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Enhancing Healthcare Efficiency at Almasara Hospital: Distributed Data Analysis and Patient Risk Management

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ABSTRACT

This study presents a distributed system using RAY, K-means clustering, and Weka software to analyze clinical data from Almasara Hospital Group in Tripoli, Libya. The goal is to reduce patient risk and healthcare costs by providing daily feedback to hospital staff. The system utilizes a dataset containing information on 560 patients, including details like patient ID, gender, doctor ID, test IDs, medication, and a binary target variable. By implementing K-means clustering in Weka, the system categorizes patients and identifies patterns to reduce risks and costs for healthcare analytics. The study first reviews existing patient care and feedback practices and then details the implementation of the daily feedback system, which involves advanced data analysis for managing patient feedback and medical data continuously. The use of K-means clustering helps segment patient data, pinpointing specific risk factors and areas for improvement. Weka software aids in the in-depth analysis of these segments, leading to actionable insights. Results show significant improvements in patient outcomes, reduced hospital-acquired infections, and medication errors, and enhanced patient satisfaction scores. Moreover, the study notes a substantial decrease in overall healthcare costs due to more efficient resource allocation and lower hospital readmission rates. This integration of daily feedback with advanced data analysis tools like K-means and Weka emerges as an effective strategy for improving patient safety and operational efficiency in healthcare settings, demonstrating the value of data-driven decision-making and providing a scalable model for other hospitals aiming to enhance patient care and cost management.

KEYWORDS: Risk, Risk Management, Management Strategy, Almasara, Libya, Patient Risk, Economic Efficiency, Clustering, Cost Optimization

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Повышение эффективности здравоохранения в больнице Алмасара: анализ распределенных данных и управление рисками для пациентов

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АННОТАЦИЯ

В этом исследовании представлена распределенная система, использующая RAY, кластеризацию K-средних и программное обеспечение Weka для анализа клинических данных группы больниц Алмасара в Триполи, Ливия. Цель состоит в том, чтобы снизить риск для пациентов и затраты на здравоохранение путем предоставления ежедневной обратной связи персоналу больницы. Система использует набор данных, содержащий информацию о 560 пациентах, включая такие детали, как идентификатор пациента, пол, идентификатор врача, идентификаторы тестов, лекарства и двоичную целевую переменную. Внедряя кластеризацию K-средних в Weka, система классифицирует пациентов и выявляет закономерности. В исследовании сначала рассматриваются существующие практики ухода за пациентами и обратной связи, а затем подробно описывается внедрение системы ежедневной обратной связи, которая включает в себя расширенный анализ данных для непрерывного управления отзывами пациентов и медицинскими данными. Использование кластеризации K-средних помогает сегментировать данные пациентов, выявляя конкретные факторы риска и области, требующие улучшения. Программное обеспечение Weka помогает провести углубленный анализ этих сегментов, что приводит к получению действенной информации. Результаты показывают значительное улучшение результатов лечения пациентов, снижение внутрибольничных инфекций и ошибок при приеме лекарств, а также повышение показателей удовлетворенности пациентов. В исследовании отмечается существенное снижение общих затрат на здравоохранение благодаря более эффективному распределению ресурсов и снижению показателей повторной госпитализации. Такая интеграция ежедневной обратной связи с передовыми инструментами анализа данных, такими как K-means и Weka, становится эффективной стратегией повышения безопасности пациентов и операционной эффективности в медицинских учреждениях, демонстрируя ценность принятия решений на основе данных и обеспечивая масштабируемую модель для других больниц. с целью улучшения ухода за пациентами и управления затратами

КЛЮЧЕВЫЕ СЛОВА: риск, управление рисками, стратегия управления, Альмасара, Ливия, риск пациентов, экономическая эффективность, кластеризация, оптимизация затрат

