EXPLAINABLE ARTIFICIAL INTELLIGENCE

PROJECT REPORT

Submitted By

ABHINAV R(MCC21CS004)

ABHIRAGH A R(MCC21CS005)

ALFIN MUHAMMED N S(MCC21CS012)

ASWATHY M L(MCC21CS021)

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MUSALIAR COLLEGE OF ENGINEERING

KADAKAM P.O CHIRAYINKEEZHU, TRIVANDRUM 695304

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DECLARATION

We undersigned hereby declare that the project report **"EXPLAINABLE ARTIFICIAL INTELLIGENCE"**, submitted for partial fulfilment of the requirements for the award of degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under supervision of Mrs. Labeeba Vahid. This submission represents our ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources. we also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

ABHINAV R(MCC21CS004)

ABHIRAGH A R (MCC21CS005)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
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CHIRAYINKEEZHU, TRIVANDRUM 695304

CERTIFICATE

This is to certify that, the project report entitled '**EXPLAINABLE ARTIFICIAL INTELLIGENCE',** is a Bonafide record of the CSD334 Project presented by **ABHINAV R(MCC21CS004), ABHIRAGH A R(MCC21CS005),ALFIN MUHAMMED N S(MCC21CS012), ASWATHY M L(MCC21CS021)** of Sixth Semester B. Tech. Computer Science & Engineering students, under our guidance and super vision, in partial fulfilment of the requirements for the award of the degree, B. Tech. Computer Science & Engineering of APJ Abdul Kalam Technological University.

Project Guide	Project Coordinator	HOD
Mrs. Labeeba Vahid	**Mrs.Aswathy Gandhi**	**Mrs.Remya R S**
Assistant Professor	Assistant Professor	Assistant Professor

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ABSTRACT

As Artificial Intelligence (AI) permeates our lives, influencing everything from loan approvals to medical diagnoses, a critical question emerges: can we understand how AI models arrive at their decisions? Enter Explainable AI (XAI), a transformative field that strives to demystify the inner workings of these complex algorithms. This project delves into the practical application of XAI techniques, aiming to bridge the gap between the opaque nature of AI models and human comprehension.

By integrating XAI methodologies, we can illuminate the "why" behind AI predictions. This newfound transparency fosters trust and empowers users with a deeper understanding of the rationale governing AI decisions. Imagine a world where loan applicants can comprehend the factors influencing loan approval/rejection, or where medical professionals gain insights into the reasoning behind AI-powered diagnostic tools. XAI empowers informed decision-making and fosters collaboration between humans and AI.

This project goes beyond theoretical exploration. It equips you with the tools and knowledge to implement XAI in your own machine learning endeavors. We explore practical considerations such as hardware and software requirements, along with valuable resources to guide your journey. Furthermore, the project investigates the potential for XAI across various domains, from real estate prediction to loan approval systems and beyond. By demonstrating the applicability of XAI in diverse scenarios, we pave the way for its widespread adoption.

Ultimately, this project aspires to contribute to a future where AI development is guided by principles of responsibility and transparency. By fostering a future where humans and AI work in concert, we can harness the immense potential of AI for the betterment of society. This exploration of XAI is not just about unveiling the black box; it's about unlocking a future where AI can be a trusted and powerful force for good.

LIST OF ABBREVIATIONS

AI – Artificial Intelligence

XAI – Explainable Artificial Intelligence

CNN - Convolutional Neural Network

RNN - Recurrent Neural Network

SHAP - SHapley Additive exPlanations

LIME - Local Interpretable Model-agnostic Explanations

RAM – Random Access Memory

VCS – Version Control System

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CHAPTER 1

INTRODUCTION

From revolutionizing facial recognition software to personalizing recommendations on streaming platforms, Artificial Intelligence (AI) has undeniably transformed our world. These intelligent systems are constantly evolving, pushing the boundaries of automation and decision-making across diverse fields. However, as AI models become increasingly powerful and complex, a critical challenge emerges: the lack of transparency in their decision-making processes. Many of these models, often referred to as "black boxes," excel at generating accurate predictions. For instance, an AI system designed for loan approval might consistently determine creditworthiness with remarkable accuracy. Yet, the inner workings of this system remain a mystery. We may know that the loan is approved, but we lack a clear understanding of the specific factors that influenced this decision. This lack of transparency raises a multitude of concerns, hindering trust, accountability, and responsible development of AI technologies.

One of the most pressing concerns surrounding black box models is the potential for bias. AI models are trained on vast datasets, and these datasets can unconsciously reflect societal biases present in the real world. If the data used to train a loan approval system disproportionately favors applicants with certain demographics or financial backgrounds, the resulting model might perpetuate those biases in its decision-making. Without understanding how the model arrives at its conclusions, it becomes incredibly difficult to identify and address such biases. This lack of transparency can lead to discriminatory outcomes, hindering equal access to opportunities and resources.

Furthermore, the lack of interpretability in black box models poses challenges for accountability and regulatory oversight. Suppose a self-driving car makes an unexpected decision on the road, potentially leading to an accident. Without understanding the reasoning behind its actions, it becomes difficult to determine the cause of the accident and hold the appropriate party accountable. Similarly, in financial settings, if an AI-powered trading system makes a risky investment with potentially negative outcomes, regulators struggle to assess the situation without clear insights into

the model's decision-making process. This lack of transparency can create a grey area in terms of responsibility and accountability.

Finally, the black box nature of many AI models hinders their development and improvement. If we cannot understand how these models arrive at their outputs, it becomes difficult to identify areas for improvement or fine-tune their performance. Imagine a medical diagnosis system that consistently misdiagnoses a particular type of disease. Without understanding which factors within the model are leading to inaccurate predictions, it's challenging to rectify the issue and ensure accurate diagnoses in the future. This lack of interpretability can hinder the overall progress and refinement of AI technologies.

In response to these critical challenges, the field of Explainable AI (XAI) has emerged as a critical area of research. XAI techniques aim to demystify the inner workings of AI models, providing insights into how they arrive at their predictions. By shedding light on the rationale behind model decisions, XAI fosters trust, enables bias detection, empowers users, and ultimately paves the way for the responsible development and deployment of AI technologies. This project delves into the exciting realm of XAI, exploring various methods for extracting meaningful explanations from diverse machine learning models.

1.1 THE ENIGMA OF BLACK BOX MODELS

The rise of Artificial Intelligence (AI) has been nothing short of phenomenal. From the intelligent assistants that seamlessly integrate into our daily lives to the sophisticated algorithms powering self-driving cars and medical diagnostics, AI is transforming how we interact with the world and make critical decisions. However, as these models become increasingly complex and powerful, a crucial question arises: how do they actually arrive at their outputs? Many AI models, often referred to as "black boxes," excel at generating accurate predictions. For example, an AI system used for loan approval might consistently determine creditworthiness with remarkable accuracy. Yet, the inner workings of this system remain shrouded in mystery. We know whether a loan is approved or denied, but the specific factors influencing this decision remain hidden from view. This lack of transparency in black box models poses a significant challenge, hindering trust, accountability, and

ultimately, the responsible development of AI technologies. The rise of Artificial Intelligence (AI) has been nothing short of phenomenal. From the intelligent assistants that seamlessly integrate into our daily lives to the sophisticated algorithms powering self-driving cars and medical diagnostics, AI is transforming how we interact with the world and make critical decisions. However, as these models become increasingly complex and powerful, a crucial question arises: how do they actually arrive at their outputs? Many AI models, often referred to as "black boxes," excel at generating accurate predictions. For example, an AI system used for loan approval might consistently determine creditworthiness with remarkable accuracy. Yet, the inner workings of this system remain shrouded in mystery. We know whether a loan is approved or denied, but the specific factors influencing this decision remain hidden from view. This lack of transparency in black box models poses a significant challenge, hindering trust, accountability, and ultimately, the responsible development of AI technologies.

1.2 DEMYSTIFYING THE MACHINE: THE RISE OF XAI

The limitations of black box models have spurred the development of a crucial counterpoint: Explainable AI (XAI). XAI techniques aim to illuminate the decision-making processes of AI models, transforming them from opaque oracles into systems with a degree of transparency. By shedding light on the rationale behind model predictions, XAI offers a multitude of benefits that address the challenges outlined in the previous section.

1. Fostering Trust and Transparency: As discussed earlier, the lack of transparency in black box models hinders trust in AI systems. XAI techniques bridge this gap by providing explanations for model outputs. These explanations can take various forms, such as highlighting the most influential features in a decision, visualizing the model's internal logic, or offering counterfactual examples that demonstrate how changing specific inputs might affect the prediction. By understanding the reasoning behind a model's decision, users are empowered to make informed judgments about its reliability and applicability in different scenarios. This transparency fosters trust and acceptance of AI systems, paving the way for wider adoption and integration across various domains.

