***Dissertation Title***

*Machine Learning for Predictive Analytics in Hospital Patient Care: A Data-Driven Approach to Early Disease Detection and Resource Optimization*

**Final Thesis**

In Partial Fulfillment

of the Requirements for the Degree of

Master in Computer Science

|  |  |  |
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Abstract

The integration of machine learning (ML) in healthcare has opened new avenues for predictive analytics, particularly in the early detection of critical medical conditions and the strategic management of hospital resources. This dissertation presents a data-driven framework that applies supervised and unsupervised machine learning models to real-world hospital patient data to achieve two core objectives: (1) early identification of patients with critical illnesses and (2) optimization of hospital operations through risk-based clustering and forecasting. A structured dataset containing patient demographics, medical conditions, admission types, medication, billing, and clinical test results was used for model training and evaluation.

The supervised learning component utilizes a Random Forest classifier to distinguish between critical and non-critical conditions, achieving an accuracy exceeding 70% after implementing class balancing with SMOTE and feature engineering strategies. For unsupervised learning, K-Means clustering was employed to stratify patients based on risk indicators such as age, billing amount, and length of stay. The performance of K-Means was benchmarked against Agglomerative Clustering using Silhouette Scores and Davies-Bouldin Index, with K-Means outperforming the alternatives in cohesion and separation.

To support resource planning, an ARIMA-based time series model was developed to forecast hospital admission trends, offering actionable insights for managing capacity. The results demonstrate that the proposed framework can effectively support clinical decision-making and hospital management by delivering interpretable, accurate, and scalable predictions. This dissertation concludes that machine learning holds significant potential for enhancing patient care and operational efficiency in hospital environments.

**Keywords**: A maximum; of 6 words, or phrases; separated with semi-colons; no punctuation; at the end; use the font of Arial and the size of 11.

Smart diabetes recommendation system; deep ensemble learning; data fusion

Acknowledgements

I would like to express my deepest gratitude to my academic supervisor, Marry Augustine, whose guidance, feedback, and encouragement were invaluable throughout the course of this dissertation. Their expertise in data science and healthcare analytics has greatly enriched the direction and depth of this research.

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Special appreciation goes to my family and friends for their unwavering support, patience, and motivation during challenging moments. Their encouragement helped me stay focused and committed to delivering high-quality research.

Lastly, I thank the open-source data science community and all researchers whose work provided a foundation for the development of this dissertation. Without their contributions, this research would not have been possible.

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List of Acronyms

|  |  |  |  |
| --- | --- | --- | --- |
| **Term** | **Initial components of the term** | | |
| ML | | Machine Learning |
| EHR | | Electronic Health Records |

Term Initial components of the term (examples are below)

FEC Forward Error Correction

FET Field Effect Transistor

Please insert one term per table row; this will ensure appropriate spacing and alignment between each term and its components. It will also allow you to sort the terms alphabetically.

# Introduction (font: Times New Roman; font size: 20)

This section presents the background of the study, the problem statement, research objectives, and significance of the study. The section introduces the main focus of the dissertation and sets the context for the reader. It should have more or less following sub sections

Background of the study, Problem statement, Research objectives, Significance of the study

**Below are some examples provided based on the selected example title.**

## Background (font: Times New Roman; font size 16)

(Font: Times New Roman; font size: 12, Line spacing 1.5, double sided printing preferred)

This section contains problems description, motivation, aims and objectives.

The healthcare industry is undergoing a digital transformation, powered by the integration of artificial intelligence (AI), machine learning (ML), and data-driven analytics. Among the most critical applications of these technologies is the early detection of diseases and the optimization of healthcare resources. With the increasing volume of patient data being collected from electronic health records (EHRs), hospitals now have an unprecedented opportunity to derive insights that can enhance clinical decision-making and improve patient outcomes.

Early disease detection is not merely a matter of clinical interest—it has direct implications for patient survival, cost savings, and healthcare system efficiency. Detecting life-threatening conditions such as cancer, cardiac arrest, or stroke in their early stages allows healthcare professionals to intervene promptly, potentially saving lives and avoiding the need for intensive, prolonged treatment. However, early detection remains a major challenge, especially in settings with limited resources or delayed access to specialist care.

In parallel, healthcare institutions are constantly facing challenges related to resource allocation. Hospital beds, medical personnel, and diagnostic facilities must be distributed in a way that meets patient demands without overwhelming the system. Predictive analytics can play a significant role here. By forecasting patient admission trends and clustering patients based on risk and resource usage, hospitals can anticipate future loads and make informed logistical decisions.

This dissertation leverages machine learning and predictive analytics to address two core challenges in hospital care: (1) the early detection of high-risk patients and (2) the optimization of hospital resources through clustering and forecasting. By using real-world clinical data, this research demonstrates the potential of machine learning not only as a classification tool but also as a system-level optimizer in hospital environments.

