FALCON INFORMATICS

Predictive Intelligence for Smarter Healthcare Systems

Driving Proactive Care and Operational Efficiency with Machine Learning

CASE STUDY

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Overview

This case study presents the application of predictive analytics in the healthcare sector with the aim of improving patient care quality and supporting efficient hospital operations. The focus is on using analytical insights to identify patient risk patterns and assist healthcare providers in making timely, informed decisions.

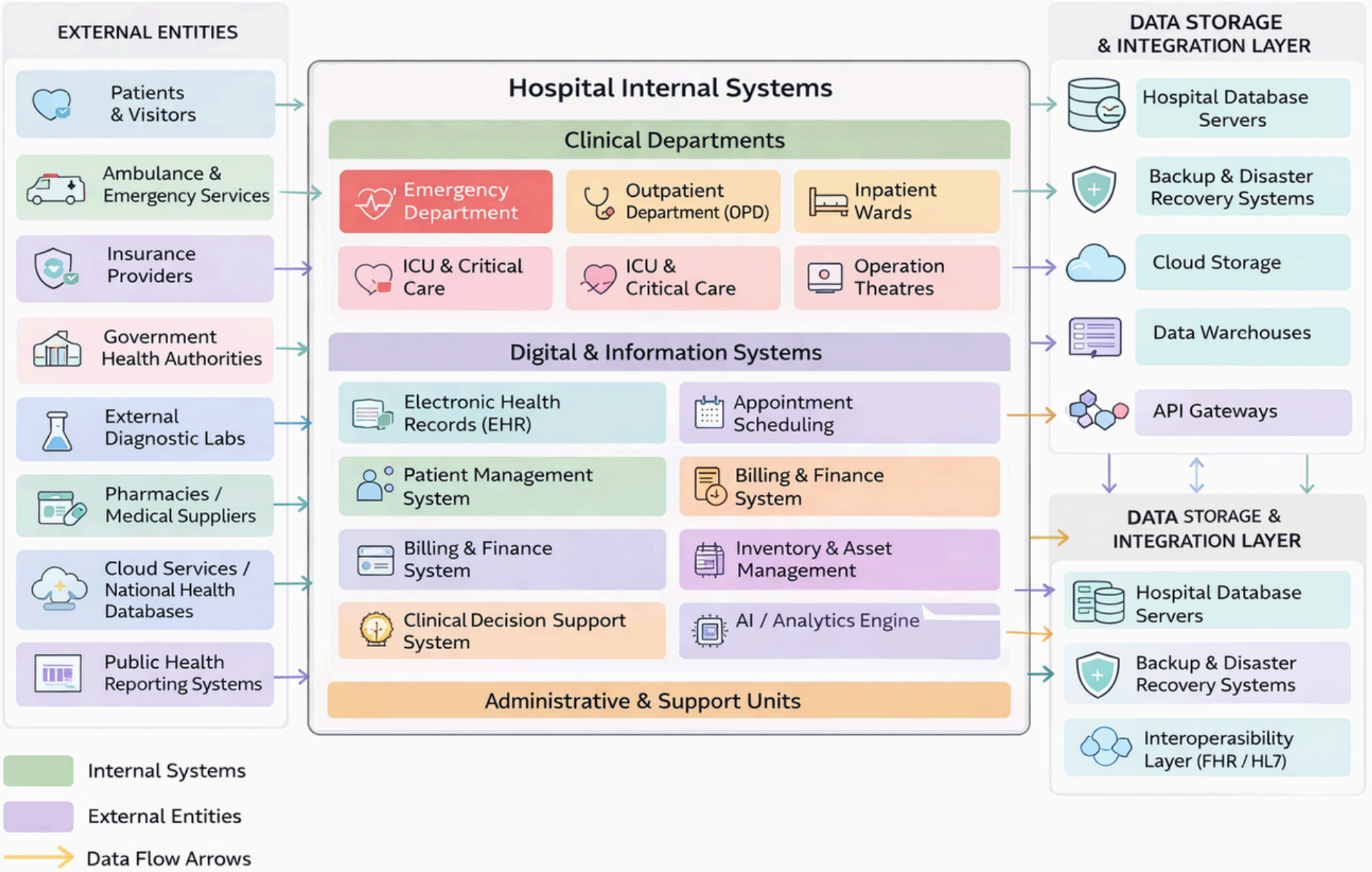
By adopting a predictive approach, healthcare systems can move beyond reactive treatment methods and toward proactive care planning. The study highlights how data-driven insights can contribute to better clinical outcomes while also addressing operational challenges such as resource utilization and hospital congestion.