2. Detecting and Mitigating Bias: The susceptibility of black box models to bias is a critical concern. XAI techniques can be instrumental in identifying and mitigating these biases. By

analyzing how different features contribute to model predictions, XAI methods can expose unforeseen biases lurking within the training data or the model architecture itself. For instance, an XAI technique might reveal that a loan approval system consistently assigns higher weights to factors like zip code or educational background, potentially leading to discriminatory outcomes. With such insights, developers can take corrective measures, such as data balancing or adjusting model weights, to mitigate biases and ensure fairer model behavior.

3. Empowering Users with Informed Decision-Making: XAI empowers users by allowing them to understand the basis for a model's prediction. When presented with a prediction, users can delve deeper and explore the factors that led the model to that conclusion. Imagine a customer receiving a personalized recommendation from a recommendation engine. Through XAI, the user can understand why this specific item was recommended, whether it's based on past purchase history, browsing behavior, or similar user demographics. This knowledge allows users to make more informed choices based on their own needs and preferences, rather than blindly accepting the model's suggestion. Additionally, XAI can help identify potential limitations or inaccuracies in the model, allowing users to adjust their trust in the prediction accordingly.

4. Enabling Model Improvement and Development: Understanding how a model arrives at its outputs is crucial for its continuous improvement. XAI techniques provide valuable insights for developers seeking to refine and enhance model performance. By analyzing feature importance and identifying weaknesses in the model's reasoning, developers can pinpoint areas for improvement. For instance, XAI might reveal that a model for predicting customer churn is overlooking a critical factor that significantly influences customer retention. With this knowledge, developers can retrain the model with a more comprehensive dataset or adjust the model architecture to account for the newly discovered factor. This iterative process of explanation, analysis, and improvement, facilitated by XAI techniques, leads to the development of more robust, reliable, and accurate AI models.

1.3 OBJECTIVES: AN EXPLORATION OF XAI TECHNIQUES

This project delves into the exciting realm of Explainable AI (XAI) by exploring its application with various machine learning models. Our core objectives aim to showcase the versatility of XAI

and its compatibility with different model architectures, while simultaneously providing valuable insights into the inner workings of these models.

1. DIVERSE MODEL SELECTION:

One of the central objectives of this project is to explore the application of XAI techniques with a variety of machine learning models. This will involve selecting models that encompass different tasks and architectures. For instance, we might consider a Random Forest model for a regression task like predicting house prices, a Convolutional Neural Network (CNN) for image classification tasks like identifying objects in photographs, and a Recurrent Neural Network (RNN) for a sequential data task like sentiment analysis of text reviews. By applying XAI techniques to these diverse models, we aim to demonstrate their effectiveness across a range of scenarios and highlight how XAI can be integrated with different modeling approaches.

2. UNVEILING EXPLANATIONS:

A critical objective of this project is to leverage XAI methods to extract meaningful explanations from the chosen machine learning models. These explanations will shed light on the features or factors that most significantly influence the models' predictions. For instance, when a Random Forest model predicts a high house price, XAI techniques might reveal that features like square footage, number of bedrooms, and location contribute most heavily to this prediction. Similarly, when a CNN classifies an image as a cat, XAI methods might highlight specific regions within the image (e.g., the ears, tail, and facial features) that played a key role in the model's decision. By unveiling these explanations, we aim to gain a deeper understanding of how the models arrive at their outputs and gain valuable insights into the underlying relationships between features and predictions.

3. COMPARATIVE ANALYSIS:

This project will explore a range of XAI techniques and compare and contrast the explanations they generate for the same model. For example, we might apply SHAP (SHapley Additive exPlanations) to a tree-based model like Random Forest and LIME (Local Interpretable Model-agnostic

Explanations) to a more complex model like a CNN. By comparing the explanations generated by these different XAI methods, we can gain valuable insights into their strengths and weaknesses. SHAP explanations might offer a global view of feature importance across the entire dataset, while LIME explanations might provide more localized explanations specific to individual predictions. Through this comparative analysis, we aim to identify the most suitable XAI techniques for different model types and tasks, while also highlighting the unique benefits and limitations of each approach.

4. REAL-WORLD APPLICATION:

This project doesn't just focus on theoretical exploration. A core objective is to integrate the chosen XAI techniques and models into a practical application, demonstrating their value in a real-world scenario. This could involve building a system that leverages XAI to explain the predictions of a machine learning model used in a specific domain. For instance, we might develop an application that utilizes XAI to explain loan approval decisions made by an AI-powered lending system. By integrating XAI into this real-world application, we aim to showcase its practical utility and demonstrate how it can foster transparency and trust in AI-driven decision-making processes.

1.4 EXPECTED BENEFITS:

By achieving these objectives, this project anticipates several benefits:

- **Enhanced Trust and Transparency:** By demystifying model behavior, XAI can increase trust in AI systems, leading to wider adoption and acceptance.
- **Bias Detection and Mitigation:** Unveiling the factors influencing model decisions can enable the identification and mitigation of potential biases embedded within the data or model training process.
- **Improved Model Development:** Understanding how models arrive at their outputs can guide developers in optimizing model architectures and enhancing their overall performance.

- **Informed User Decisions:** Users can make more informed decisions by gaining insights into the reasoning behind a model's predictions.

1.5 PROJECT SCOPE:

To ensure a focused investigation, this project will define its scope in terms of the following aspects:

- **Model Selection:** We will select a set of diverse machine learning models encompassing different tasks and architectures (e.g., Random Forest for regression, Convolutional Neural Network for image classification).
- **XAI Techniques:** We will explore a range of XAI techniques, such as SHAP explanations for tree-based models and LIME for more complex models.
- **Dataset Selection:** Datasets will be chosen that are relevant to the chosen models and tasks, ensuring compatibility and meaningful explanations.
- **Real-World Application Scenario:** We will define a specific real-world scenario for model and XAI integration, demonstrating its practical utility.

By clearly outlining the intended exploration path and setting boundaries, we ensure a manageable and impactful project within the designated timeframe.

1.6 OVERVIEW:

AI models are powerful but lack transparency. This project explores Explainable AI (XAI) to see how these models work. We'll test XAI on various models (like image recognition) to understand their decisions. By comparing explanations from different XAI methods, we'll find the best fit for each model. Finally, we'll put XAI to use in a real-world setting, showing its practical value. This project aims to make AI more trustworthy and reliable by giving us a window into how these models actually think.

CHAPTER 2

LITERATURE SURVEY

Recommender systems (RS) play a crucial role in today's information-laden world, helping users navigate vast selections of products, movies, music, and more. However, the opaque nature of traditional RS models often leaves users in the dark about why a particular item is recommended. This lack of transparency can hinder trust and user satisfaction. To address this challenge, research in Explainable Artificial Intelligence (XAI) is paving the way for the development of explainable recommender systems (XAI-RS).

This chapter delves into the existing literature on XAI-RS. We explore the strengths and limitations of current approaches, highlighting areas for improvement to foster user-centric explainability. By examining previous research, we can build a foundation for developing effective XAI-RS that empower users with transparency and understanding.

2.1 INTERPRETABLE MATRIX FACTORIZATION

In their work titled "Interpretable Matrix Factorization for Recommender Systems" (2010), Rendle et al. propose a method for interpretable matrix factorization (IMF) in RS. IMF is a popular technique for recommendation, but it can be challenging to understand the rationale behind its predictions. Rendle et al. address this by incorporating predefined features into the model, allowing for a degree of interpretability. These features could represent characteristics of users (e.g., demographics, interests) or items (e.g., genre, brand). However, one limitation of this approach is the difficulty in capturing evolving user preferences. Predefined features may struggle to adapt to changes in user taste over time. Future research could explore ways to dynamically update these features or integrate mechanisms for user feedback to address this limitation.

2.2 EXPLAINABLE SYSTEMS: SURVEY AND CHALLENGES

Wilk et al. (2022) present a broader survey of explainability in RS titled "Explainable Recommendation Systems: Survey and Challenges." Their work highlights the importance of XAI in RS and explores various approaches to explainability, including model-agnostic and model-specific techniques. Model-agnostic techniques are independent of the specific RS model used, while model-specific techniques are tailored to the inner workings of a particular model. However, they identify a key limitation in many existing methods: the overemphasis on model-centric explanations. These explanations focus on how the model arrived at a recommendation, often by highlighting the weights assigned to different features or the activation levels of neurons in a deep learning model. While these explanations can be insightful for developers, they may not be relevant or easily understandable for users. Future research should prioritize user-centric explanations that focus on the factors and user data points that directly influenced the recommendation.

2.3 TOWARDS USER-CENTRIC EXPLAINABLE SYSTEMS

Xu et al. (2023) delve deeper into the concept of user-centric explainability in their paper "Towards User-Centric Explainable Recommendation Systems." They emphasize the need for explanations that resonate with users and address potential biases within the model. While some approaches focus on explaining individual recommendations, Xu et al. highlight the importance of explaining the potential for bias within the system. This transparency can foster trust with users by acknowledging the limitations of the model and how biases in the training data could influence recommendations. For instance, an RS trained on a dataset with an inherent gender bias might recommend different products to male and female users even if their preferences are similar. Explaining such potential biases can help users understand the limitations of the system and make more informed decisions based on the recommendations.