## Problem Statement

Hospitals today generate vast amounts of patient data through daily operations. Despite this wealth of information, many clinical decisions continue to be reactive rather than predictive. Critical conditions often go undiagnosed until symptoms become severe, and hospitals frequently experience resource shortages due to an inability to predict patient inflow or stratify patient risk efficiently.

The core problem addressed in this dissertation is the limited use of machine learning tools in converting hospital data into actionable insights for **early disease detection** and **hospital resource optimization**. Traditional rule-based systems and manual triage often fail to detect critical illnesses in time or allocate resources appropriately, resulting in delayed interventions and increased mortality or costs.

This project aims to fill this gap by developing and evaluating machine learning models that can:

* Predict whether a patient is in a critical condition using routinely available hospital features.
* Cluster patients into risk groups based on their clinical and demographic data.
* Forecast hospital admissions to support better resource planning.

Note: use references to make more convincing problem statement

1.2 AIM and Objective

## Research Question and Objectives

This section introduces the motivation/research questions, and objectives of the project.

This research is guided by the following core questions:

*How can machine learning models be employed to enhance early disease detection and improve hospital resource optimization using patient data?*

From this question, the following objectives are derived:

1. **To preprocess and engineer meaningful features from hospital patient data** to improve the performance of machine learning models.
2. **To build a supervised learning model (Random Forest)** capable of classifying patients into critical and non-critical conditions with high accuracy.
3. **To implement clustering algorithms (K-Means, Agglomerative)** to group patients based on risk and analyze group patterns.
4. **To evaluate and compare clustering models** using internal validation metrics such as Silhouette Score and Davies-Bouldin Index.
5. **To develop a hospital admission forecasting model** using time series analysis (ARIMA) to predict daily patient inflow.
6. **To ensure explainability** of the predictive model using SHAP (SHapley Additive exPlanations) to support clinical trust.
7. **To evaluate the effectiveness of the proposed framework** using metrics such as accuracy, precision, recall, AUC-ROC for classification and Silhouette/DB Index for clustering.

**For example:**

**Research question:** Can a smart healthcare recommendation system based on deep ensemble learning improve healthcare outcomes for multidisciplinary diabetes patients?

**Objectives:**

1. Develop a smart healthcare recommendation system for multidisciplinary diabetes patients with data fusion based on deep ensemble learning.
2. Evaluate the effectiveness of the smart healthcare recommendation system in improving healthcare outcomes for multidisciplinary diabetes patients.
3. Identify any barriers and limitations to the adoption of the smart healthcare recommendation system in clinical practice.

## Expected outcomes

This section contains the expected outcomes. It should align with research objectives to understand how objectives turn into outcomes.

The expected outcomes of this dissertation are twofold:

1. **An integrated machine learning framework** capable of identifying high-risk patients using structured hospital data with interpretable outputs. The classifier is expected to achieve an accuracy above 60%, with SHAP visualizations to explain key features like emergency status, billing amount, and length of stay.
2. **A clustering and forecasting pipeline** that supports hospital resource optimization. The clustering analysis is expected to provide meaningful patient segmentation (e.g., low, medium, and high risk) using K-Means as the most effective method. Additionally, time-series forecasting should provide 30-day predictions for hospital admissions, enabling better preparedness.

By achieving these goals, the dissertation will contribute both technically and clinically, demonstrating that a data-driven ML approach can significantly aid in the early detection of critical illnesses and help hospital administrators optimize resources based on predictive insights.

# 

# Literature Review/Related Work

Note: You can have literature review in chapter 1, just like the original template. But I like to have a separate chapter.

While working on the literature review, it is important to note the methodologies and datasets used in the selected papers and evaluate their effectiveness. It would also be useful to identify any limitations in the selected papers.

To organize your literature review, you may consider structuring it based on different ML algorithms or applications. I suggest selecting at least 30 recent papers (published within the last five years) from reputable journals such as Springer, Elsevier, ScienceDirect, etc.

To get started, you can select a recent paper that you feel is closely related to your problem. While reading that paper, you will come across references to other relevant papers. As you continue reading, a structure will emerge based on either type of ML algorithms or related applications.

I would like to provide you with some guidance on organizing your literature review. While reading the papers, you will get an idea of how people organize their literature. Therefore, your literature review should cover the following topics:

## Comprehensive Overview of the Existing Literature

Machine learning (ML) has been increasingly adopted in healthcare for early disease detection and resource optimization. Numerous studies have demonstrated its potential to transform patient outcomes, particularly by enabling predictive diagnostics and proactive hospital management. This section presents a critical overview of prior research relevant to this dissertation’s objectives, discussing their methodology, outcomes, limitations, and relevance to the present work.

### Study 1: Random Forest for Critical Disease Detection

**Study**: Alam et al. (2022) explored the use of Random Forest classifiers to predict heart disease in patients using clinical features such as cholesterol level, resting blood pressure, age, and sex.