Problem Statement

The key problems addressed in this case study include:

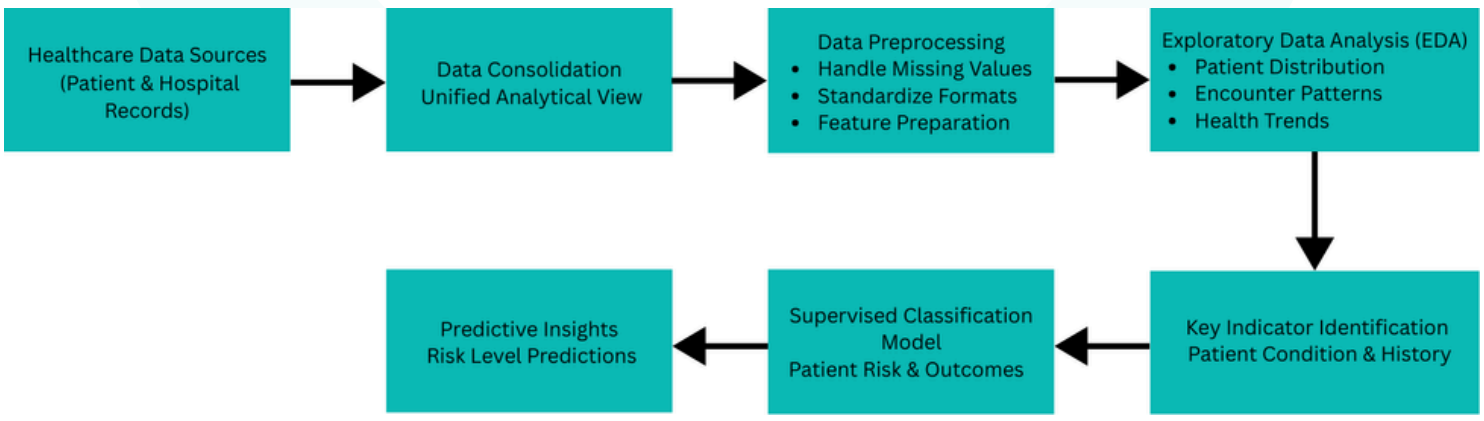
- Inefficient utilization of hospital resources such as beds, medical staff, and equipment
- Difficulty in identifying high-risk patients at an early stage
- Delayed clinical decision-making due to limited predictive support
- Increased operational pressure caused by unplanned patient inflow
- Lack of proactive insights to support effective treatment planning and hospital management

These challenges highlight the need for analytical solutions that enable early risk identification and informed, proactive decision-making.


EXTERNAL ENTITIES
Patients & Visitors
Ambulance & Emergency Services
Insurance Providers
Government Health Authorities
External Diagnostic Labs
Pharmacies / Medical Suppliers
Cloud Services / National Health Databases
Public Health Reporting Systems
Hospital Internal Systems
Clinical Departments
Emergency Department
Outpatient Department (OPD)
Inpatient Wards
ICU & Critical Care
ICU & Critical Care
Operation Theatres
Digital & Information Systems
Electronic Health Records (EHR)
Appointment Scheduling
Patient Management System
Billing & Finance System
Billing & Finance System
Inventory & Asset Management
Clinical Decision Support System
AI / Analytics Engine
Administrative & Support Units
DATA STORAGE & INTEGRATION LAYER
Hospital Database Servers
Backup & Disaster Recovery Systems
Cloud Storage
Data Warehouses
API Gateways
DATA STORAGE & INTEGRATION LAYER
Hospital Database Servers
Backup & Disaster Recovery Systems
Interoperasibility Layer (FHR / HL7)
Internal Systems
External Entities
Data Flow Arrows

