Unified Healthcare Data Management and Predictive Analytics for Enhanced Patient Care and Decision Support

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***Abstract*—Healthcare data, encompassing patient admissions, mortality rates, and environmental factors like pollution, is critical for improving patient outcomes and guiding healthcare decisions. This study integrates diverse datasets into a centralized repository, utilizing SQL for efficient data management and ETL (Extract, Transform, Load) processes to clean and organize data into a relational database. By creating a unified data system, the study enables healthcare providers to access reliable and organized information that supports data-driven decision-making. A web application complements this system by providing a user-friendly interface for analyzing trends and interacting with the data, offering actionable insights into healthcare dynamics and influencing factors. To refine healthcare decision-making, three predictive models have been created: one concerning probability of ICU admission, other focused on predicting the risk of death, and the last one revolves around determining pollution's impact on health. Rigorously developed models showed that the pollution health risk assessment model outshined the others by providing stunning results of 99% accuracy. Furthermore, the mortality prediction model developed also achieved astonishing results with an accuracy of 91%. This surely enables the systematic and automatic identification of high-risk patients. Finally, the ICU admission model strengthened its place with a Mean Absolute Error (MAE) of 1.52 and outstanding R^2 score of 0.63. These models enable the integration of machine learning with historical healthcare data to assist healthcare professionals with more effective treatment strategies. Leveraging the structured data management alongside the predictive analytics, this research pushes forth the digital transformation of health care.**

***Index Terms*—Healthcare data, Patient outcomes, Centralized repository, SQL, Predictive models, ICU admission likelihood, Mortality prediction.**

I. Introduction

There is a paradigm shift towards digitization in the healthcare industry which is improving the efficiency of patients outcomes through data and advanced analytics. The healthcare data boom, which includes patient admissions, deaths, and even pollution rates, makes it possible to improve decision making, care quality, and health results. At the same time, many healthcare systems today suffer from fragmented data silos, zero interoperability, poor data retrieval, and practically no predictive analytics. This makes it impossible for care staff to make timely and educated decisions, ultimately affecting patient management and resource distribution.

This study aims to tackle this issue by designing a unified healthcare data management system that maintains various datasets within a single central repository. A Relational Database Management System (RDBMS) is used with the intent of bringing structure, efficiency, and management to the querying and storing of patient data. This database is a crucial component of the data warehouse that allows for the incorporation of multiple healthcare data resources.The study comprehensively integrates ETL processes by gathering, cleaning, transforming, and consolidating the data from different sources for a high accuracy and quality standard.

A Key component of this research is creating risk predictive models for nuanced decision-making in critical healthcare. Three ML models have been deployed to solve some crucial problems in healthcare practices. The first predictive model provides estimates on the intensity and likely time frame of a patient's ICU admission, assisting hospitals with effective allocation of their resources. The second model predicts possible mortality rates, which aids in the diagnosis of patients who require immediate medical treatment. The third model combines health deterioration factors that stem from pollution and focus on various environmental indicators in relation to the patient's health for public health planning.

The study also includes the development of a web application designed to provide healthcare professionals with an easy-to-use interface for accessing data and predictive models. This application features data visualization tools, predictive analytics dashboards, and trend analysis capabilities, helping healthcare providers identify patterns and gain meaningful insights. By incorporating machine learning models, the platform enhances its functionality, delivering real-time predictive insights that empower medical professionals to take proactive steps in patient care.

This research is driven by the need for a comprehensive, data-driven healthcare system that strengthens predictive analytics, optimizes resource utilization, and supports evidence-based decision-making. The study's key contributions include creating a centralized healthcare data repository using a relational database to ensure organized storage and seamless data management. It also implements ETL processes to clean and standardize raw healthcare data, integrates predictive analytics models for ICU admissions, mortality risk, and pollution-related health effects, and develops a web-based application that enables data-driven decision-making through interactive dashboards and predictive insights.

By integrating structured data storage, predictive analytics, and real-time decision support, this study plays a vital role in advancing digital healthcare transformation.