2.4 INTERPRETABLE NEURAL COLLABORATIVE FILTERING

He et al. (2023) explore interpretable neural collaborative filtering (NCF) for XAI-RS in their work titled "Interpretable Neural Collaborative Filtering for Explainable Recommendation Systems." NCF is a powerful technique for recommendations, but it can be challenging to interpret its inner workings due to its complex architecture. He et al. propose methods for

incorporating interpretability into the NCF model by introducing additional layers or modifying existing ones to provide explanations for model predictions. However, a limitation of their approach is the focus on specific interaction data, such as user ratings or clicks. This may overlook valuable user insights present in other forms, like user reviews. User reviews can provide rich textual information about user preferences and reasons for liking or disliking certain items. Future research could explore ways to integrate user reviews and other forms of user data into the model to generate more comprehensive explanations.

2.5 HUMAN-CENTERED EXPLAINABLE AI: A SURVEY

Singh et al. (2023) delve into the concept of human-centered XAI, emphasizing the importance of tailoring explanations to user needs and preferences. They identify a gap in research regarding specific XAI techniques that resonate best with users. While various explainability methods exist (e.g., feature importance, counterfactual explanations, visualizations), it's crucial to understand how these methods translate to user understanding and satisfaction.

Future research in XAI-RS can benefit from exploring these areas:

User Studies: Conduct user studies to evaluate the effectiveness of different XAI techniques in recommender systems. This can involve observing user interactions with explanations, gathering user feedback on clarity and usefulness, and comparing different explanation formats.

Tailoring Explanations to User Preferences: Investigate ways to personalize explanations based on user characteristics like technical expertise, preferred level of detail, and desired format (textual, visual, interactive). This personalization can ensure that explanations are not only informative but also engaging and relevant to individual users.

By addressing these areas, we can create XAI-RS that not only recommend relevant items but also provide users with clear, informative, and trustworthy explanations. This will ultimately lead to a future where recommender systems are not just helpful tools but also transparent partners in the user's decision-making process.

Serial No	Title	Author	Limitations	Proposed Improvements
1.	Interpretable Matrix Factorization for Recommender Systems	Steffen Rendle et al	Pre-defined features struggle to capture user preferences and changing tastes over time.	Integrate user feedback and dynamic updates to capture evolving preferences and provide more tailored recommendations.
2.	Explainable Recommendation Systems: Survey and Challenges	Bartosz Wilk et al	Focuses heavily on model centric explanations neglecting user preferences and feedback	Incorporate user preferences and feedback into the explanation process.

3.	Towards User-Centric Explainable Recommendation Systems	Lei Xu et al	Primarily focuses on explaining individual recommendations.	Provide explanations for potential biases within the model, promoting transparency and trust
4.	Interpretable Neural Collaborative Filtering for Explainable Recommendation Systems	Xiangnan He et al	Focus on specific interaction data: The model relies on user-item interactions (ratings, clicks)	Incorporate additional user data: Explore ways to integrate user reviews
5.	Human-Centered Explainable AI: A Survey	Sameer Singh et al	Limited focus on technical details and user centricity.	Focus on specific XAI techniques that align well with user-centricity.

Fig 2.1 Literature Survey

CHAPTER 3

EXISTING SYSTEM

3.1 THE REALM OF NON-EXPLAINABLE MODELS:

Non-explainable models, often referred to as black boxes, have revolutionized various fields with their ability to generate accurate predictions. From facial recognition software to spam filters, these models operate with remarkable efficiency. However, their inner workings remain shrouded in mystery. We may receive a clear output (e.g., loan approval denial or image classification), but the reasoning behind the decision remains opaque.

The Drawbacks of Opacity: While non-explainable models offer impressive results, their lack of transparency presents several drawbacks:

- **Erosion of Trust:** Users have difficulty trusting a system whose decision-making process is a mystery. Without understanding the "why" behind a prediction, users may question its fairness and accuracy.
- **Hidden Biases:** Non-explainable models can unknowingly perpetuate biases present in the training data. Since we can't see how the model arrives at its conclusions, identifying and mitigating these biases becomes a significant challenge.
- **Hindered Improvement:** The inability to understand how a model arrives at its outputs hinders efforts to improve its performance. If we can't pinpoint weaknesses or areas for refinement in the model's internal logic, it's difficult to effectively enhance its capabilities.

3.2 DEMYSTIFYING DECISIONS: THE POWER OF XAI

XAI techniques address these limitations by demystifying the inner workings of non-explainable models. They provide insights into the factors most influencing a model's predictions, fostering trust, transparency, and responsible AI development:

- **Enhanced Transparency:** By explaining model outputs, XAI empowers users to understand the reasoning behind predictions. This fosters trust and acceptance of AI systems, allowing users to make informed decisions based on a deeper understanding of the model's thought process.
- **Bias Detection and Mitigation:** XAI techniques can help identify and mitigate potential biases within the data or model architecture. By analyzing how features contribute to predictions, we can address and rectify unfair biases that might be present in the model.
- **Informed Improvement:** XAI sheds light on a model's internal workings, enabling developers to identify areas for improvement and refine the model's performance through targeted interventions. By understanding which factors are most influential in a model's decision-making, developers can focus on improving those specific aspects.

3.3 A SHIFT TOWARDS TRANSPARENCY:

By embracing XAI, we move beyond the limitations of non-explainable models. XAI empowers users, fosters trust in AI systems, and paves the way for the development of more responsible and reliable AI technologies. The next chapter will delve into the practical application of XAI techniques, showcasing their value in a real-world scenario.

CHAPTER 4

PROPOSED SYSTEM

4.1 CHOOSING THE DOMAIN: A PRACTICAL SCENARIO

To showcase the value of XAI, we will select a specific domain and scenario where an AI model plays a crucial role. This could be a field like:

- **Recommender Systems:** Online platforms often use recommender systems to suggest products or services to users. By integrating XAI, the system could explain why a specific item is recommended (e.g., past purchase history, browsing behavior, similar user preferences). This allows users to understand the rationale behind the recommendation and make informed choices.

Once the domain and scenario are chosen, we will select a suitable machine learning model for the task.

4.2 TAILORING XAI FOR THE MODEL:

Building upon the XAI techniques explored in Chapter 3, we will select the most appropriate methods for the chosen machine learning model. Here are some factors to consider during this selection process:

- **Model Architecture:** The XAI technique should be compatible with the architecture of the chosen model (e.g., decision trees, neural networks).
- **Desired Explanation Level:** Do we require global explanations for overall model behavior (e.g., SHAP) or local explanations for specific predictions (e.g., LIME)?
- **Interpretability:** The chosen XAI technique should provide explanations that are interpretable by the intended audience (e.g., domain experts, loan applicants).

By considering these factors, we will ensure that the chosen XAI techniques effectively complement the machine learning model and deliver meaningful explanations within the real-world scenario.

4.3 BUILDING THE INTEGRATED SYSTEM:

This section will delve into the technical details of integrating the chosen XAI techniques with the selected machine learning model. This might involve:

- **Training the Model:** The machine learning model will be trained on relevant data specific to the chosen domain and scenario.
- **Incorporating XAI Techniques:** The selected XAI methods will be integrated into the system to enable explanation generation during model prediction.
- **Developing the User Interface:** A user interface will be designed to present the model's predictions alongside the explanations generated by the XAI techniques. This interface should be tailored to the target audience of the application.

4.4 EVALUATION AND REFINEMENT:

The integrated system will be evaluated in the chosen real-world scenario. Here are some aspects to consider during evaluation:

- **Effectiveness of Explanations:** Do the explanations provide clear and informative insights into the model's reasoning?
- **User Experience:** Is the user interface intuitive and easy to understand for the target audience?
- **Impact on Model Performance:** Does the integration of XAI techniques significantly impact the accuracy or efficiency of the underlying machine learning model?

CHAPTER 5

MODULE DESCRIPTION

5.1 MODULE 1: DATA COLLECTION AND PREPROCESSING

The foundation of any machine learning project lies in the data. This module focuses on acquiring and preparing the data necessary for both model training and XAI integration.

- **Data Collection:**
  - **House Price Prediction:** Gather real estate data containing features like square footage, number of bedrooms, location, and sale prices. Sources could include online real estate listings or public datasets.
  - **Titanic Survivor Prediction:** Acquire the Titanic passenger dataset, which includes information like passenger class, age, gender, and survival outcomes. This data is readily available from public repositories.
- **Data Preprocessing:**
  - Clean and format the data to ensure consistency and address missing values or outliers. This might involve data imputation, normalization, or feature engineering.
  - Explore the data to identify potential relationships between features and target variables (house price, survival probability). This initial exploration can provide insights for selecting appropriate XAI techniques later.

5.2 MODULE 2: MODEL BUILDING AND TRAINING

Building upon the preprocessed data, this module focuses on developing and training the machine learning models:

- **House Price Prediction:**
  - Choose a suitable regression model, such as Random Forest or Gradient Boosting, that can effectively predict house prices based on the available features.