Methodology

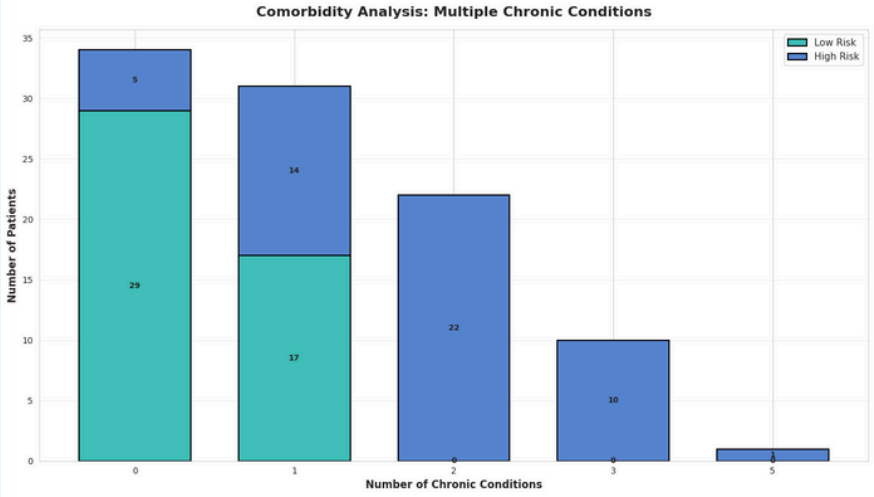
- Healthcare-related records were consolidated and organized to create a unified analytical view.
- Data preprocessing steps were applied to handle missing values, standardize formats, and prepare features suitable for analysis.
- Exploratory data analysis was performed to understand patient distributions, encounter patterns, and health-related trends.
- Key indicators representing patient condition and historical patterns were identified to support predictive analysis.
- A supervised classification model was developed to assess patient risk levels and health outcomes.
- The generated predictions provided actionable insights to support timely treatment planning and informed resource management.



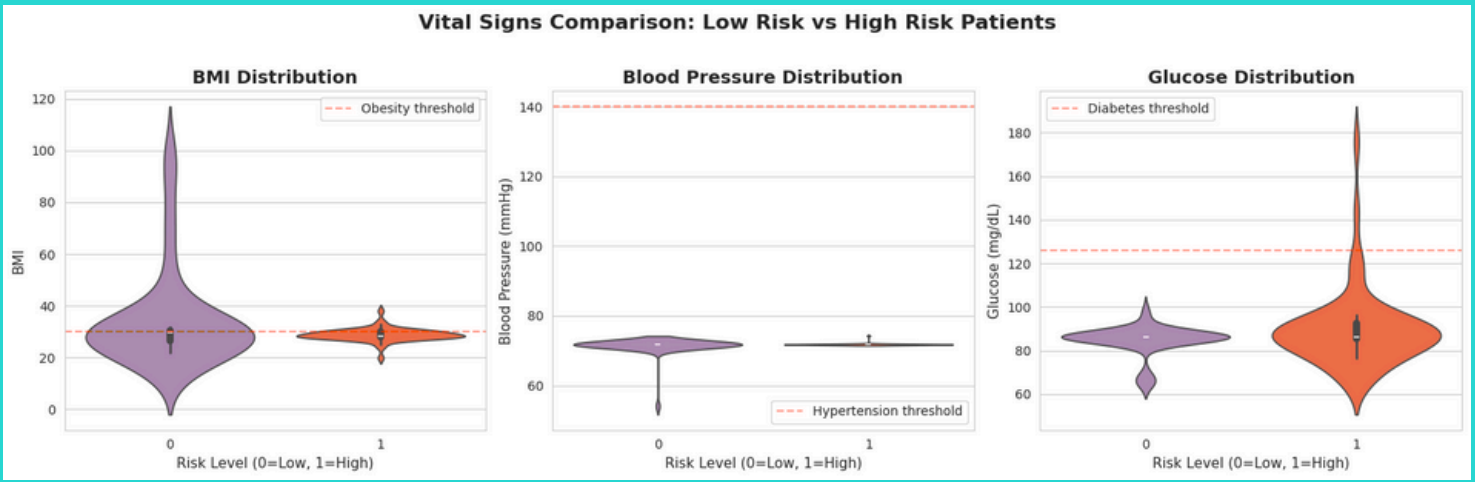
Key Insights

The analysis provided several important insights that support both clinical decision-making and hospital operations.

- Clear patterns emerged that help differentiate patients based on their overall risk levels, enabling early attention for those requiring closer monitoring.
- Historical health indicators and encounter patterns played a significant role in understanding patient condition trends over time.
- Predictive assessment supports timely treatment planning by highlighting potential risks before conditions escalate.
- Analytical insights help hospitals anticipate patient demand more effectively, supporting better planning of beds, staff, and resources.
- Data-driven visibility into patient health trends enables a shift from reactive responses to proactive healthcare management.