II. Literature Survey

Himu et al. [1] presented a study on designing and implementing a National Health Data Warehouse (NHDW) for Bangladesh's healthcare system. The study aimed to collect and organize data from various medical sources, including hospitals, clinics, and government healthcare centers, to enable comprehensive Big Data analysis.

Moharram et al. [2] conducted a study to predict no-shows in pediatric outpatient clinics at King Faisal Specialist Hospital and Research Centre (KFSH&RC) using machine learning. Analyzing data from 2019, covering 101,534 appointments, they evaluated three algorithms: logistic regression, JRip, and Hoeffding tree. The models showed precision and recall around 90% and an F-score of 0.86, effectively identifying pediatric patients at high risk of missing appointments.

Shan et al. [3] introduced a book management system that utilizes database design and SQL to enhance library operations. The system's design includes an E-R diagram and relational model, emphasizing efficiency and practicality. By implementing efficient SQL statements, the system allows for faster and more accurate book searches, even for books not in the library. It also helps users manage their borrowing status, encouraging timely returns and increasing library engagement.

Zaabar et al. [4] proposed HealthBlock, a blockchain-based system to enhance the security and privacy of electronic healthcare records (EHRs). By utilizing decentralized storage with OrbitDB and IPFS, and managing data access through a Hyperledger Fabric blockchain, the system mitigates the vulnerabilities of centralized databases. Performance evaluations show that HealthBlock meets critical security and privacy requirements, offering improved throughput and latency over traditional healthcare data management systems.

Rahutomo et al. [5] enhanced StuntingDB, a database management system for child stunting data collection in Indonesia, enabling parallel projects across multiple observation areas. Using Connolly and Begg's design principles and the Waterfall model, they developed a new Entity Relationship Diagram (ERD) and Use Case Diagram to support system improvements for stunting research. Keertham et al. [6] developed a Cloud-based Automobile Database Management System using AWS services, which offered scalable storage, secure access, and real-time communication, improving vehicle selection. AWS services provided 38% faster retrieval times than Google Cloud Platform.

Turhan et al. [7] compared graph and relational databases in healthcare data management, using diabetic patient data. Neo4j outperformed PostgreSQL in query performance, despite minor data entry inconsistencies.

Xiu et al. [8] designed a data storage system for an International Students Information Management System based on the SqlServer database, addressing educational management needs with big data and IoT technologies.

Nazir et al. [9] analyzed healthcare big data management and emphasized scientific programming for better decision-making, highlighting challenges like data storage, retrieval, and cost-efficiency.

Bhat et al. [10] presented a small-scale relational DBMS for beginners, developed with Java, storing data in serializable files and supporting basic SQL commands. The user-friendly system ensures data preservation without needing an internet connection, using JavaCC for parsing and organizing data in tables.

Garg et al. [11] introduced an integrated e-healthcare management system using machine learning and Flask to enhance healthcare services, particularly during the COVID-19 pandemic. By incorporating machine learning, the system optimizes healthcare delivery while addressing key issues such as cost-saving, privacy concerns, and electronic medical records.

Mamatha et al. [12] introduced a full-stack Enterprise Hospital Management Application using AngularJS, Java, and PL/SQL to improve Electronic Medical Records (EMR) management. Their system aims to reduce medical errors, enhance treatment quality, and streamline patient data management, improving overall healthcare efficiency.

Devi et al. [13] developed a User Interactive Hospital Management System that allows online appointment booking, remote access to patient histories, and efficient data management by administrators. Its design focuses on improving overall operational efficiency while ensuring patient and staff safety.

Ogbuke et al. [14] reviewed data-driven technologies like AI, Big Data, 3D printing, and Blockchain in healthcare during COVID-19. Their analysis highlights significant improvements in patient care and operational efficiency enabled by these technologies.

Macriga et al. [15] introduced a blockchain and NFC-based Hospital Management System to secure patient records, enhance interoperability, and streamline healthcare operations.