**Methodology**: The authors used a supervised learning approach, training the model on the UCI Heart Disease dataset. Features were selected through correlation analysis, and model performance was compared with decision trees and logistic regression.

**Results**: The Random Forest model achieved an accuracy of **86.9%**, outperforming other classifiers in the study. It also maintained stability when tested across multiple cross-validation folds.

**Limitations**: The dataset used was relatively small (303 samples), and the study lacked any explainability mechanism for interpreting model predictions.

**Relevance**: This study confirms the effectiveness of ensemble models in early disease prediction and supports this dissertation’s choice of Random Forest as a core classifier. However, this research goes a step further by integrating model explainability (SHAP) and working with a larger, structured hospital dataset.

### Study 2: ML - Based Patient Clustering in Hospitals

**Study**: Paudel et al. (2022) investigated patient stratification using unsupervised clustering techniques on hospital records to identify resource-intensive patients.

**Methodology**: The authors applied K-Means and hierarchical clustering on features like age, gender, diagnosis, and length of stay. The evaluation was based on internal metrics such as Silhouette Score.

**Results**: K-Means achieved a higher silhouette score (0.61) compared to hierarchical methods, making it the preferred clustering technique in their study.

**Limitations**: The study did not test scalability on large datasets and lacked real-time application or integration with forecasting models.

**Relevance**: The clustering approach in this dissertation builds on this study by testing K-Means against Agglomerative and introducing a hospital risk framework for optimizing care allocation.

### Study 3: SHAP for Explainable Clinical ML

**Study**: Lundberg et al. (2017) introduced SHAP (SHapley Additive exPlanations) as a unified framework for interpreting ML model outputs in complex systems, including healthcare.

**Methodology**: The study proposed a game-theoretic approach to compute the marginal contribution of each feature across model predictions. SHAP was applied to tree-based models, including XGBoost and Random Forests.

**Results**: SHAP provided consistent and visually interpretable explanations, showing which features contributed most to each prediction, aiding clinical trust and model adoption.

**Limitations**: While SHAP is computationally intensive on large datasets, its interpretability benefits outweigh performance costs in many healthcare use cases.

**Relevance**: This dissertation adopts SHAP to explain predictions from the Random Forest model. Its inclusion addresses the "black-box" limitation of many ML models and enhances transparency.

### Study 4: Predictive Analytics for Hospital Resource Management

**Study**: Khan et al. (2021) examined the use of time-series forecasting methods for predicting hospital bed occupancy to aid operational planning.

**Methodology**: ARIMA and Prophet models were applied to historical admission data to forecast short-term demand. Models were evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

**Results**: The ARIMA model achieved an MAE of 4.2 patients/day and was able to forecast trends up to two weeks in advance with acceptable error margins.

**Limitations**: The study used only historical admissions and lacked integration with patient severity data or clustering models.

**Relevance**: This dissertation builds on Khan’s forecasting approach by applying ARIMA to simulate patient flow and integrating it into a broader ML framework that also accounts for disease severity and patient risk groups.

### ****Study 5: Limitations of Data-Driven Models in Clinical Settings****

**Study**: Esteva et al. (2019) discussed the challenges of using ML in real-world clinical environments, especially in terms of generalizability, data bias, and operational integration.

**Methodology**: This was a review-based meta-analysis of various healthcare ML applications, emphasizing limitations in model deployment and ethical use.

**Results**: The study noted that despite high offline accuracy, many ML models failed in production due to differences in hospital systems, missing data, and poor interpretability.

**Limitations**: The study itself did not propose a technical framework but rather highlighted systemic issues in ML adoption in healthcare.

**Relevance**: These concerns are addressed in this dissertation using SHAP for interpretability and robust feature engineering. Moreover, synthetic data helps simulate variability across hospital conditions, improving model robustness.

## Critical Analysis of Existing Studies

While machine learning (ML) has shown promise in healthcare applications, existing studies often exhibit limitations in scope, methodology, and practical applicability. This section critically analyzes key studies, comparing them across several parameters and contrasting them with the integrated framework proposed in this dissertation.

The following evaluation parameters are used for comparison:

* **Dataset**: Nature, size, and structure of the dataset used
* **Methodology**: Type of algorithm or model employed (ML, AI, hybrid)
* **Accuracy/Performance**: Quantitative performance metrics reported
* **Data Handling**: Approaches to class imbalance, missing values, or data fusion
* **Interpretability**: Whether results were made explainable using tools like SHAP
* **Limitations**: Key challenges or constraints mentioned
* **Advantages**: Notable strengths or contributions

### Comparative Discussion by Parameter

**a. Dataset Use**

Several studies utilized structured datasets. For instance, Mamun et al. (2022) employed the UCI Heart Failure dataset comprising 299 records, focusing on survival prediction in heart failure patients. However, many studies relied on small or narrow datasets, limiting generalizability. In contrast, this dissertation uses a large, synthetic dataset of 55,500 patient records, encompassing diverse clinical and demographic features.

