Chapter 1

PREAMBLE

1.1. Introduction

Patient readmission is a major challenge faced by hospitals and healthcare systems around the world. It not only has a negative impact on patient outcomes, but it also significantly increases healthcare costs. Predicting which patients are at risk of readmission is a key step in addressing this problem. In recent years, machine learning and artificial intelligence (AI) have shown great promise in this regard, but we are unable to know how it makes certain decisions. This black box nature of the models makes it vague and unreliable. In this work, we present a patient readmission prediction system based on explainable AI, which is designed to provide transparent and understandable predictions. This is achieved using interpretable machine learning models and techniques that allow us to understand the factors that contribute to the risk of readmission for individual patients. By providing this level of transparency, our system aims to support healthcare professionals in their decision-making and help them to better understand and address the needs of their patients.

1.2. Existing System

There are several existing systems for patient readmission prediction that use machine learning and artificial intelligence (AI) techniques. These systems typically involve the use of large datasets of patient data, which are analysed using machine learning algorithms to identify patterns and trends that may be predictive of readmission risk. One commonly used approach is to build a predictive model using a supervised machine learning algorithm, such as a decision tree or a logistic regression model. These models are trained on a dataset of patient records, with each record containing a set of features and a label indicating whether the patient was readmitted within a certain time period after their initial discharge. The model is then used to predict the readmission risk for new patients based on their feature values. Overall, the effectiveness of these systems varies and depends on several factors, including the quality and complexity of the machine learning algorithms used, the quality and relevance of the data, and the specific context in which the system is being used.

1.3. Drawback

One of the key challenges in healthcare is the prevention of patient readmissions, which occur when a patient is discharged from the hospital but then requires readmission within a short period of time due to a worsening of their condition or the emergence of new health issues. To address this problem, healthcare professionals have traditionally relied on their clinical expertise and judgement to identify the patients that may get readmitted. However, this approach has its limitations, and there is growing recognition that machine learning and AI can play a valuable role in predicting which patients are at risk of readmission. By analysing large datasets of patient data, machine learning models can identify patterns and trends that may not be immediately apparent to humans and can provide more accurate and reliable predictions. However, the black-box nature of it can be difficult to understand and explain the factors that contribute to their predictions. This lack of transparency can be a barrier to the adoption of machine learning and AI in healthcare, as it can make it difficult for healthcare professionals to trust and rely on these systems.

1.4. Proposed system

In this work, we present a patient readmission prediction system based on explainable AI(XAI), which is designed to overcome these limitations. By using interpretable machine learning models and techniques, our system is designed to provide transparent and understandable predictions, allowing healthcare professionals to better understand and address the needs of their patients. Using explainable AI, our system aims to support healthcare professionals in their decision making and help them to better understand and address the needs of their patients.

1.5. Plan of Implementation

1. Obtain data from 130 US hospitals [6] in a zipped format.
2. Extract and load the data onto a Python kernel for analysis.
3. Perform data understanding, cleaning, and preprocessing.
4. Appropriately select relevant features, manipulate them, remove outliers, and normalise the data as per the model requirements.
5. Train and test several machine learning models, including Support Vector Machine, Boosted Decision Tree, Decision Forest, and Logistic Regression.
6. Evaluate the models using metrics such as accuracy, recall, precision, F1, and AUC.
7. Introduce and examine using an Explainable AI model.
8. Present the information in a format that is easily understandable for humans and show how a decision was made.
9. Using this information, try improving the model.

1.6. Problem Statement

In this project we are going to decrease the opaqueness of this blackbox and use some of the techniques of explainable deep learning to know what exactly causes the results. Also we will present explainable classification of a medical data set using suitable deep learning techniques.

1.7. Objective of the Project

- To improve the accuracy and reliability of readmission risk predictions: By using advanced machine learning techniques and interpretable models, the system aims to provide more accurate and reliable predictions of readmission risk, which can help healthcare professionals to identify and intervene with high-risk patients.
- To increase transparency and explainability: The use of explainable AI techniques allows the system to provide transparent and understandable explanations of its predictions, which can help healthcare professionals to better understand the factors that contribute to readmission risk and make more informed decisions.
- To support clinical decision-making: The system aims to provide real-time, actionable insights to healthcare professionals, helping them to identify and address the needs of patients at risk of readmission.

Chapter 2

Literature Survey

➔ **Hu, Y. and Sokolova, M., 2020. Explainable Multi-class Classification of Medical Data. arXiv preprint arXiv:2012.13796.**

◆ This paper presents a multi-class classification method for a large medical dataset.

◆ The authors discuss various techniques such as knowledge-based feature engineering, dataset balancing, parameter tuning, and model selection.

◆ Six algorithms are evaluated in this study: Logistic Regression, Gradient Boosting, Decision Trees, Naive Bayes, Random Forest, and Support Vector Machine.