III. METHODOLOGY

A. Data Acquisition and Preprocessing

The initial phase focuses on collecting diverse datasets vital for patient care and hospital management from Kaggle, such as detailed admissions data, mortality statistics, and environmental pollution records. These datasets undergo a comprehensive ETL (Extract, Transform, Load) process. In this phase, data is extracted from various original sources, transformed through cleaning and encoding to ensure consistency, accuracy, and relevance, and then loaded into a centralized Oracle database. This ensures that the data is optimally formatted and ready for seamless analysis and querying in subsequent stages.

B. Dataset Overview

*1) **Admissions Data**:* The dataset includes detailed records of 8,632 patients, capturing 56 features that provide a comprehensive overview of patient information. These features cover demographics such as age, gender, and rural/urban classification, as well as hospital admission and discharge details, clinical outcomes, and comorbidities like hypertension, diabetes, and coronary artery disease. Additionally, key clinical metrics such as hemoglobin (HB), glucose, urea, and creatinine levels are recorded, alongside metrics like ICU stay duration and patient outcomes (e.g., stable angina or heart failure). This dataset serves as a cornerstone for trend analysis and forms the primary input for predictive models targeting ICU stay prediction and mortality risk assessment.

*2) **Mortality Data**:* This dataset comprises records for 1,105 deceased patients and includes six critical features such as demographic details (age, gender, rural/urban classification) and the date of death reporting. It offers valuable insights into mortality patterns and trends, serving as a foundation for developing predictive models focused on mortality risk. By leveraging the dataset's demographic and clinical attributes, healthcare providers can identify high-risk patients and implement targeted interventions, improving outcomes and optimizing care strategies.

*3) **Pollution Data**:* This dataset comprises 737 daily records with 28 attributes that detail environmental and pollution metrics, including the Air Quality Index (AQI), particulate matter levels (PM2.5 and PM10), gaseous pollutants (NO2, SO2, CO, and Ozone), and meteorological factors such as temperature and humidity. It provides a comprehensive perspective on environmental factors influencing public health. By integrating this pollution data with patient records, the dataset supports predictive modeling to assess health risks related to pollution and enables analysis of the environmental impact on hospital admissions and mortality rates, offering critical insights for healthcare planning and intervention.

C. Database Design and Implementation

The structured and cleaned data was stored in a Relational Database Management System (RDBMS) using Oracle, forming the backbone of the system. A carefully designed relational schema organizes the datasets into normalized tables, ensuring efficient data management and clear relationships between admissions, mortality, and pollution data. This structure facilitates seamless querying and analysis, enabling robust integration and utilization of the datasets for healthcare insights.

D. Database Design Features:

1) Normalization: Data redundancy was minimized by normalizing the database while preserving relationships between entities. This ensured efficient data storage and maintained the logical integrity of the system.

2) Indexes: Indexes were implemented on frequently queried columns, such as primary keys and date fields, to enhance query performance and speed up data retrieval processes.

3) Complex Querying: SQL queries were designed to handle complex tasks, including data aggregation, trend analysis, and predictive modeling. These queries enabled users to extract insights, such as identifying seasonal patterns in hospital admissions or assessing the impact of pollution on mortality rates.

4) Security and Integrity: The database was secured with constraints like foreign keys, data type validations, and unique keys, ensuring data integrity and reliability. These measures safeguarded the accuracy and consistency of the stored information.

This centralized repository offered a scalable and well-structured data storage solution, facilitating efficient data retrieval, robust analytics, and seamless support for predictive modeling.

E. Predictive Analytics Using Machine Learning

To improve healthcare decision-making, three machine learning models were developed, each addressing specific aspects of patient care and environmental impacts:

1) Likelihood Of ICU Admission Prediction: A Gradient Boosting Regressor was employed to predict the duration of ICU stays. This model aids in optimizing patient care and resource allocation by providing accurate estimates of ICU requirements. The length of stay in the ICU is forecasted with a Gradient Boosting Regressor that optimizes the Mean Squared Error (MSE) as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

where y_i is the true ICU stay length, $\hat{y}_i$ is the estimated length, and n is the number of patients. The model minimizes the loss function through repeated diminution of residual errors at each stage of boosting.