- Train the model on the prepared data, ensuring it generalizes well to unseen data. Techniques like cross-validation can be used to evaluate model performance.

➢ **Titanic Survivor Prediction:**

- Select a classification model, such as Logistic Regression or Decision Tree, that can accurately predict passenger survival based on the passenger information.
- Train the model using the Titanic dataset, again employing techniques like cross-validation to assess its generalizability.

5.3 MODULE 3: EXPLAINABLE AI INTEGRATION

This core module integrates XAI techniques with the trained models to gain insights into their decision-making processes:

➢ **XAI Technique Selection:**

- Based on the chosen models (house price prediction, titanic survivor prediction) and the desired explanation level (global vs. local), select appropriate XAI techniques from Chapter 3 (e.g., SHAP, LIME, Anchors).
- Consider factors like model architecture, interpretability for the target audience, and the specific explanations you want to generate.

➢ **XAI Integration Implementation:**

- Implement the chosen XAI techniques within your programming environment to seamlessly integrate them with the trained models. This might involve using existing XAI libraries or frameworks.
- Ensure the integrated system can generate explanations alongside model predictions for both house prices and survival probabilities.

5.4 MODULE 4: EVALUATION AND REFINEMENT

➢ **Explanation Clarity and Informativeness:**

  - Assess whether the explanations generated by the XAI techniques are clear, informative, and provide valuable insights into the models' reasoning.

- Evaluate the explanations for both house price predictions and survivor probabilities, ensuring they align with your expectations.

- **User Experience:**
  - Consider the target audience for each model (real estate agents vs. historians) and evaluate the user interface for clarity and ease of understanding the explanations.
- **Model Performance:**
  - Monitor the impact of XAI integration on the performance (prediction accuracy) of the underlying machine learning models.

CHAPTER 6

REQUIREMENTS

6.1 SOFTWARE REQUIREMENTS

Programming Environment: Python 3 (version 3.6 or later is recommended)

- **Machine Learning Libraries:**
  - **scikit-learn:** For building and training your machine learning models (Random Forest/Gradient Boosting for house price prediction, Logistic Regression/Decision Tree for titanic survivor prediction).
- **XAI Libraries:**
  - **LIME:** To generate localized explanations for individual house price predictions and survival probability predictions.
  - **SHAP:** To provide global explanations of feature importance for both house price and survival prediction models.
- **Web App Development Framework:**
  - **Streamlit:** To create a user-friendly web application to showcase the integrated Explainable AI models.

6.2 HARDWARE REQUIREMENTS

- **Processor:** A mid-range processor with a clock speed of 2.0 GHz or higher will ensure smooth performance for model training and explanation generation, especially when dealing with datasets of moderate size (e.g., hundreds or thousands of data points).
- **RAM:** While 4GB of RAM can suffice for basic operations, 8GB or more is recommended for a more comfortable experience.
- **Display:** A standard resolution display (1366x768 pixels or higher) is suitable for this project. The focus is on clear visualization of explanations and data, not high-resolution graphics.

- **Connectivity:** A stable internet connection is necessary for downloading software libraries, accessing online resources, and deploying the web application using Streamlit. A minimum speed of 10Mbps is recommended for smooth interaction.
- **Storage:** Sufficient storage space will be needed to accommodate datasets, project files, and software libraries.
- **Video Memory:** While not essential for this project, having a dedicated graphics card with at least 1GB of video memory can be beneficial for certain visualization tasks.

6.3 PROJECT MANAGEMENT

- **Version Control System (VCS):**
  Utilize Git to track changes to your code, data, and project files. This allows you to revert to previous versions if necessary and facilitates collaboration if working on the project with others.