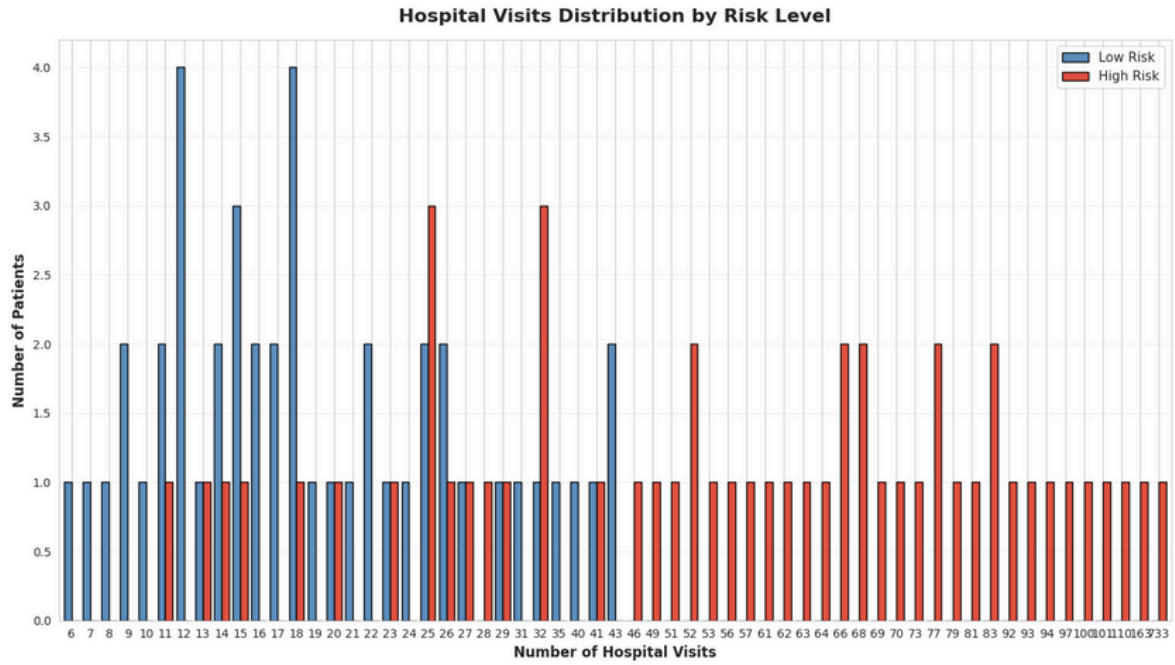
Comorbidity Analysis: Risk levels rise sharply with the number of chronic conditions; patients with multiple conditions are predominantly categorized as high-risk.