- The results from their paper show that 2 algorithms (Gradient Boosting and Random Forest) outperformed the other algorithms when it came to three-class classification accuracy.

➔ **Tjoa, E. and Guan, C., 2020. A survey on explainable artificial intelligence (XAI): Toward medical XAI. IEEE transactions on neural networks and learning systems, 32(11), pp.4793-4813.**

◆ This research investigates the use of Explainable AI (XAI) in the medical field, particularly for the purposes of improving transparency and trust in AI/ML applications.

◆ The focus is on data sources such as images, omics data, and text. The goal is to facilitate the adoption of AI/ML in the medical domain.

➔ **Ashfaq, A., Sant'Anna, A., Lingman, M. and Nowaczyk, S., 2019. Readmission prediction using deep learning on electronic health records. Journal of biomedical informatics, 97, p.103256.**

◆ This paper presents a survey on the explainability and interpretability of machine learning (ML) algorithms.

◆ It categorises different approaches to interpretability, including those that are formalised mathematically, provide visual explanations, or focus on improving task performance with explanations.

◆ The survey applies these categories to the medical field.

➔ **Moradi, M. and Samwald, M., 2021. Post-hoc explanation of black-box classifiers using confident itemsets. Expert Systems with Applications, 165, p.113941.**

- In this paper, the authors suggest CIE for explaining the predictions made by black-box classifiers.
- CIE (Counterfactual Explanations) is a post-hoc and model agnostic-model that categorises the input and extracts itemsets from features highly associated with a class label.
- These itemsets are used to create concise explanations for individual instances and class-wise explanations through optimization of fidelity, interpretability, and coverage objectives.

➔ **Ashfaq, A., Sant'Anna, A., Lingman, M. and Nowaczyk, S., 2019. Readmission prediction using deep learning on electronic health records. Journal of biomedical informatics, 97, p.103256.**

- In this study, a deep learning framework was developed to detect patients that have a high risk of being readmitted at the time of discharge.
- The paper uses a cost-sensitive deep learning model called LSTM. They use human and machine derived features for most accurate results.
- They also highlighted the annual cost saving of implementing the LSTM model.The authors conclude by stating that the model has room for improvement and wants to conduct further study on the model's feasibility.

Chapter 3

System Requirements Specification

3.1 Functional Requirements

- The AI model should be able to provide clear and understandable explanations for the reasoning behind its decisions so that it is comprehensible by non technical humans.
- The system should be able to determine the model that gives the most accurate and precise result after recalibration.
- The system should be able to present the explanations in a clear and concise manner, using language and visualisations that are easy for a non-expert to understand.
- The system should be able to provide different levels of detail in the explanations, depending on the needs and goals of the user.
- The system should be able to trace the reasoning behind the AI model's decisions, showing how specific input data and rules led to the final outcome.
- The system should be able to identify and highlight the most important factors that contributed to the AI model's decisions.
- The system should be able to evaluate the reliability and trustworthiness of the explanations, and provide warnings if the explanations are based on uncertain or incomplete data.

3.2 Non -Functional Requirements

- The system should be secure, protecting sensitive data and preventing unauthorised access.
- The system should be reliable, with a high uptime and a low rate of errors or failures.
- The system should be flexible, able to adapt to changing requirements or conditions without requiring major rework.
- The system should be able to handle complex, multi-faceted problems, and provide explanations that take into account the interactions and trade-offs between different factors.
- The system should be able to operate in real-time, providing explanations as decisions are made, or in batch mode, providing explanations for a large number of decisions at once.
- A model that has been designed to consider cost factors and utilises a combination of features generated both by human and machine processes.
- The system should be efficient, with a fast response time and low resource usage.

3.3 System Configurations

The recommended system specification would include:

- Processor: A computer processor with at least 4 cores and a frequency of 2.0 GHz or higher.
- Memory: At least 8 GB of RAM to allow for efficient data processing and model training.
- Storage: A solid-state drive with at least 128 GB of storage space to store data and machine learning models.
- Operating System: A 64-bit operating system such as Windows, macOS, or Linux to support machine learning frameworks and libraries.
- Software: A machine learning framework such as TensorFlow, PyTorch, or scikit-learn to build and train machine learning models along with SHAP framework.
- Development Environment: A programming language like Python and Integrated Development Environment (IDE) like Jupyter or PyCharm to write and run the code with.