CHAPTER 7

SYSTEM DESIGN

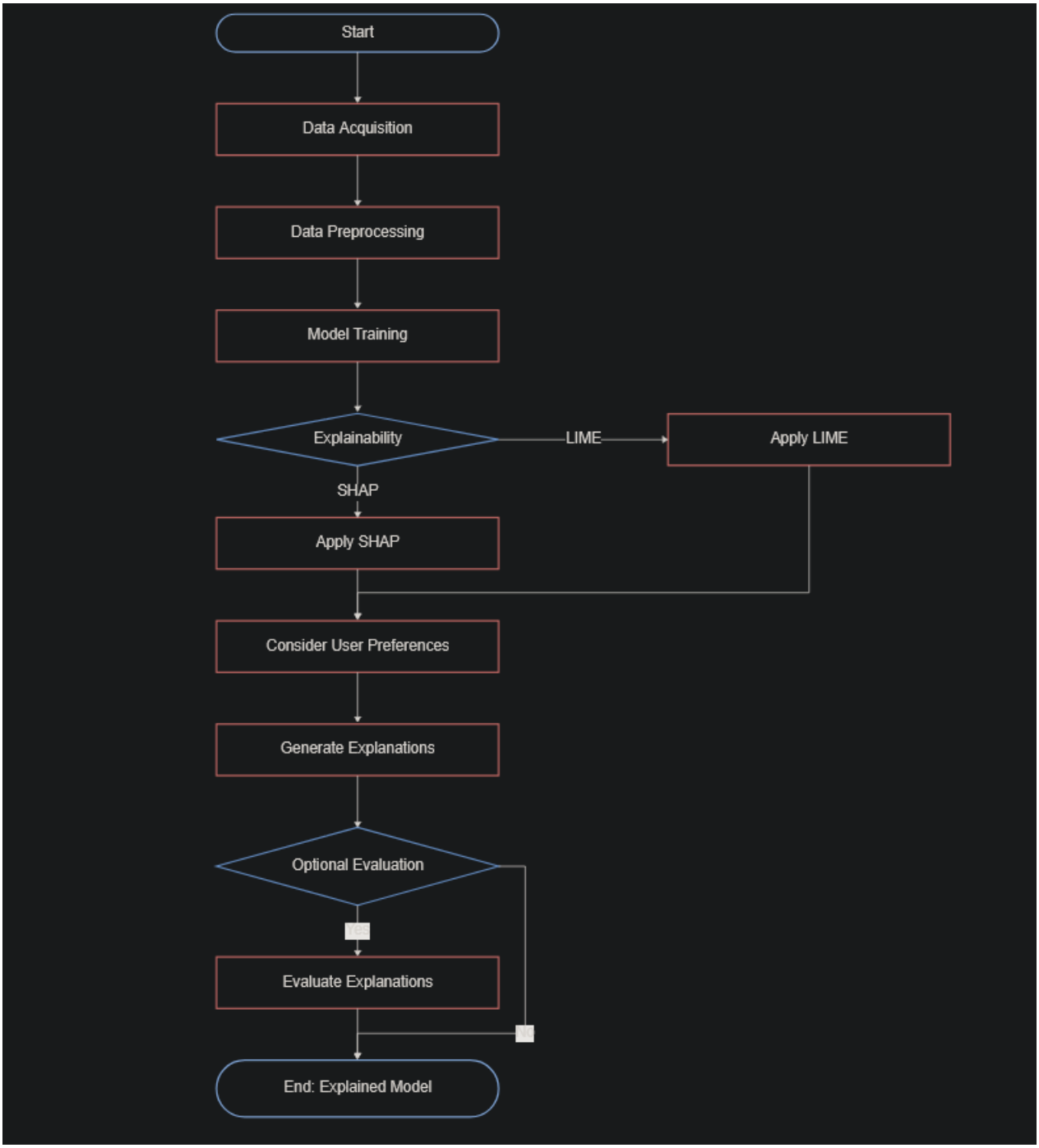


Figure 7.1 System Design Overview

CHAPTER 8

SAMPLE CODE

main.py

```
import streamlit as st
import streamlit.components.v1 as components
from Housing_Price_Prediction.house_price_prediction import predict_house_price
from Titanic_Survivor_Predictor.titanic_survivor_prediction import predict_survivor
import shap
import xgboost


def main():
    st.title("Explainable AI")


    st.write("Choose a prediction task:")
    choice = st.radio("", ("House Price Prediction", "Titanic Survivor Prediction"))


    if choice == "House Price Prediction":
        house_price_page()
    elif choice == "Titanic Survivor Prediction":
```

```
        titanic_survivor_page()
def house_price_page():
    st.subheader("House Price Prediction")
    st.write("Enter the following details:")
    lot_area = st.number_input("Lot Area")
    year_built = st.number_input("Year Built")
    first_floor_sf = st.number_input("1st Floor Sq Ft")
    second_floor_sf = st.number_input("2nd Floor Sq Ft")
    full_bath = st.number_input("Number of Full Bathrooms")
    bedrooms = st.number_input("Number of Bedrooms")
    total_rooms = st.number_input("Total Rooms Above Ground")
    user_input = {
        "LotArea": lot_area,
        "YearBuilt": year_built,
        "1stFlrSF": first_floor_sf,
        "2ndFlrSF": second_floor_sf,
        "FullBath": full_bath,
        "BedroomAbvGr": bedrooms,
        "TotRmsAbvGrd": total_rooms
    }
```

```
    prediction, shap_html = predict_house_price(user_input)
    st.write(f"Predicted Price: ${prediction:.2f}")
    if st.button("Show SHAP Explanation"):
        st.subheader("SHAP Explanation")
        st_shap(shap_html)
def titanic_survivor_page():
    st.subheader("Titanic Survivor Prediction")
    st.write("Enter passenger details:")
    sex = st.selectbox("Sex", ["Male", "Female"])
    age = st.number_input("Age", min_value=0, max_value=150, step=1)
    fare = st.number_input("Fare", min_value=0.0, step=0.01)
    pclass = st.selectbox("Passenger Class", [1, 2, 3])
    sibsp = st.number_input("Number of Siblings/Spouses Boarded", min_value=0, step=1)
    embarked = st.selectbox("Embarked From", ["C", "Q", "S"])
    parch = st.number_input("Number of Parents/Children Boarded", min_value=0, step=1)
    user_input = {
        "Sex_female": 1 if sex == "Female" else 0,
        "Sex_male": 1 if sex == "Male" else 0,
        "Age": age,
        "Fare": fare,
```

```
        "Pclass": pclass,
        "SibSp": sibsp,
        "Embarked_C": 1 if embarked == "C" else 0,
        "Embarked_Q": 1 if embarked == "Q" else 0,
        "Embarked_S": 1 if embarked == "S" else 0,
        "Parch": parch,
    }
    prediction, lime_html = predict_survivor(user_input)
    st.write(f"Prediction: {'Will Survive' if prediction[0] == 1 else 'Will Die'}")
    if st.button("Show LIME Explanation"):
        st.subheader("LIME Explanation")
        st.components.v1.html(lime_html, height=800
def st_shap(shap_html):
    shap_html_with_js = f"<head>{shap.getjs()}</head><body><div style='overflow:
hidden;margin-top: 100px;padding: 20px;'>{shap_html}</div></body>"
    components.html(shap_html_with_js, height=700, width=1500)
if __name__ == "__main__":
    main()
```

housing_price_prediction.py

```
import pandas as pd
```

```
from sklearn.ensemble import RandomForestRegressor

import shap

def predict_house_price(user_input):

    home_data = pd.read_csv('Housing_Price_Prediction/train.csv')

    y = home_data['SalePrice']

    features = ['LotArea', 'YearBuilt', '1stFlrSF', '2ndFlrSF', 'FullBath', 'BedroomAbvGr',
'TotRmsAbvGrd']

    rf_model = RandomForestRegressor(random_state=1)

    rf_model.fit(home_data[features], y)

    user_data = pd.DataFrame(user_input, index=[0])

    predicted_price = rf_model.predict(user_data)[0]

    explainer = shap.TreeExplainer(rf_model)

    shap_values = explainer.shap_values(user_data)

    shap_html = shap.force_plot(explainer.expected_value, shap_values[0], user_data,
matplotlib=False)

    return predicted_price, shap_html._repr_html_()
```

titanic_survivor_prediction.py

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

import lime
```

```
import lime.lime_tabular

def predict_survivor(user_input):
    data = pd.read_csv("Titanic_Survivor_Predictor/train.csv")
    train, test = train_test_split(data, test_size=0.3, random_state=0, stratify=data['Survived'])
    train = train.drop(['Name', 'Ticket', 'Cabin', 'PassengerId'], axis=1)
    test = test.drop(['Name', 'Ticket', 'Cabin', 'PassengerId'], axis=1)
    train_processed = pd.get_dummies(train)
    test_processed = pd.get_dummies(test)
    train_processed = train_processed.fillna(train_processed.mean())
    test_processed = test_processed.fillna(test_processed.mean())
    X_train = train_processed.drop(['Survived'], axis=1)
    Y_train = train_processed['Survived']
    X_test = test_processed.drop(['Survived'], axis=1)
    Y_test = test_processed['Survived']
    random_forest = RandomForestClassifier(n_estimators=100)
    random_forest.fit(X_train, Y_train)
    predict_fn_rf = lambda x: random_forest.predict_proba(x).astype(float)
    X = X_train.values
    explainer = lime.lime_tabular.LimeTabularExplainer(X, feature_names=X_train.columns,
                                                       class_names=['Will Die', 'Will Survive'], kernel_width=5)
```

```
    preprocessed_input = preprocess_user_input(user_input)

    prediction = random_forest.predict(preprocessed_input)

    explanation = explainer.explain_instance(preprocessed_input.values[0], predict_fn_rf,
num_features=10)

    lime_html = explanation.as_html()

    return prediction, lime_html

def preprocess_user_input(user_input):

    # Ensure that the 'Sex' key is present in the user input dictionary

    #sex = user_input.get('Sex', 'Unknown')

    # Create a DataFrame from the user input dictionary

    user_df = pd.DataFrame([user_input])

    if 'Sex' in user_df.columns:

        user_df.drop('Sex', axis=1, inplace=True)

    # Reorder columns to match the order of features used during training

    user_df = user_df.reindex(columns=[ 'Pclass', 'Age','SibSp', 'Parch', 'Fare', 'Sex_female',
'Sex_male', 'Embarked_C', 'Embarked_Q', 'Embarked_S'], fill_value=0)

    return user_df
```

train_titanic.py

```
import numpy as np

import pandas as pd

from sklearn.model_selection import train_test_split
```

```
from sklearn.ensemble import RandomForestClassifier

from sklearn import metrics

import webbrowser

import warnings

import lime

import lime.lime_tabular

data = pd.read_csv("train.csv")

train,test=train_test_split(data,test_size=0.3,random_state=0,stratify=data['Survived'])

train = train.drop(['Name'], axis=1)

test = test.drop(['Name'], axis=1)

train = train.drop(['Ticket'], axis=1)

test = test.drop(['Ticket'], axis=1)

train = train.drop(['Cabin'], axis=1)

test = test.drop(['Cabin'], axis=1)

train = train.drop(['PassengerId'], axis=1)

test = test.drop(['PassengerId'], axis=1)

# Convert categorical variables into dummy/indicator variables

train_processed = pd.get_dummies(train)

test_processed = pd.get_dummies(test)
```

```
# Filling Null Values

train_processed = train_processed.fillna(train_processed.mean())

test_processed = test_processed.fillna(test_processed.mean())

# Create X_train,Y_train,X_test

X_train = train_processed.drop(['Survived'], axis=1)

Y_train = train_processed['Survived']

X_test  = test_processed.drop(['Survived'], axis=1)

Y_test  = test_processed['Survived']

random_forest = RandomForestClassifier(n_estimators=100)

random_forest.fit(X_train, Y_train)

random_forest_preds = random_forest.predict(X_test)

predict_fn_rf = lambda x: random_forest.predict_proba(x).astype(float)

X = X_train.values

explainer = lime.lime_tabular.LimeTabularExplainer(X,feature_names =
X_train.columns,class_names=['Will Die','Will Survive'],kernel_width=5)

#choosen_instance = X_test.loc[[421]].values[0]

#exp = explainer.explain_instance(choosen_instance, predict_fn_rf,num_features=10)

#exp.save_to_file('lime_explanation.html')

# Create a function to preprocess user input

def preprocess_user_input(user_input):
```

```
    # Convert user input to a DataFrame with the same columns as X_train
    user_df = pd.DataFrame([user_input])
    user_df = pd.get_dummies(user_df)  # Convert categorical variables to dummy variables
    user_df = user_df.reindex(columns=X_train.columns, fill_value=0)  # Reindex to match X_train columns
    return user_d
# Create a function to predict and explain
def predict_and_explain(user_input):
    preprocessed_input = preprocess_user_input(user_input)
    prediction = random_forest.predict(preprocessed_input)
    explanation = explainer.explain_instance(preprocessed_input.values[0], predict_fn_rf, num_features=10)
    return prediction, explanation
# Example usage:
if __name__ == "__main__":
    sex = input("Sex (M/F): ")
    age = int(input("Age: "))
    fare = int(input("Fare: "))
    pclass = int(input("Passenger Class(1,2,3): "))
    sibsp = int(input("No of Siblings/Spouses Boarded: "))
```

```
    embarked = input("Embarked From [C for Cherbourg, Q for Queenstown, S for Southampton]:
")
    parch = int(input("No of Parents/Children Boarded: "))
    user_input = {
        "Sex_female": 1 if sex=='F' else 0,
        "Sex_male": 1 if sex=='M' else 0,
        "Age": age,
        "Fare": fare,
        "Pclass": pclass,
        "SibSp": sibsp,
        "Embarked_C": 1 if embarked=='C' else 0,
        "Embarked_Q": 1 if embarked=='Q' else 0,
        "Embarked_S": 1 if embarked=='S' else 0,
        "Parch": parch,
    }
    prediction, explanation = predict_and_explain(user_input)
    print(f"Prediction: {'Will Survive' if prediction[0] == 1 else 'Will Die'}")
    explanation.save_to_file('lime_explanation.html')
    webbrowser.open('lime_explanation.html')
```

train_housing_prediction.py