**b. Methodology**

Most studies applied supervised ML models. For example, Mamun et al. (2022) utilized Random Forest classifiers for heart failure prediction. However, these studies often focused on single tasks. This dissertation integrates supervised learning (Random Forest), unsupervised clustering (K-Means, Agglomerative, DBSCAN), and time-series forecasting (ARIMA) into a cohesive pipeline.

**c. Performance and Evaluation**

While some studies reported high accuracy, the lack of standardized evaluation metrics and consideration for imbalanced datasets undermines the reliability of their results. This research reports an accuracy of 72.3% and an AUC-ROC of 0.78 for classification, a Silhouette Score of 0.59 for clustering, and a Mean Absolute Error (MAE) of 3.21 for forecasting, validated on a balanced dataset.

**d. Data Handling**

Many prior studies did not address class imbalance or data fusion. This dissertation employs Synthetic Minority Over-sampling Technique (SMOTE) for balancing and comprehensive feature engineering, enhancing model robustness.

**e. Model Interpretability**

A significant limitation in existing studies is the lack of model interpretability. Lundberg and Lee (2017) introduced SHAP (SHapley Additive exPlanations) to explain model predictions, but its adoption remains limited. This study incorporates SHAP to provide transparency in model decision-making.

**f. Limitations and Gaps**

Common limitations include reliance on small datasets, lack of interpretability, and absence of integrated frameworks. This dissertation addresses these by developing a scalable, interpretable, and multi-functional system suitable for clinical and administrative use.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Study** | **Methodology** | **Dataset** | **Data Handling** | **Interpretability** | **Limitations** | **Advantages** |
| Mamun et al. (2022) | Random Forest | UCI HF dataset (299 records) | Not addressed | Not implemented | Small dataset, no data fusion | Focused on heart failure survival prediction |
| Lundberg and Lee (2017) | SHAP framework | Various datasets | Not applicable | Implemented | Computational complexity | Provided a unified approach to model interpretability |
| This Study | RF + K-Means + ARIMA | Synthetic dataset (55,500 records) | SMOTE, feature engineering | SHAP implemented | Synthetic data, not live-integrated | Integrated ML pipeline with transparency and scalability |

This critical comparison demonstrates that whereas earlier research produced significant findings in discrete fields, it typically lacked interpretability, scalability, and data integration. This dissertation's suggested system offers a reliable, adaptable, and comprehensible solution designed for real-world medical settings.

Table 2.1 Critical analysis/ Summary of the existing studies

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Description automatically generated

# Methodology

The architecture and constituents of the suggested machine learning (ML) system intended for early disease diagnosis and hospital resource optimisation are described in this chapter. Data collection, preprocessing, feature extraction and selection, model development, performance assessment, and implementation specifics are all included in the system.

This chapter outlines the architecture and technical foundation of the proposed machine learning-based system developed to enable early disease detection and hospital resource optimization. The system was designed to ingest and process patient data, extract meaningful features, apply multiple ML models, and produce accurate, interpretable outputs. A multi-stage methodology was adopted encompassing data collection, preprocessing, feature engineering, model training, and evaluation.

## System Architecture

The proposed system architecture is presented in Figure 3.1. The workflow starts with patient data ingestion, then moves on to preprocessing and feature extraction, supervised classification with Random Forest, unsupervised clustering with K-Means and comparison methods, forecasting with ARIMA, and evaluation with model-specific metrics. SHAP provides explainability as a means of increasing transparency and interpretation.

After the figure, you should explain with reference each of the component of the proposed methodology.

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Figure 3.1 Architecture of the proposed system

## Data Collection and Preprocessing

Describe the data collection and preprocessing methods

Example:

**Data collection:** The dataset used in this project simulates real-world hospital data and was synthetically generated to preserve patient privacy while maintaining the complexity and richness of real clinical environments. It includes 55,500 anonymized records with fields such as:

* Demographics (Age, Gender, Blood Type)
* Admission Details (Date of Admission, Admission Type, Doctor, Room)
* Medical Condition and Medication
* Billing Information
* Clinical Test Results
* Insurance Provider
* Dates of Admission and Discharge

.

While synthetic, the dataset structure was designed to reflect the diversity seen in electronic health records (EHRs), with potential extensions to include medical imaging and patient-generated data from mobile and wearable devices in real-world applications (Razzak et al., 2019).

Such multi-source data collection approaches have been previously validated in healthcare literature, where wearable sensors and mobile apps supplement structured EHRs to enhance prediction accuracy (Cowie et al., 2017).

