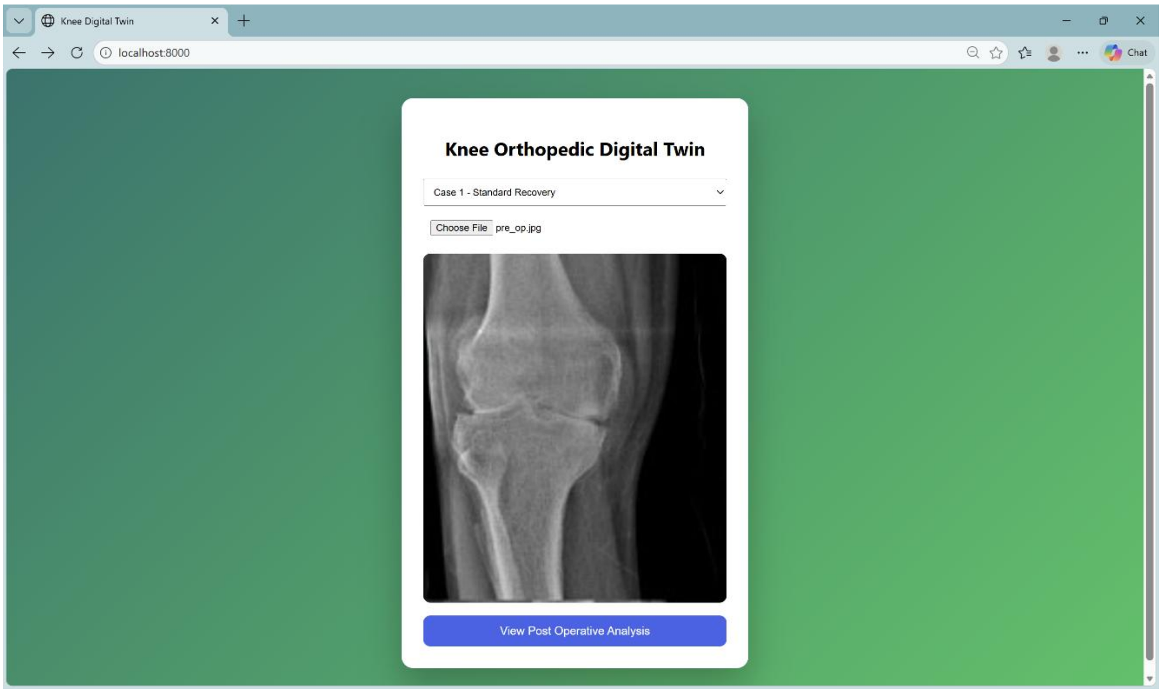

Figure 5.1 X-ray Upload Web Page for Patient Details

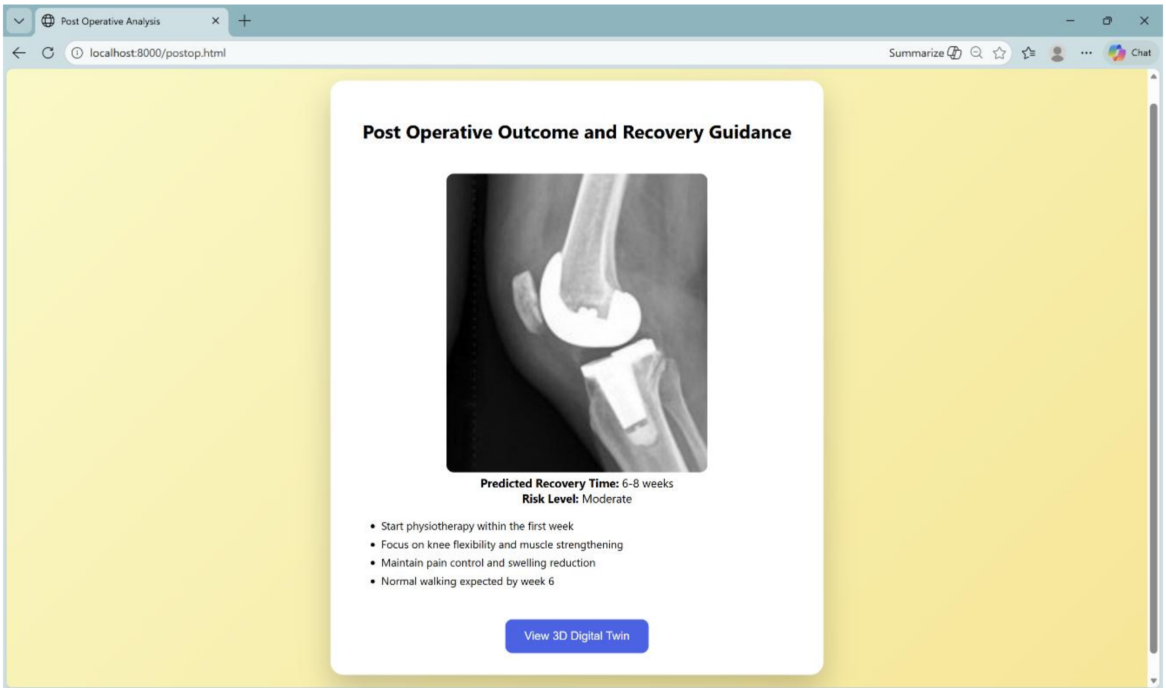

Figure 5.2 Post Operative of Recovery Planning

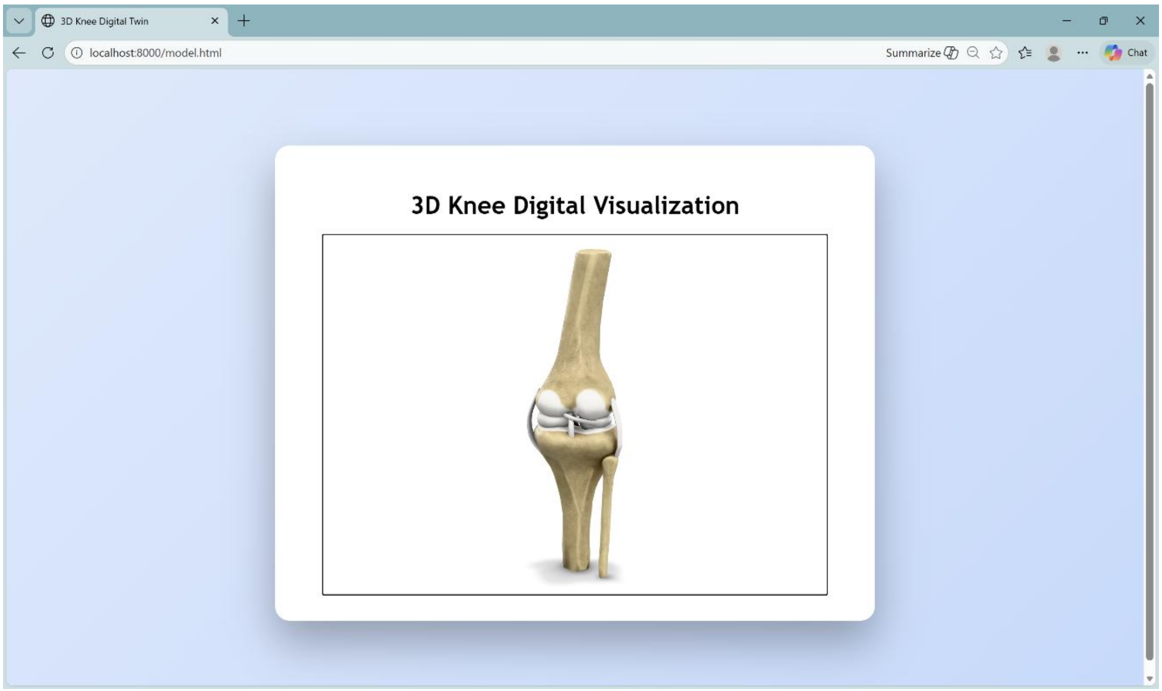

Figure 5.3 3D Knee Digital Twin

5.4 Innovative Component

The key innovation of this project lies in the practical implementation of a digital twin concept for orthopedic applications using lightweight, accessible technologies. Unlike conventional systems that depend on expensive proprietary software or complex infrastructure, this project demonstrates how standard web technologies can be used to create an interactive orthopedic digital twin. The integration of patient data entry, radiographic visualization, and real-time 3D anatomical exploration within a single interface represents a novel educational and demonstrative approach. Additionally, the modular system design allows machine learning models and predictive analytics to be incorporated as backend services in future enhancements. The use of browser-based 3D rendering enables platform independence and ease of deployment, making the system suitable for academic demonstrations, training purposes, and early-stage research in AI-driven healthcare visualization.