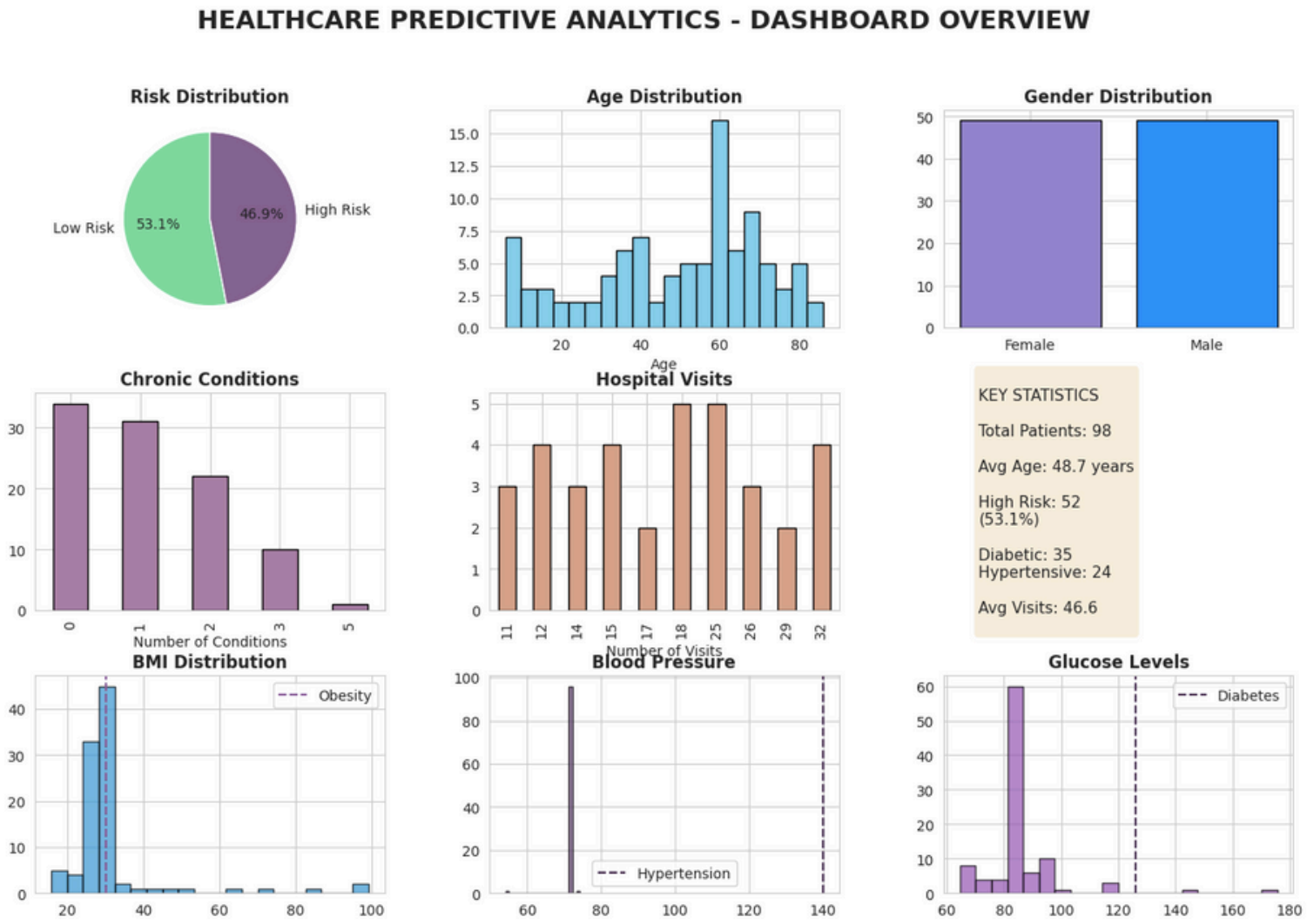
BMI Distribution: High-risk patients are more densely concentrated near the obesity threshold, whereas the low-risk group shows a wider variance with extreme upper-end outliers

Blood Pressure Distribution: Both risk groups show similar median values, indicating that BP alone is a less distinctive differentiator for risk in this specific dataset

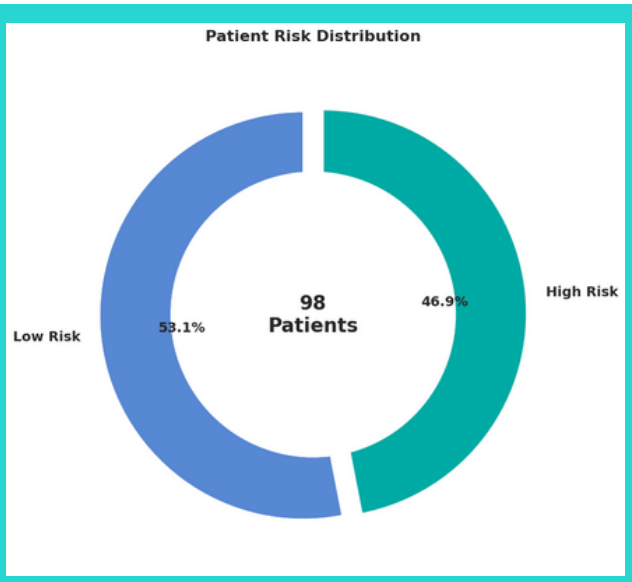
Glucose Distribution: High-risk patients exhibit a significantly higher median and a broader spread of values that frequently cross the diabetes threshold of 125 mg/dL.