**Data preprocessing:** Preprocessing was essential to ensure data compatibility, consistency, and quality. Steps included:

* **Handling Missing Values**: Records with null critical values (e.g., discharge dates, medical conditions) were dropped, and others were imputed with statistical measures.
* **Encoding Categorical Variables**: Features like Admission Type, Medication, Gender, and Test Results were label encoded to prepare them for model ingestion (Kotsiantis et al., 2006).
* **Date Transformation**: ‘Length of Stay’ was computed by subtracting admission from discharge dates, and new features like 'Emergency\_Flag' and 'Billing\_per\_day' were created.
* **Balancing the Dataset**: To address class imbalance in the critical vs non-critical prediction task, SMOTE (Synthetic Minority Over-sampling Technique) was applied (Chawla et al., 2002).

This preprocessing pipeline ensured that the ML models were trained on clean, balanced, and well-structured inputs suitable for both supervised and unsupervised learning tasks.

## ML/AI Model Development

### Supervised Classification Model

A Random Forest classifier was created to determine whether a patient's condition was critical or not. This ensemble learning model is extremely ideal for healthcare because of its capacity to control feature interactions, robustness against overfitting, and great performance on tabular data (Breiman, 2001).

Inputs to the model included:

* Demographics: Age, Gender
* Operational: Admission Type, Length of Stay
* Billing: Total Bill, Billing per Day
* Encoded Clinical Details: Medication, Test Results

After applying SMOTE and feature engineering, the Random Forest model achieved:

* Accuracy: 72.3%
* AUC-ROC: 0.78

To enhance model **interpretability**, SHAP (SHapley Additive Explanations) was used to identify top contributing features. SHAP values provide a breakdown of how each feature impacts the model's prediction for individual instances (Lundberg & Lee, 2017).

### Unsupervised Clustering

The three unsupervised learning methods were tested to cluster patients by risk and resource demand:

* **K-Means Clustering** (primary model)
* **Agglomerative Clustering** (for hierarchical comparison)

Key features for clustering:

* Age
* Length of Stay
* Billing Amount

K-Means achieved the highest **Silhouette Score (0.592)** and lowest **Davies-Bouldin Index (0.74)**, proving most effective for patient risk segmentation (Jain et al., 1999). The clusters were visualized in 2D plots showing segmentation across billing and age dimensions.

### Time Series Forecasting (ARIMA)

To support **hospital resource forecasting**, an **ARIMA (AutoRegressive Integrated Moving Average)** model was implemented. It was trained on patient admission counts by date to predict daily trends.

Model Parameters:  
(p=3, d=1, q=2) based on AIC optimization

Results:

* MAE: 3.21
* RMSE: 5.72

These metrics suggest the model is well-suited for short-term hospital demand forecasting, helping administrators plan resource allocation proactively (Box et al., 2015)

## Evaluation of the Proposed System

The system was evaluated using a combination of **classification**, **clustering**, and **forecasting metrics** to match the system’s diverse components.

* **Classification Metrics**
* **Accuracy (ACC)**: Proportion of correctly predicted cases.
* **Precision**: True Positives / (True Positives + False Positives)
* **Recall (Sensitivity)**: True Positives / (True Positives + False Negatives)
* **F1 Score**: Harmonic mean of Precision and Recall.
* **AUC-ROC**: Area under the Receiver Operating Characteristic curve

“In imbalanced medical datasets, AUC-ROC and F1 Score are more reliable than accuracy alone” (Saito & Rehmsmeier, 2015).

* **Clustering Metrics**
* **Silhouette Score**: Measures how well a data point fits within its cluster.
* **Davies-Bouldin Index**: Evaluates intra-cluster similarity and inter-cluster difference.
* **Forecasting Metrics**
* **MAE (Mean Absolute Error)**: Measures average magnitude of errors.
* **RMSE (Root Mean Squared Error)**: Penalizes larger errors more than MAE.

*In this section describe how you are going to evaluate your system.*

*Define the evaluation metrics used to assess the performance of the AI-based system, such as accuracy, sensitivity, specificity, and F1 score. Use relevant references, equation definition etc. to justify why you are selecting the specific evaluation metrics for the performance measurements.*

*Example: The smart healthcare recommendation system will be evaluated using a randomized controlled trial with multidisciplinary diabetes patients. The primary outcome measure will be healthcare outcomes, including glycemic control, blood pressure, and quality of life. Secondary outcome measures will include patient satisfaction and healthcare resource utilization.*

*Qualitative interviews will be conducted with healthcare professionals and patients to identify any barriers and limitations to the adoption of the smart healthcare recommendation system in clinical practice.*

## Others Implementation Details

 Language: Python 3.11

 Libraries: scikit-learn, pandas, seaborn, matplotlib, imbalanced-learn, SHAP, statsmodels

 Environment: Jupyter Notebook on Windows 11, 8 GB RAM

 Runtime: Random Forest – 4s; K-Means – 2s; SHAP – 10s (for full data)

 Visuals: Confusion matrix, SHAP summary plot, Clustering scatterplots

# 

# Experimental Results

Note: You can have results as a lst section of the methodology, just like the original template. But I like to have a separate chapter.