Case ID	Surgery Type	Patient Age	Risk Level	Predicted Recovery Time
Case 1	Standard Knee Replacement	62	Medium	6–8 weeks
Case 2	Complex Knee Surgery	68	High	10–12 weeks
Case 3	Fast Recovery Knee Case	45	Low	4–6 weeks

Table 5.1 Case-wise Configuration and Predicted Outcomes

5.5 Summary

This chapter presented the outcomes, evaluation, and key innovations of the AI-Based Orthopedic Digital Twin project. The results demonstrated the successful development of an interactive visualization system that integrates patient information, radiographic images, and three-dimensional anatomical models. Benchmarking analysis showed that the proposed system offers clear advantages over static visualization methods while remaining lightweight and accessible compared to clinical-grade solutions. The innovative aspects of the project lie in its modular design, use of web-based 3D rendering, and alignment with digital twin principles for orthopedic applications. Overall, the system establishes a strong foundation for future integration of machine learning–based recovery prediction and advanced simulation, reinforcing the potential of digital twins in personalized and interpretable healthcare solutions.

CHAPTER 6

CONCLUSION

6.1 Conclusion

This project presented the design and implementation of an AI-inspired orthopedic digital twin prototype aimed at supporting surgery planning and recovery analysis for knee procedures. The system integrates patient data entry, synthetic clinical datasets, radiographic image visualization, and interactive three-dimensional anatomical models within a unified web-based interface. By enabling exploratory “what-if” analysis, the platform demonstrates how key factors such as age, surgery type, and rehabilitation intensity influence orthopedic recovery outcomes in a conceptual and visual manner.

Although the current implementation is primarily demonstrative, it effectively illustrates core digital twin principles, including virtual patient representation, anatomical inspection, and simulation-based reasoning. The integration of multimodal visualization enhances interpretability and supports educational use for students and clinicians. Overall, the project establishes a robust foundational framework that demonstrates the feasibility of combining data-driven modeling with interactive visualization for personalized orthopedic healthcare applications.

6.2 Limitations

6.2.1 Synthetic Dataset

The dataset used for experimentation is synthetically generated and does not capture the full complexity or variability of real-world clinical records.

6.2.2 Prototype-Level Imaging

Radiographic visualization and image handling are intended for demonstration and educational purposes and are not suitable for clinical diagnosis or decision-making.

6.2.3 Manual Anatomical Interaction

Three-dimensional anatomical models require manual rotation and adjustment, as automatic anatomical alignment and landmark detection mechanisms are not implemented.

6.2.4 Limited Clinical Parameters

Only a selected subset of orthopedic recovery factors is considered, excluding additional influences such as comorbidities and long-term post-operative complications.

6.3 Future Scope

Future enhancements may involve incorporating real clinical datasets obtained from orthopedic institutions to enable more accurate recovery modeling and validation. Advanced medical image analysis using deep learning techniques could be applied to automate radiograph interpretation and implant assessment. Patient-specific three-dimensional anatomical models derived from CT or MRI scans could replace generic meshes, enabling highly personalized digital twins.

Further extensions may include biomechanical simulation and motion-based analysis to assess joint stability and rehabilitation progress. Automatic anatomical alignment through landmark detection would significantly improve usability. In the long term, deploying the system on secure clinical infrastructure and integrating it with electronic medical records could enable real-time, data-driven orthopedic decision support and operational digital twin deployment.