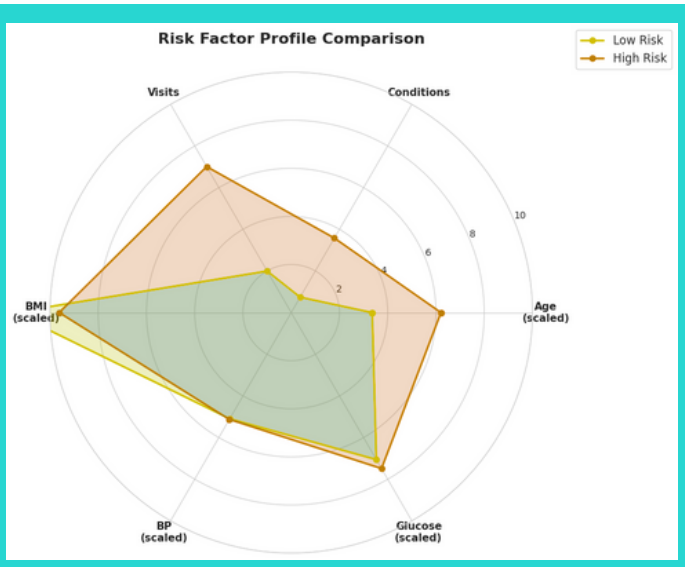
Hospital Visits Distribution: High-risk patients exhibit a higher frequency of encounters, with many recording between 15 and 25 visits.



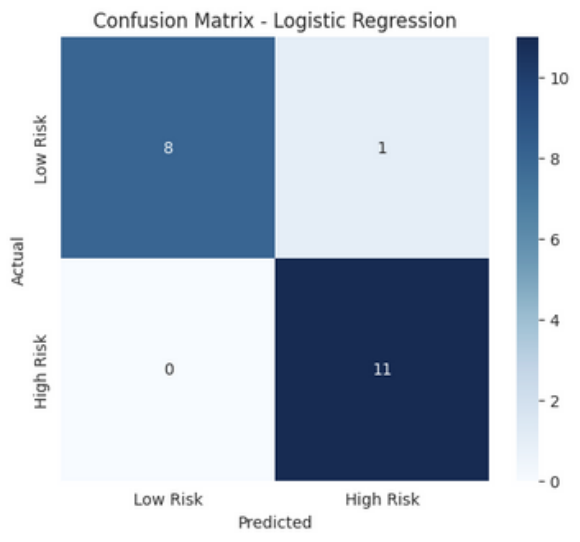
The dashboard provides a unified view of 98 patients , revealing that high-risk status (46.9%) is primarily driven by advanced age , frequent hospital visits , and multiple chronic conditions , rather than BMI or blood pressure alone.



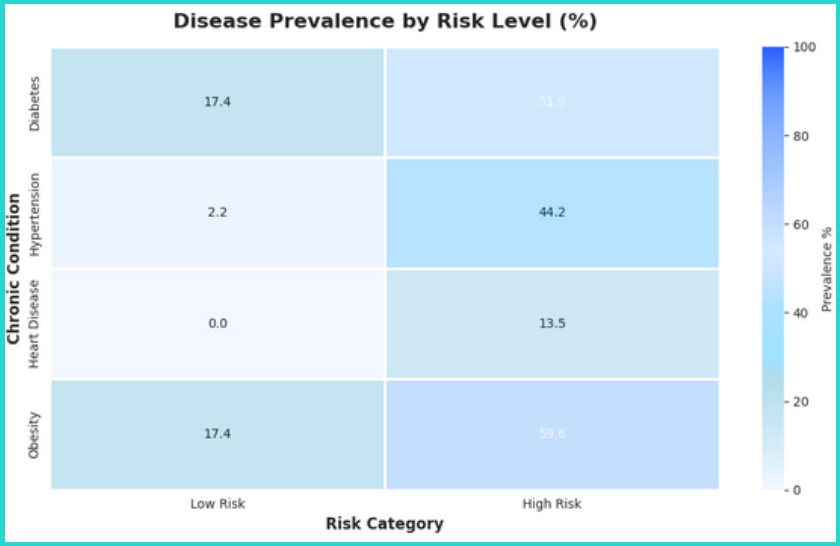
Patient Risk Distribution (Pie Chart): The population is split into 53.1% Low Risk and 46.9% High Risk.