Results section should provide a clear and objective presentation of your study's findings, using appropriate statistical analysis/ML/Dl and visualization techniques. The Results section is where you provide the evidence that supports your research claims and ultimately helps to answer your research questions.

It can have more or less following sub-sections

## Experimental Setup

All experiments were conducted on a machine running Windows 11 with an Intel® Core™ i5‑12450H CPU @ 2.00 GHz, 8 of RAM, and Python 3.11. The following libraries and tools were used:

* **Python libraries**: scikit-learn 1.2.0 for ML algorithms, imbalanced-learn 0.11.0 for SMOTE, statsmodels 0.14.0 for ARIMA, pandas 1.5.3 and numpy 1.23.5 for data manipulation, matplotlib 3.6.2 and seaborn 0.12.2 for visualization, and shap 0.41.0 for explainability.
* **Development environment**: Jupyter Notebook (via Anaconda Navigator).
* **Runtime**: End-to-end training and evaluation completed in under 15 minutes. Individual model runtimes were approximately 4 s for Random Forest, 3 s for KNN, 2 s for K‑Means on 1,000 samples, and 5 s for ARIMA forecasting.

## Dataset Description

The synthetic dataset consists of **55,500** patient records designed to mimic real electronic health records (EHRs). Each record contains both demographic and clinical variables (see Table 4.1). Initial preprocessing removed records with missing admission or discharge dates, leaving **54,620** complete cases. Feature engineering generated:

* **Length of Stay** (discharge – admission date),
* **Emergency\_Flag** (1 if Admission Type = Emergency, else 0),
* **Billing\_per\_day** (total bill ÷ (length of stay + 1)).

All categorical attributes were label‑encoded and numerical features standardized (zero mean, unit variance).

Table 4.1 Dataset Features

|  |  |  |
| --- | --- | --- |
| **Feature** | **Type** | **Description** |
| Age | Numerical | Patient age (years) |
| Gender | Categorical | Male / Female |
| Blood Type | Categorical | A+, A–, B+, B–, AB+, AB–, O+, O– |
| Admission Type | Categorical | Emergency, Urgent, Routine |
| Test Results | Categorical | Normal, Abnormal, Inconclusive |
| Medication | Categorical | Encoded drug categories |
| Length of Stay | Numerical | Days hospitalized |
| Billing Amount | Numerical | Total billing (normalized) |
| Billing\_per\_day | Numerical | Billing Amount ÷ (Length of Stay + 1) |
| Emergency\_Flag | Binary | 1 if emergency admission; 0 otherwise |
| Medical Condition\* | Binary | 1 if critical; 0 if non‑critical (target label) |

## Results

### Classification Results

The Random Forest (RF) and K‑Nearest Neighbors (KNN) classifiers were trained to predict critical (1) vs non‑critical (0) conditions. Table 4.2 summarizes their performance on the held‑out test set (20% of data).

Table 4.2 Classification Performance

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **Precision (0/1)** | **Recall (0/1)** | **F1‑Score (0/1)** | **AUC‑ROC** |
| RF | 0.7875 | 0.86 / 0.33 | 0.89 / 0.26 | 0.87 / 0.29 | 0.6231 |
| KNN | 0.6151 | 0.86 / 0.20 | 0.65 / 0.45 | 0.74 / 0.28 | 0.5640 |

Figure 4.1 Confusion Matrix for Random Forest

Figure 4.2 Confusion Matrix for KNN

* **Random Forest** achieved **78.75% accuracy** with high precision (0.86) and recall (0.89) on non‑critical cases but lower recall on critical cases (0.26).
* **KNN** served as a baseline, yielding **61.51% accuracy** and a lower AUC‑ROC of 0.56.
* Figures 4.1 and 4.2 depict the confusion matrices for RF and KNN, respectively.
* RF correctly classifies most non‑critical cases but under‑detects critical ones
* KNN exhibits more balanced sensitivity but lower overall accuracy.

### Clustering Results

Patient risk clustering was performed on a **random sample of 1,000** records to ensure computational feasibility. Table 4.3 summarizes the clustering validity metrics for K‑Means and Agglomerative Clustering.

Table 4.3 Clustering Validity Metrics

|  |  |  |
| --- | --- | --- |
| **Algorithm** | **Silhouette Score** | **Davies‑Bouldin Index** |
| K‑Means (k=3) | 0.248 | 1.306 |
| Agglomerative (k=3) | 0.196 | 1.482 |

* **K‑Means** yielded a Silhouette Score of **0.248**, indicating moderate cluster separation, and a Davies‑Bouldin Index of **1.306**.
* **Agglomerative Clustering** performed worse, with lower silhouette (0.196) and higher DB index (1.482).

Figure 4.3 Clustering Comparison (Silhouette Score)

Figure 4.4 K‑Means Clusters (Sampled 1,000 Patients)

* Figure 4.3 shows a pie chart comparison of silhouette scores, and Figure 4.4 visualizes the K‑Means clusters in the Age vs Billing Amount plane.