2) Mortality Risk Prediction: A regression model was designed to predict the likelihood of mortality by analyzing a combination of patient health data, demographic details, and clinical indicators. This model helps identify high-risk patients, enabling timely interventions.

3) Pollution-Driven Health Deterioration Prediction : This model integrates environmental data with patient records to assess health risks associated with pollution levels. It predicts the potential for health deterioration due to environmental factors, assisting healthcare providers in addressing pollution-related health issues.

The development process involved feature engineering to identify key attributes such as patient age, medical history, and clinical parameters, ensuring model accuracy. Models were trained using algorithms like the Gradient Boosting Regressor and fine-tuned with GridSearchCV to optimize hyperparameters. Performance was rigorously evaluated using metrics like

Mean Absolute Error (MAE) and Mean Squared Error (MSE). Once validated, the models were serialized with joblib for seamless integration into the web application, enabling real-time analytics. These predictive models empower healthcare professionals to prioritize patient care, allocate resources effectively, and address health risks proactively.

F. Web Application Development

A Flask-based web application was developed to provide healthcare professionals with an intuitive and accessible interface for interacting with data and predictive models. Serving as the operational front end, the application ensures seamless data management and real-time analytics.

The application includes comprehensive CRUD (Create, Read, Update, Delete) functionalities for managing records related to admissions, mortality, and pollution through dynamic web forms. It features dynamic dashboards that display real-time trends, aggregated statistics, and correlations, enabling healthcare professionals to analyze data effectively. Integrated predictive tools allow users to input patient-specific data and instantly receive predictions regarding ICU stay durations, mortality risks, and pollution-related health impacts, supporting timely and informed decision-making.

To enhance the user experience, the application incorporates Jinja2 for responsive and dynamic content rendering, interactive features like dropdowns, and input validation mechanisms. Robust error-handling processes ensure stable and reliable performance. This combination of advanced features and user-friendly design enables healthcare providers to efficiently manage data, derive insights, and leverage predictive analytics to improve patient outcomes.

IV. RESULTS AND DISCUSSION

The study achieved significant results in several critical areas, including efficient data management, advanced predictive modeling, actionable analytics, and seamless web application integration. These outcomes highlight the transformative potential of data-driven systems in improving healthcare decision-making, optimizing resource allocation, and enhancing patient care quality.

A. Database Implementation and Query Efficiency

A robust and structured relational database was developed to centralize and manage diverse datasets, including admissions, mortality, and pollution data. The schema was designed with a focus on normalization to reduce redundancy while maintaining strong relationships between datasets. Indexed primary and foreign keys facilitated efficient query execution, enabling the database to perform complex operations seamlessly and reliably.

SQL queries played a crucial role in extracting meaningful insights and identifying trends. For instance, seasonal analysis revealed a significant increase in hospital admissions during winter months, strongly correlated with higher pollution levels. Mortality rates could be analyzed dynamically, filtered by demographic attributes, clinical parameters, and time-based variables, providing healthcare professionals with detailed insights into patient outcomes. Additionally, the implementation of constraints such as foreign keys, unique keys, and data type validations ensured the system's integrity, reliability, and scalability, creating a solid foundation for advanced analytics and decision-making.

B. HealthCare Data Analysis

Analyzing healthcare data is crucial for understanding patient outcomes, identifying trends, and supporting decision-making. By examining key metrics such as admissions, mortality rates, and environmental factors, healthcare providers gain insights to optimize resources, predict risks, and improve care delivery effectively.

A complete data preprocessing pipeline was utilized prior to analysis. Missing values were treated with mean imputation for numerical attributes, and categorical data was transformed with one-hot encoding. Min-Max scaling was used to normalize the dataset to enhance model convergence. The data was then divided into 80% training and 20% testing to provide a balanced assessment of predictive models.