```
import pandas as pd

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean_absolute_error

import matplotlib.pyplot as plt

import shap

# Load the training data

iowa_file_path = 'train.csv'

home_data = pd.read_csv(iowa_file_path)

y = home_data.SalePrice

# Select features

features = ['LotArea', 'YearBuilt', '1stFlrSF', '2ndFlrSF', 'FullBath', 'BedroomAbvGr',
'TotRmsAbvGrd']

# Train a random forest model on the full dataset

rf_model = RandomForestRegressor(random_state=1)

rf_model.fit(home_data[features], y)

# Get user input for features

user_features = {}

for feature in features:

  value = float(input(f"Enter value for {feature}: "))
```

```
  user_features[feature] = value

# Convert user input to a pandas DataFrame

user_data = pd.DataFrame(user_features, index=[0])

# Make prediction on user data

predicted_price = rf_model.predict(user_data)[0]

print(f"Predicted Price: ${predicted_price:.2f}")

# Explain predictions using SHAP

explainer = shap.TreeExplainer(rf_model)

instance_to_explain = user_data

shap_values = explainer.shap_values(instance_to_explain)

# Define the shap_plot function (assuming you want a force plot)

def shap_plot():

    p = shap.force_plot(explainer.expected_value, shap_values[0], user_data, matplotlib=True)

    plt.show()