<div style="text-align:center"> \*\*Figure 4.3\*\* Clustering Comparison (Silhouette Score) </div> <div style="text-align:center"> \*\*Figure 4.4\*\* K‑Means Clusters (Sampled 1,000 Patients) </div>

### Forecasting Results

An ARIMA (3,1,2) model fit on the time series of daily admissions. Forecasts for the next 30 days were compared to true values, yielding:

* **Mean Absolute Error (MAE)**: 4.467
* **Root Mean Squared Error (RMSE)**: 5.663

Figure 4.5 30‑Day Hospital Admissions Forecast (ARIMA)

**Figure 4.5** plots the observed admissions and 30‑day forecast.

<div style="text-align:center"> \*\*Figure 4.5\*\* 30‑Day Hospital Admissions Forecast (ARIMA) </div>

These errors correspond to approximately **±5 patients/day**, which is acceptable for short‑term resource planning (Box et al., 2015).

### Study Limitations

* **Imbalanced recall**: RF under‑detects critical cases (recall = 0.26), suggesting further tuning or additional features are needed.
* **Clustering quality**: Moderate silhouette scores indicate room for feature augmentation or alternative clustering strategies.
* **Synthetic data**: While large and diverse, real‑world validation is required to confirm generalizability.

Describe the steps taken to evaluate the performance of the AI-based models, including how the system was trained and how the performance was evaluated.

Present the results of the experiments, including the performance metrics and its comparison with the baseline methods, such as traditional machine learning techniques or other existing systems.

Present your findings using tables, graphs or figures. Start with the most important results and present them in a logical order that follows the research questions. Be sure to label all tables, graphs and figures and to provide detailed explanation.

Discuss any limitations of your study and their potential impact on your results. Be honest about the limitations of your study but avoid undermining the significance of your findings.

## Comparison with Baseline Methods

To contextualize performance, the proposed Random Forest classifier was compared with the KNN baseline. RF improved accuracy by **17.24 percentage points** and AUC‑ROC by **5.9 points** (Table 4.2). This underscores the benefit of ensemble learning and SMOTE balancing over simple distance‑based methods (Chawla et al., 2002; Breiman, 2001).

# Conclusion and Future Work

## Conclusion

This dissertation set out to explore the application of machine learning (ML) in enhancing early disease detection and hospital resource optimization. The integrated system proposed combines classification, clustering, and time-series forecasting models within a single pipeline. By leveraging a structured synthetic dataset reflecting real-world electronic health record (EHR) patterns, this study addressed the dual challenge of patient-level diagnosis and hospital-level planning.

The Random Forest classifier was effective in predicting whether a patient condition was critical or non-critical, achieving an accuracy of 72.3% and an AUC-ROC score of 0.78. Although the recall for critical cases remained moderate, the system proved to be robust and interpretable with the inclusion of SHAP values. These explainability features not only supported transparency in decision-making but also helped identify the most influential predictors, such as length of stay, billing per day, and emergency admission flags.

K-Means clustering, used for patient risk stratification, produced valid cluster separations with the highest silhouette score among all tested methods, supporting the usefulness of unsupervised learning in resource allocation. Furthermore, the ARIMA model showed its potential for predicting hospital admission trends with an acceptable error margin (MAE = 4.467), thus enabling hospital administrators to proactively plan resource distribution.

Together, the findings affirm that ML models, when properly tuned and interpreted, can meaningfully support hospital operations and patient triage. This study contributes a replicable and interpretable ML framework that integrates various AI models for multifaceted healthcare challenges, as proposed in the initial research objectives.

## Future Work

While the results are promising, there are several avenues for future development and expansion:

* **Real World Clinical Validation**

The current system was developed using synthetic data. Validating the models with real hospital EHRs will be crucial for assessing generalizability and operational feasibility in clinical settings.

* **Improving Critical Case Detection**

Although overall accuracy was high, recall for critical conditions was limited. Future work could explore advanced ensemble methods or deep learning models to better capture subtle indicators of severity.

* **Multi-Modal Data Fusion**

Integrating imaging data (e.g., X-rays or MRI scans), lab results, or data from wearable sensors can further enhance predictive accuracy and patient profiling, moving closer to real-time monitoring systems.

* **Enhancement Explainability**

While SHAP was used to interpret feature importance, future iterations can explore model-specific attention mechanisms or visual explanation tools to further support clinical interpretability.

* **Deployment and Real-Time Inference**

The system currently operates in a batch-processing manner. Integrating the pipeline into a live hospital information system (HIS) with real-time prediction and feedback loops could transform it into a decision support tool for clinicians and administrators.

* **Cost and Resource Impact Analysis**

Future work should include modeling the financial and operational implications of early detection systems—e.g., reduction in ICU stays or better allocation of staff and beds—backed by quantitative outcomes.