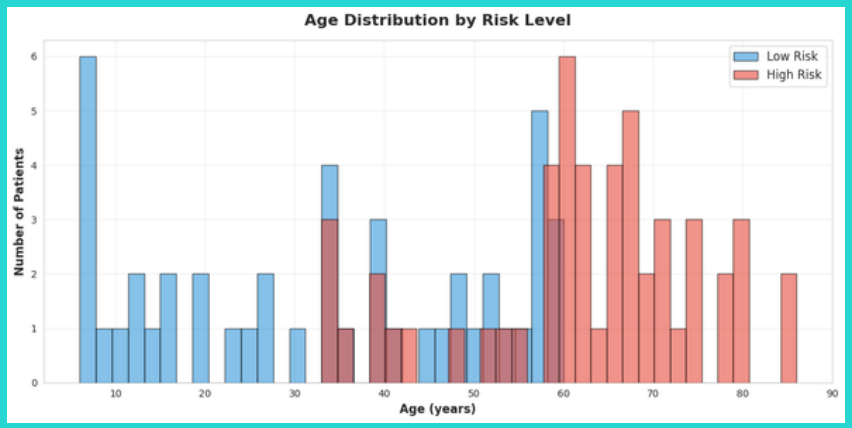
The radar chart reveals that High-risk patients are primarily distinguished by significantly higher frequencies of hospital visits, chronic conditions, age, and glucose levels.



Confusion Matrix (Logistic Regression): The model shows high precision, accurately predicting 11 out of 11 high-risk patients and misclassifying only 1 low-risk patient.



Age Distribution by Risk: There is a clear shift toward high-risk status as age increases, with the highest concentration of high-risk patients falling in the 60–80 year range.



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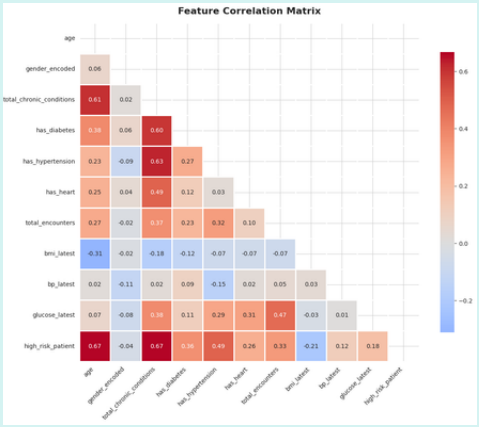
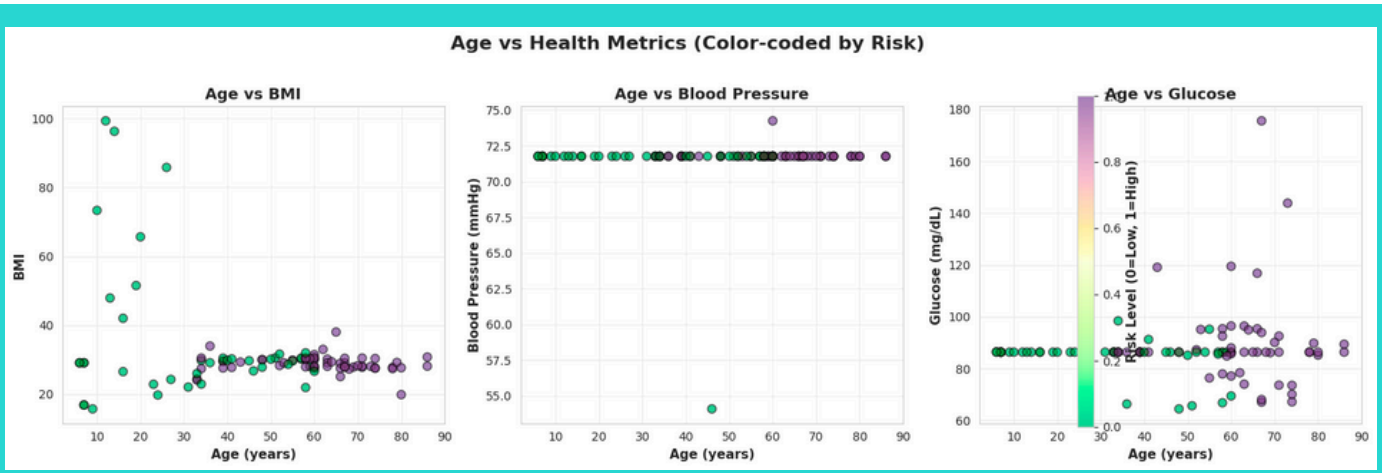


Feature Correlation Matrix: Identifies strong inter-relationships between Age, BMI, and Glucose, which serve as the primary predictive features for the classification model



Age vs. Health Metrics (Scatter Plots): These visualizations confirm that while BMI and BP are scattered, elevated Glucose levels correlate most consistently with high-risk status in older age groups.

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