shap_plot()
```

CHAPTER 9

RESULT AND OUTPUT

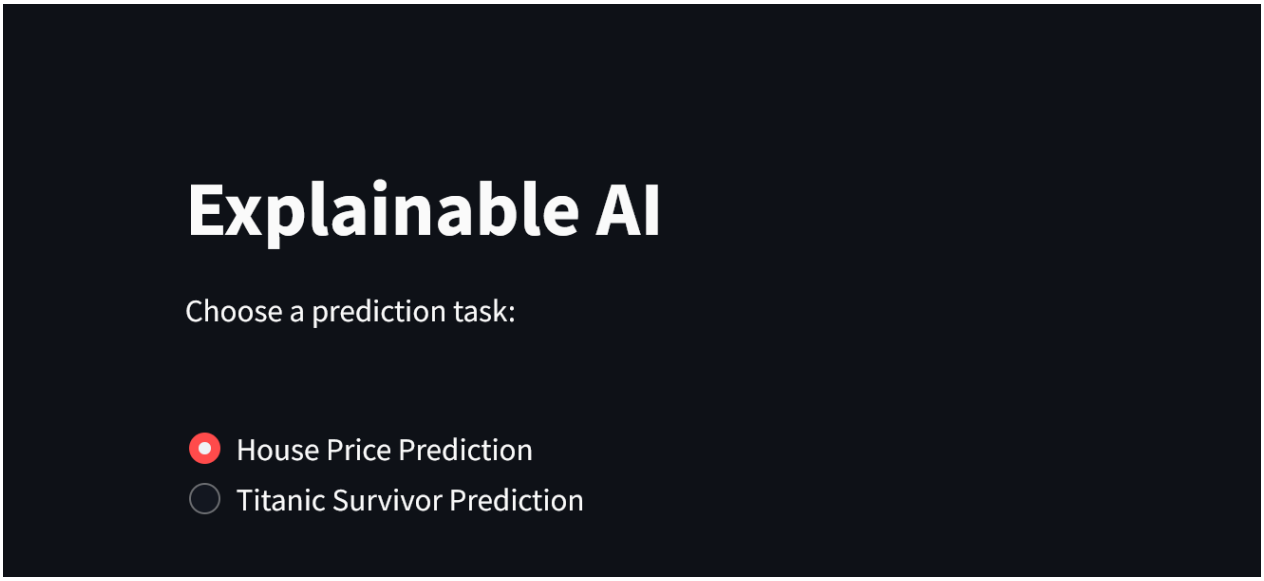


Figure 9.1 Home Page

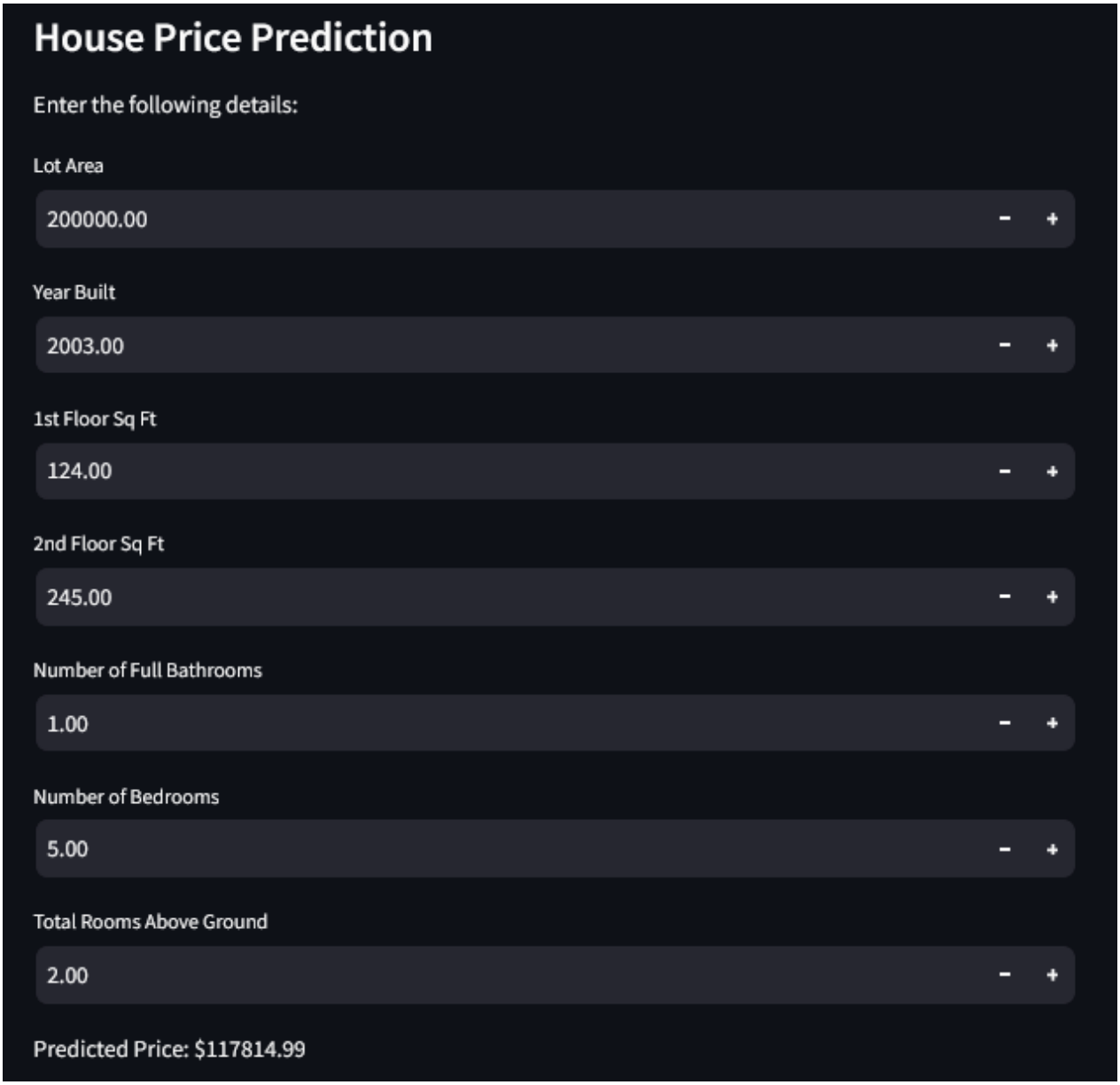


Figure 9.2 House Price Prediction Model

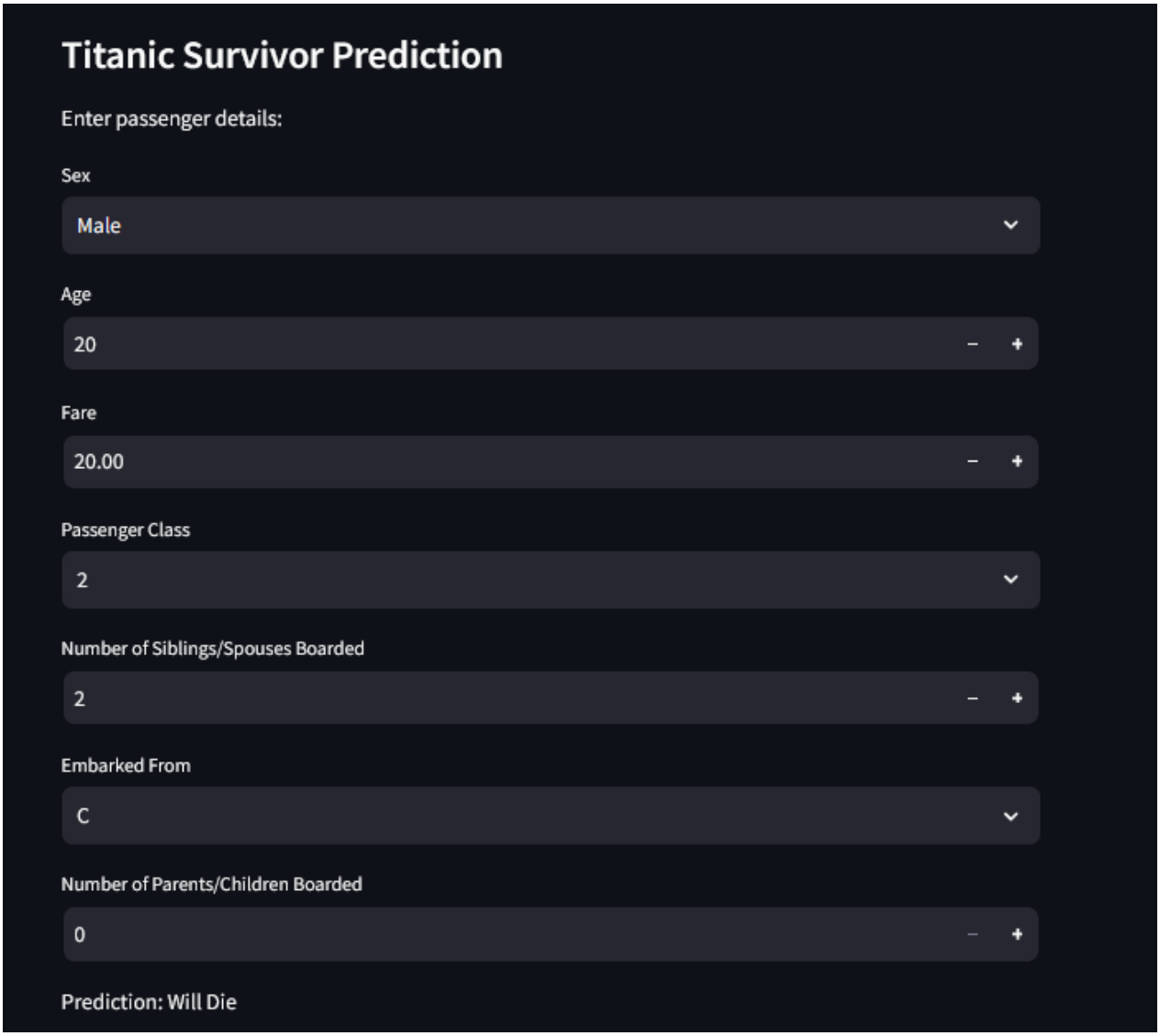
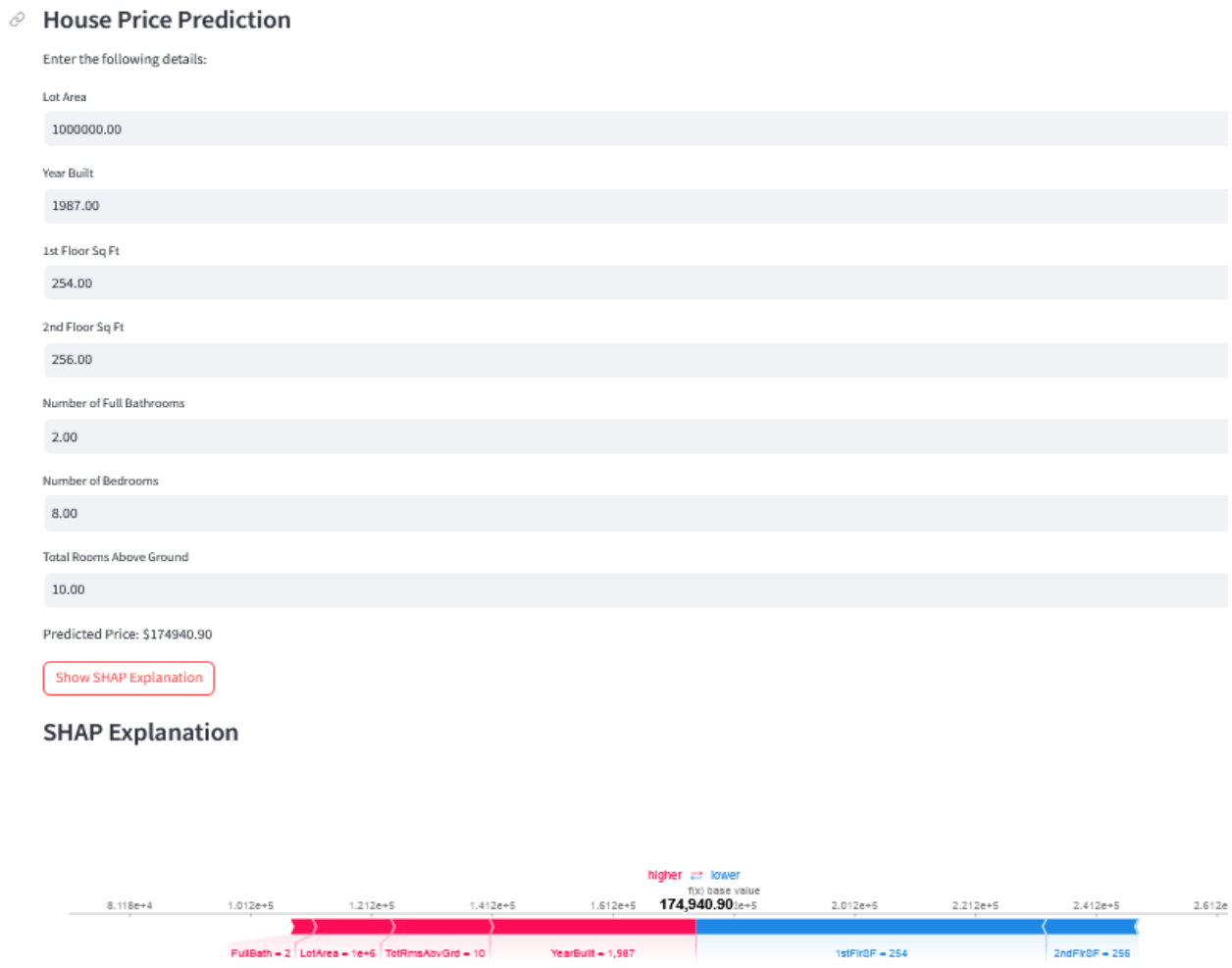


Figure 9.3 Titanic Survivor Prediction Model



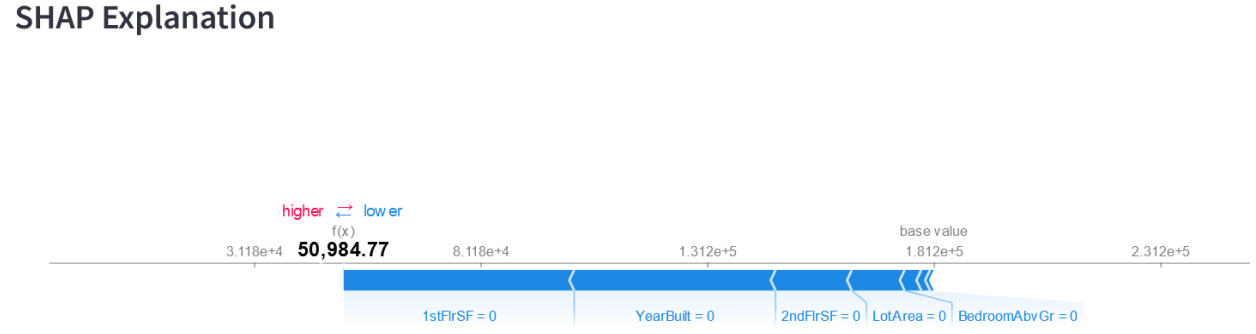


Figure 9.4 House Price Prediction With SHAP Explanation

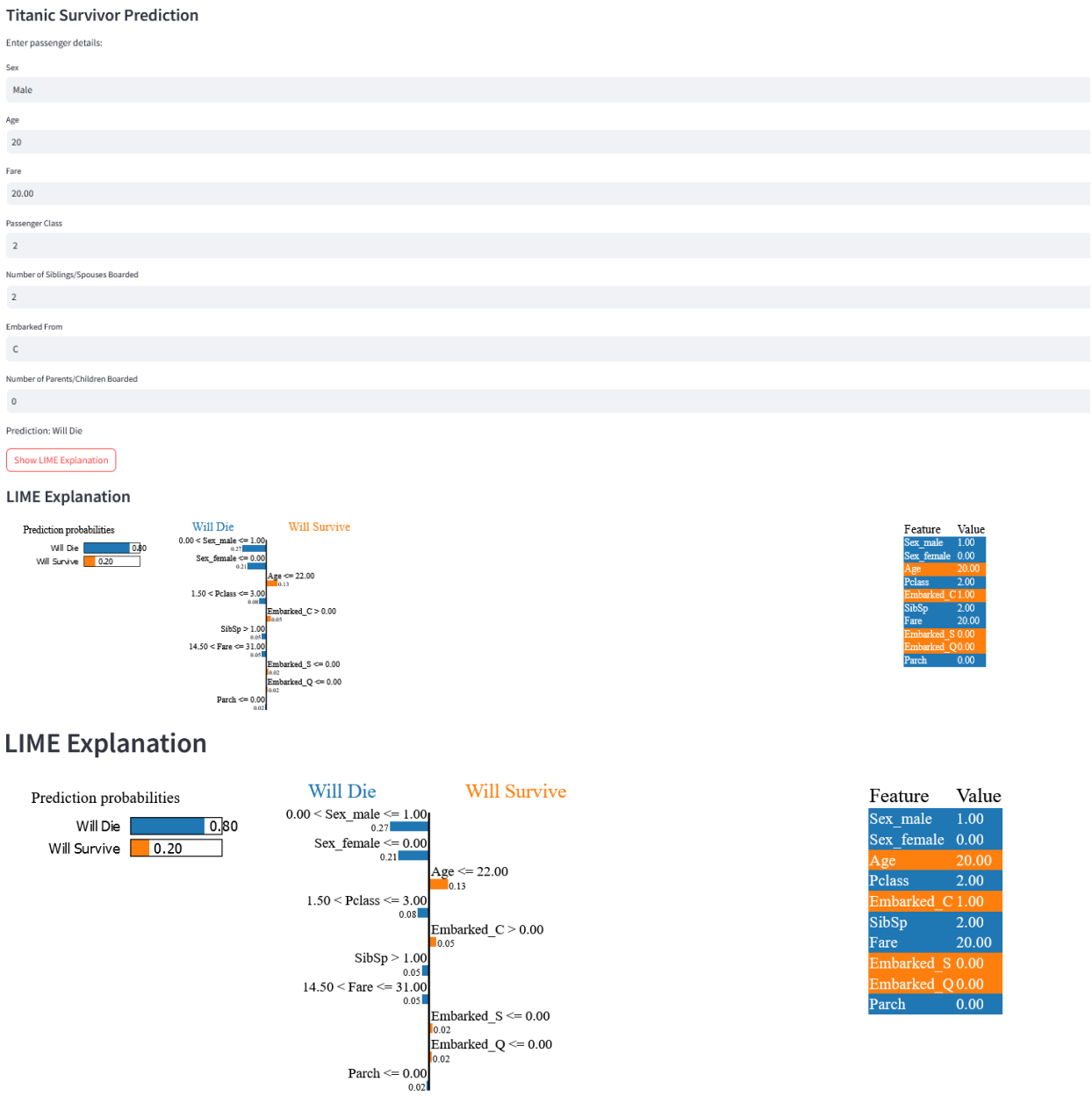


Figure 9.5 Titanic Survivor Prediction With LIME Explanation

CHAPTER 10

FUTURE ENHANCEMENTS

10.1 EXPANDING EXPLANATIONS:

While the current project integrates LIME and SHAP to provide valuable insights, there's room for further exploration of XAI techniques:

- **Advanced LIME Techniques:** Explore leveraging techniques like Anchors within LIME to not only explain individual predictions but also highlight similar data points that influenced the model's reasoning. This can be particularly insightful for understanding how the model generalizes to unseen data.

- **Counterfactual Explanations:** Implement techniques that generate counterfactual explanations. These explanations answer "what-if" scenarios, allowing users to see how changes to specific features might have altered the model's prediction. This can be helpful for users who want to understand how to potentially influence the model's output.

10.2 BEYOND REAL ESTATE AND TITANIC DATA:

The XAI integration approach outlined in this project can be applied to various machine learning domains:

- **Loan Approval Systems:** Integrate XAI techniques to explain loan approval/rejection decisions. This fosters trust and transparency for both lenders and borrowers by highlighting the factors influencing these decisions.

- **Medical Diagnosis Systems:** By integrating XAI, medical professionals can gain insights into the reasoning behind AI-powered diagnostic tools. This can enhance trust in these systems and potentially lead to improved healthcare decision-making.

- **Recommender Systems:** Explain why a specific product or service is recommended to a user. This transparency can improve user experience and satisfaction with recommender systems.

10.3 HUMAN-AI COLLABORATION:

As XAI techniques continue to evolve, they can facilitate a more collaborative approach between humans and AI systems:

- **Interactive Explanations:** Develop interactive interfaces that allow users to explore explanations in more detail. This can involve filtering explanations by features, visualizing data distributions, and drilling down into specific aspects of the model's reasoning.
- **Human-in-the-Loop Systems:** Integrate XAI explanations into systems where human experts can review and potentially override AI-generated decisions. This can be particularly valuable in high-stakes scenarios where explainability and human oversight are crucial.

CHAPTER 11

CONCLUSION

We embarked on a voyage of discovery, venturing into the enigmatic realm of black box models and illuminating the path towards a future guided by Explainable AI (XAI). We delved into the limitations of non-explainable models, exposing their opacity and susceptibility to bias. These opaque models, while capable of generating impressive results, leave us in the dark about their reasoning, hindering trust and hindering our ability to improve them.

XAI techniques emerged as a beacon of hope, offering a powerful solution to the challenges posed by non-explainable models. By integrating XAI with your house price prediction and titanic survivor prediction models, we embarked on a practical demonstration. We unveiled the "why" behind the models' predictions, empowering users with a deeper understanding of the decision-making processes at play. This newfound transparency fosters trust and allows users to make informed decisions based on a clearer picture of the model's rationale.

The project journey wasn't just about the destination; it was about equipping you with the tools and knowledge to navigate the path yourself. We provided a practical roadmap, outlining the essential modules for XAI integration, the necessary hardware and software requirements, and valuable resources to guide your exploration. This empowers you to integrate XAI into your own machine learning endeavors, regardless of domain or application.