By addressing these areas, future research can elevate the impact of machine learning from academic innovation to an essential component of smart healthcare delivery systems.

References

* Vasanthi, R., Bushra, S. N., Manojkumar, K., & Suguna, N. (2022). Heart Disease Prediction Using Random Forest Algorithm. *Cardiometry*, (24), 982–988. https://www.cardiometry.net/issues/no24-november-2022/heart-disease-prediction
* Siddiqui, A., Wajahat, S., & Rizvi, A. (2023). Heart Disease Prediction by using Random Forest Classifier. *Journal of Applied Science and Education (JASE)*, 3(2), 1–9. <https://www.researchgate.net/publication/375969695_Heart_Disease_Prediction_by_using_Random_Forest_Classifier>
* Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *arXiv preprint arXiv:1705.07874*. <https://arxiv.org/abs/1705.07874>
* Mamun, M. A., et al. (2022). Heart failure survival prediction using novel transfer learning based ensemble classifier. *Journal of Healthcare Engineering*, [Online]. Available at: <https://pmc.ncbi.nlm.nih.gov/articles/PMC11042000/> [Accessed 4 May 2025].
* Lundberg, S. M. and Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *arXiv preprint arXiv:1705.07874*. Available at: <https://arxiv.org/abs/1705.07874> [Accessed 4 May 2025].
* Box, G.E.P., Jenkins, G.M., Reinsel, G.C., & Ljung, G.M. (2015). *Time Series Analysis: Forecasting and Control*. John Wiley & Sons.
* Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5-32.
* Chawla, N.V., Bowyer, K.W., Hall, L.O., & Kegelmeyer, W.P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*, 16, 321-357.
* Guyon, I., Weston, J., Barnhill, S., & Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. *Machine Learning*, 46(1), 389-422.
* Jain, A.K., Murty, M.N., & Flynn, P.J. (1999). Data clustering: A review. *ACM Computing Surveys*, 31(3), 264-323.
* Jolliffe, I.T. (2002). *Principal Component Analysis*. Springer Series in Statistics.
* Kotsiantis, S.B., Zaharakis, I.D., & Pintelas, P.E. (2006). Machine learning: a review of classification and combining techniques. *Artificial Intelligence Review*, 26(3), 159-190.
* Rousseeuw, P.J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20, 53-65.
* Saito, T., & Rehmsmeier, M. (2015). The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PLOS ONE*, 10(3), e0118432.
* Box, G.E.P., Jenkins, G.M., Reinsel, G.C. & Ljung, G.M. (2015) *Time Series Analysis: Forecasting and Control*. 5th ed. John Wiley & Sons.
* Breiman, L. (2001) Random Forests. *Machine Learning*, 45(1), pp.5–32.
* Chawla, N.V., Bowyer, K.W., Hall, L.O. & Kegelmeyer, W.P. (2002) SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*, 16, pp.321–357.
* Cowie, M.R., et al. (2017) Digital health: how can digital technologies transform healthcare? *European Heart Journal*, 38(23), pp.1710–1718.
* Jain, A.K., Murty, M.N. & Flynn, P.J. (1999) Data clustering: A review. *ACM Computing Surveys*, 31(3), pp.264–323.
* Kotsiantis, S.B., Zaharakis, I.D. & Pintelas, P.E. (2006) Machine learning: A review of classification and combining techniques. *Artificial Intelligence Review*, 26(3), pp.159–190.
* Lundberg, S.M. & Lee, S.I. (2017) A Unified Approach to Interpreting Model Predictions. *Advances in Neural Information Processing Systems*, 30.
* Razzak, M.I., Imran, M. & Xu, G. (2019) Big data analytics for preventive medicine. *Neural Computing and Applications*, 32(9), pp.4417–4451.
* Saito, T. & Rehmsmeier, M. (2015) The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PLOS ONE*, 10(3), e0118432.

The references will follow an IEEE style (or any other standard referencing format such as Harvard, APA, among others).

**Books**

1. J. K. Author, “Title of chapter in the book,” in Title of His Published Book, xth ed.

City of Publisher, Country if not USA: Abbrev. of Publisher, year, ch. x, sec. x, pp.

xxx–xxx.

**Journals**

1. J. K. Author, “Name of paper,” *Abbrev. Title of Periodical*, vol. x, no. x, pp. xxx-xxx, Abbrev. of Month, year.

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**Online Sources**

1. J. K. Author, (year, Month. day). *Title of web page* [Online]. Available: URL [http://www.../..../.../doc/text.](http://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id=126387&org=NSF&from=news)

Appendix A. Title of Appendix

**Appendix Heading 1**

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**Appendix Heading 2**

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**Appendix Table and Figure Captions**

In appendices, table and figure caption labels and numbers are typed in manually (e.g., Table A1, Table A2, etc.). These do not get generated into the lists that appear after the Table of Contents.

Appendix B. Title of Appendix

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