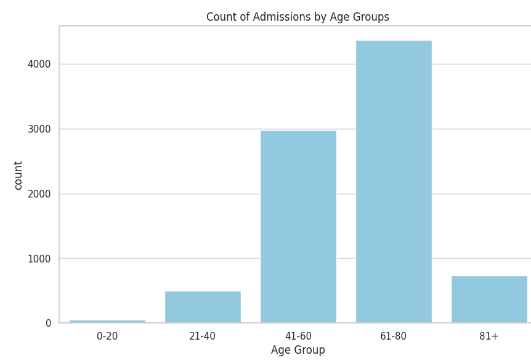

Fig. 1. Count Of Admissions by Age Groups

This bar chart in Fig 1 illustrates the count of hospital admissions segmented by age groups. The age group 61-80 has the highest number of admissions, followed by the 41-60 group. Admissions are significantly lower in the 81+ and 21-40 groups, with the 0-20 group having the least admissions. This distribution highlights that middle-aged and older adults account for the majority of hospital admissions, suggesting a higher prevalence of healthcare needs in these demographics.

This line chart in Fig 2 illustrates the mortality trend over time, showing fluctuations in the number of mortality cases across various months from April 2017 to April 2019. The data reveals distinct peaks, particularly around January 2018 and January 2019, with mortality cases reaching their highest levels during these periods. Conversely, there are significant drops in mortality, such as around April 2018 and April 2019, indicating seasonal or other external factors influencing the trend.

This line chart in Fig 3 represents pollutant concentrations over time, showing trends for PM2.5, PM10, NO2, and SO2 from 2017 to 2019. The data reveals that PM2.5 and PM10

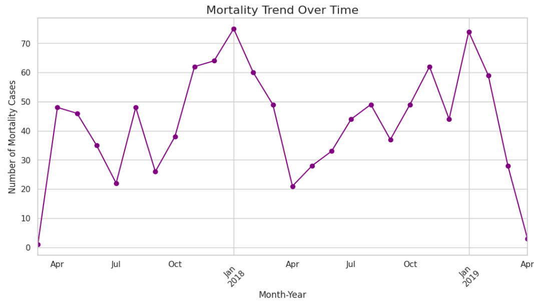

Fig. 2. Mortality Trend Over Time

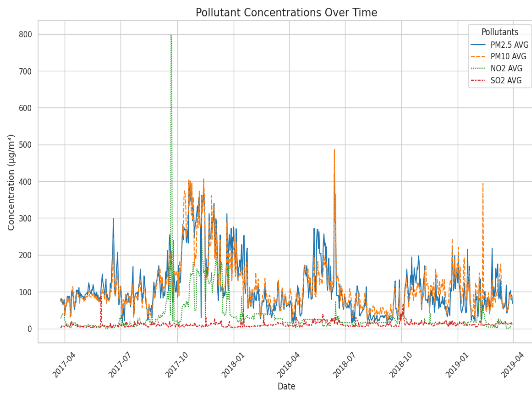

Fig. 3. Pollutant Concentrations Over Time

exhibit significantly higher and more variable concentrations compared to NO2 and SO2, which remain relatively stable at lower levels. Notable spikes in PM2.5 and PM10 are observed around late 2017 and early 2018, indicating periods of heightened air pollution. These patterns suggest potential seasonal or episodic pollution events, which may have implications for public health, particularly during peak pollution periods.

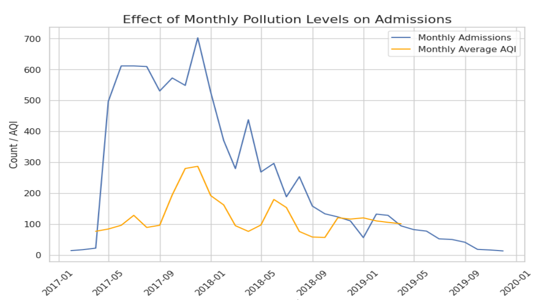

Fig. 4. Effect Of Monthly Pollution Levels on Admissions

This line chart Fig 4 illustrates the relationship between monthly pollution levels, represented by the average Air Quality Index (AQI), and hospital admissions over time from 2017 to 2019. The chart shows that peaks in admissions often coincide with higher AQI values, particularly during late 2017 and early 2018, suggesting a correlation between pollution levels and increased healthcare demand. As pollution levels decrease after 2018, admissions also show a declining trend. This indicates that elevated pollution may contribute to higher hospital admission rates, emphasizing the importance of monitoring and mitigating air quality to reduce health impacts and strain on healthcare systems.