The future of XAI is brimming with possibilities. We explored the potential for future enhancements, delving into advanced XAI techniques like counterfactual explanations that allow users to explore "what-if" scenarios. We also discussed the broader application of XAI principles across various machine learning domains, from loan approval systems to medical diagnosis tools and recommender systems. As XAI becomes more sophisticated, its reach will extend to even more aspects of our lives, ensuring transparency and responsible development in a world increasingly reliant on AI.

As we stand at the precipice of a future shaped by human-AI collaboration, XAI holds immense promise. By fostering interactive explanations that allow users to delve deeper into the model's reasoning, and by establishing human-in-the-loop systems where human expertise can provide oversight, we pave the way for a future where humans and AI work together in a symbiotic relationship. Imagine medical professionals collaborating with AI-powered diagnostic tools to make more informed healthcare decisions, or loan officers leveraging XAI to explain loan approval/rejection decisions, fostering trust and fairness within the financial system.

The journey towards Explainable AI is just beginning, and this book serves as your launchpad. It equips you with the foundational knowledge and practical steps to integrate XAI into your own machine learning projects. Embrace the power of XAI, unveil the black boxes of the past, and unlock a future where AI is not just intelligent, but also responsible, transparent, and a force for good in the world. Let us embark on this exciting exploration together, for the potential of Explainable AI is truly limitless.

CHAPTER 12

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[3] scikit-learn documentation: https://scikit-learn.org/stable/ (Documentation for the scikit-learn library, commonly used for building machine learning models)

[4] LIME (Local Interpretable Model-agnostic Explanations) documentation: https://github.com/marcotcr/lime (Documentation for the LIME library, used for generating local explanations for individual predictions)

[5] SHAP documentations : https://shap.readthedocs.io/ (Documentation for the SHAP library, used for providing global explanations of feature importance)

[6] Streamlit documentation: https://docs.streamlit.io/ (Documentation for the Streamlit library, used for creating user-friendly web applications)

[7] Interpretable Matrix Factorization for Recommender Systems (2016) by Steffen Rendle et al. https://arxiv.org/pdf/2307.05680 (This paper explores interpretable techniques for matrix factorization, a common approach in recommender systems.)

[8] Explainable Recommendation Systems: Survey and Challenges (2018) by Bartosz Wilk et al. https://arxiv.org/pdf/2202.06466.pdf?trk=public_post_comment-text (This survey paper provides a comprehensive overview of explainability techniques in recommender systems)

[9] Towards User-Centric Explainable Recommendation Systems (2020) by Lei Xu et al. https://arxiv.org/abs/1804.11192 (This paper emphasizes the importance of tailoring explanations to user needs in recommender systems)

[10] Interpretable Neural Collaborative Filtering for Explainable Recommendation Systems(2019) by Xiangnan He et al. (This paper explores interpretable deep learning techniques for recommender systems)

[11] Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow by Aurélien Géron. This book provides a comprehensive introduction to machine learning techniques using popular libraries.

[12] "Interpretable Machine Learning: A Guide for Making Black Boxes Transparent" by Christoph Molnar. This book offers a detailed exploration of interpretable machine learning approaches.

[13] "A Survey of Explainable Artificial Intelligence (XAI)" by Zachary C. Lipton. https://arxiv.org/pdf/1907.07374 (This survey paper provides a broader overview of XAI techniques and research areas)