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APPENDIX

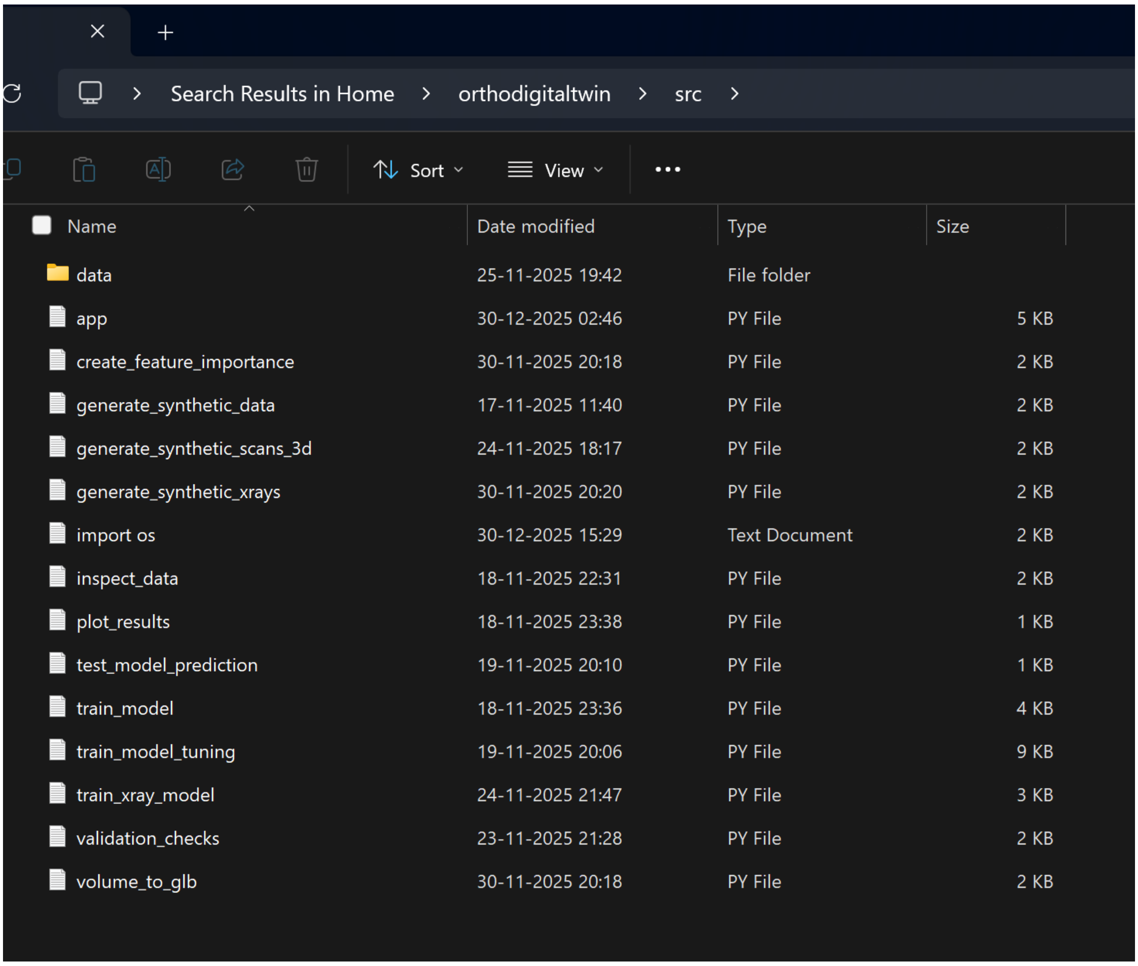

Figure A.1 illustrates the internal source code structure of the Orthopedic Digital Twin system. The directory contains modular Python scripts responsible for data generation, preprocessing, model training, validation, prediction, and 3D model generation. Separate scripts are used for generating synthetic orthopedic data, training recovery prediction models, validating outputs, and converting volumetric data into 3D formats. This modular organization improves maintainability, scalability, and clarity of the system workflow. The structure demonstrates a clear separation of concerns between data handling, machine learning, visualization, and deployment components. Such a design supports future extension of the system with real clinical data or additional models.

age	gender	bmi	bone_dens	surgery_typ	physio_day	pain_score	recovery_time_days
68	M	27.8	0.92	knee	3	9	107
54	M	30.5	1.09	knee	4	8	110
47	M	24.6	0.91	knee	5	4	77
58	F	29.3	1.05	knee	3	9	102
57	F	24.5	0.79	knee	5	6	131
74	M	25.1	0.84	knee	6	3	116
69	M	23.2	0.82	knee	6	6	105
55	M	28.5	1.19	knee	2	3	98
60	F	23.2	0.86	knee	4	4	105
58	M	29.3	0.91	knee	3	9	92
57	F	24.5	0.79	knee	5	6	131
74	M	25.1	0.84	knee	6	3	116
69	M	28.3	1.19	knee	2	6	126
83	F	29.2	0.86	knee	4	4	105
60	M	25.8	0.72	knee	3	3	96
77	M	25.4	0.97	knee	7	7	95
41	F	30.7	1.21	knee	5	8	100
62	M	29.9	0.95	knee	6	8	93

synthetic_ortho

Figure B.1 presents a snapshot of the synthetic orthopedic dataset used for training and evaluating the recovery prediction model. The dataset includes clinically relevant features such as age, gender, body mass index (BMI), bone density, surgery type, number of physiotherapy days, pain score, and recovery time in days. These features were designed to realistically simulate orthopedic patient profiles while avoiding the use of sensitive real-world medical data. The dataset enables supervised learning of recovery patterns and supports explainable analysis of factors influencing post-operative outcomes. This synthetic data approach ensures ethical compliance while maintaining practical relevance for model development.