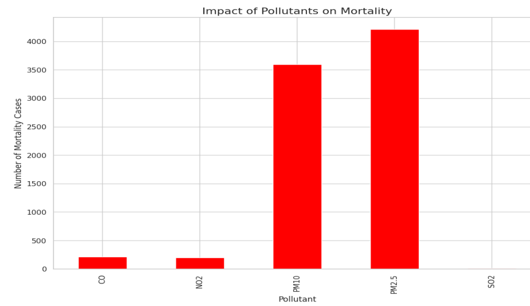

Fig. 5. Impact of Pollutants on Mortality

This bar chart in Fig 5 highlights the impact of various pollutants on mortality cases. PM2.5 and PM10 show the highest association with mortality, significantly exceeding other pollutants such as CO, NO2, and SO2, which have much lower contributions. This indicates that particulate matter (PM2.5 and PM10) poses a greater risk to public health, underscoring the importance of targeting these pollutants in air quality improvement efforts to reduce mortality rates.

C. Predictive Model Performance

The predictive models developed as part of the study showcased remarkable accuracy and practical applications in forecasting critical healthcare metrics:

1) Likelihood Of ICU Admission Prediction: The Gradient Boosting Regressor effectively predicted ICU stay durations, achieving a Mean Absolute Error (MAE) of 1.52, a Mean Square Error (MSE) of 5.01, and an R^2 Score of 0.63.

To maximize the performance of the model, hyperparameter tuning was performed using GridSearchCV, identifying the optimal learning rate and number of estimators. The chosen hyperparameters were a learning rate of 0.1 and 100 estimators. A 10-fold cross-validation was also done to validate the robustness of the model. Analysis of feature importance showed that age, comorbidities, and oxygen saturation levels contributed the most to ICU admission predictions.

The R^2 value of 0.63 indicates that 63% of the variation in the length of ICU stay can be accounted for by the model, which is a useful tool for ICU management and hospital resource planning.

2) Mortality Risk Prediction: The mortality prediction model was 91% accurate, proving its utility in classifying high-risk patients.

To improve model performance, L2 regularization (ridge regression) was used to avoid overfitting. The most important features that led to mortality predictions were age, history of chronic disease, hemoglobin, and history of ICU admissions. Misclassification was mostly in borderline cases, where patients had unstable health conditions, hence difficult to classify.

By incorporating this model into hospital management information systems, early detection of patients at high risk can improve clinical decision-making and lower mortality rates through early interventions.

3) Pollution-Driven Health Deterioration Predictions: The pollution impact model achieved an impressive 99% accuracy, establishing a strong correlation between environmental conditions and patient admissions.

Feature importance analysis revealed that PM2.5, PM10, and NO2 had the most significant impact on hospitalizations, particularly for patients with pre-existing respiratory conditions. The model showed that hospital admissions due to respiratory issues peaked during winter months, aligning with periods of increased pollution.

A seasonality trend was observed, where pollution-linked hospitalizations increased by 20-30% during high-AQI months, highlighting the need for proactive healthcare measures during pollution surges. This model can assist policymakers in developing strategies to mitigate health risks associated with environmental pollution.

V. CONCLUSION AND FUTURE SCOPE

This study successfully integrates structured healthcare information with predictive analytics, providing a solid platform for effective data management, real-time analysis, and decision-making. Predictive models yield meaningful insights into ICU admissions, mortality risk, and pollution-driven health deterioration, arming healthcare professionals with evidence-based tools for anticipatory intervention. The web application's user-friendly design improves usability, allowing seamless interaction with data and models. Though the system reflects high precision and performance, its dependence on past data restricts its responsiveness to abrupt healthcare emergencies. Enhancements in the future will involve cloud deployment for scalability, real-time patient monitoring through wearable technology, and more sophisticated deep learning methodologies to enhance prediction accuracy. Augmenting the scope of the system with other environmental and behavioral health indicators will increase its potential impact, creating smarter, more responsive healthcare outcomes.

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