Chapter 4

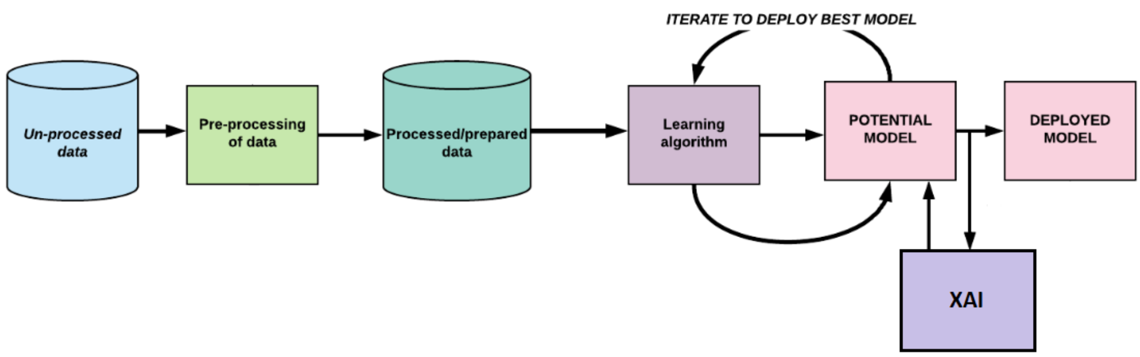
System Design

4.1 System Development Methodology

In this project we use Agile software development methodology.It works on the principle of iterative development,where a team works together to continuously improve and adapt the system to enhance the project. This methodology requires disciplined project management and frequent inspection. This helps us have a structured plan thus improving our efficiency.Also self-organisation, teamwork and accountability are encouraged for rapid development of the system . The Agile Manifesto ,outlines the key principles of Agile development.Some of the principles like having a working software rather than a theoretical documentation and prioritising responding to change will be used as core values in this project as well.

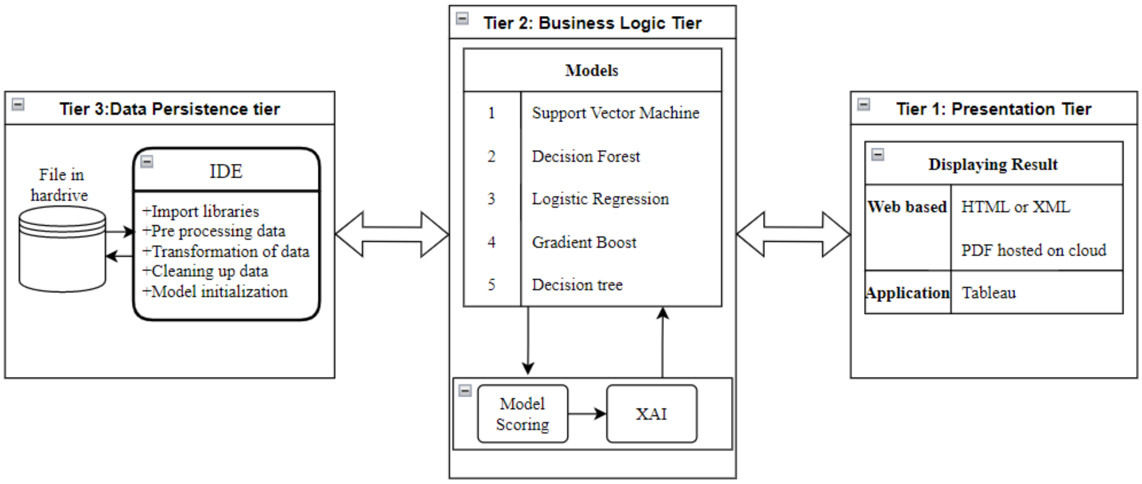
4.2 Data flow diagram

A data flow diagram is a graphical representation of how the data flows in your system. This helps us visualise how the data moves from source to sink as well as understand how it is transformed along the way.Thus we can describe the functionalities of each system.This is important since it helps an outsider understand the current system.



4.3 System Architecture

The architecture of a system outlines the interconnectedness of its components and the flow of data between them. It reflects the structure, functions, and relationships of the system and how it interacts with other systems and the external environment. This architecture can be thought of as the blueprint for the system, and it may evolve as the system is utilised. In the field of architecture, the term "system" typically refers to the architecture of software rather than the physical layout of structures or machinery.



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3. Tjoa, E. and Guan, C., 2020. A survey on explainable artificial intelligence (XAI): Toward medical XAI. IEEE transactions on neural networks and learning systems, 32(11), pp.4793-4813.

4. Moradi, M. and Samwald, M., 2021. Post-hoc explanation of black-box classifiers using confident itemsets. Expert Systems with Applications, 165, p.113941.

5. Ashfaq, A., Sant'Anna, A., Lingman, M. and Nowaczyk, S., 2019. Readmission prediction using deep learning on electronic health records. Journal of biomedical informatics, 97, p.103256.

➢ DataSet:

6. https://archive.ics.uci.edu/ml/datasets/diabetes+130-us+hospitals+for+years+1999-2008