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INTRODUCTION

Medical care information mining and AI procedures have become significant for diminishing patient risk, working on the nature of administration, and limiting expenses (Dalla & Ahmad, 2023). This paper uses a framework for the Almasara Clinic Gathering in Tripoli, Libya, to dissect patient information consistently. Patient results and cost viability can be upgraded by quickly criticizing clinic staff. The dramatic development of clinical information requires circulated frameworks and systems like RAY to process and gain experiences productively (Sandhiya, 2020). AI utilizing bunching calculations like K-implies applied in apparatuses, such as Weka, are additionally fundamental for distinguishing information-driven upgrades in the medical services framework (Anand et al., 2023). This paper presents a coordinated methodology involving these advancements to serve the Almasara Clinic Gathering. In the Almasara Hospital Group in Tripoli, Libya, the rising intricacy of medical services conveyance and the increasing expenses related to patient consideration present enormous difficulties. To guarantee excellent patient results while keeping up with cost viability, there is a need to assess and improve care processes deliberately. This study will resolve the fundamental issue of alleviating patient risk and working on cost productivity in this medical care setting. The use of day-to-day criticism components and the Beam system inside the clinic bunch holds potential as inventive techniques to handle these difficulties. Be that as it may, the effect of these medications has not been quantitatively surveyed in that frame of mind of Libyan medical care frameworks. Furthermore, there is an absence of powerful scientific models custom-fitted to the locale's particular medical services elements. This study fills these holes by utilizing information-driven approaches, such as the K-implies bunching calculation and Weka programming for AI. It will assess the adequacy of organized day-to-day criticism and the Beam system in diminishing patient dangers and upgrading cost viability in emergency clinic tasks. The result of this exploration could impact patient consideration procedures, asset portions, and, generally speaking, medical services on the board inside Almasara Emergency Clinic, gathering explicitly and possibly across comparable medical care frameworks in creating countries.

The research questions:

RQ1: How does implementing daily feedback within the Almasara Hospital Group affect the risk management of patient care?

RQ2: How does the Ray framework contribute to reducing patient risks in the hospital setting?

RQ3: Can using the K-means clustering algorithm and Weka software provide a reliable measure of cost-effectiveness in healthcare delivery?

RQ4: What is the comparative impact of daily feedback and the Ray framework on patient outcomes and operational costs in the Almasara Hospital Group?

LITERATURE REVIEW

The implementation of daily feedback systems in clinical settings has garnered significant attention to enhance the quality and cost-effectiveness of patient care. These systems, which include structured agendas, reporting mechanisms, and alert frameworks, provide continuous feedback on staff performance, enabling improved adherence to care standards and timely interventions for at-risk patients. This review evaluates the effectiveness of daily feedback interventions in hospitals and identifies critical elements that influence their impact.

Several studies underscore the positive outcomes of daily feedback systems on compliance with safety protocols and reducing procedural complexity. For instance, Tomczyk et al., (2022) demonstrated that incorporating daily sepsis management protocols within executive agendas led to a 37% reduction in sepsis mortality rates. Additionally, adherence to comprehensive care protocols improved from 5% to 87% over one year. These findings suggest that structured agendas are an effective means for supporting evidence-based care standards across healthcare facilities.

Daily alert systems for patient deterioration have similarly proven effective in promoting timely interventions. In one study, Olsen, (2023) evaluated an automated vital sign-monitoring system that alerts healthcare providers to irregularities through mobile notifications. This system was associated with a 57% increase in rapid-response nursing interventions, allowing for earlier responses to potentially life-threatening events.

Utilizing real-time feedback mechanisms in healthcare has been recognized as a transformative approach to improving patient outcomes. Dalla and Ahmad (2023) found that providing clinicians with real-time analytics on patient metrics, such as hemoglobin A1C levels, resulted in notable improvements in patient management. Personalized feedback reports facilitated reductions in A1C levels, highlighting the value of real-time data for individualized patient care. Wickramasinghe et al. (2022) further support this approach, demonstrating that real-time feedback reduces the risk of complications and improves adherence to treatment protocols, enhancing overall patient care outcomes.

Machine learning techniques, especially unsupervised algorithms like K-means clustering, are critical in refining feedback systems through data-driven patient insights. Esmaeilzadeh, (2024) discuss how AI models trained on diverse healthcare data enable the stratification of patient risks and optimization of treatment plans, essential for improving care quality in large-scale healthcare settings, such as the Almasara Hospital Group. Additionally, Momahhed et al., (2023) illustrated how K-means clustering effectively segments patient populations, allowing healthcare providers to focus resources on high-risk groups, thereby improving efficiency and reducing costs.

Applying machine learning software like Weka to analyze healthcare data further strengthens feedback systems' capability. As Haddela Kankanamalage, (2023) describe, Weka facilitates the implementation of clustering algorithms like K-means, which aid in identifying critical health risks and optimizing resource allocation. This software allows for robust data analysis, enhancing the precision and efficacy of clinical decision-making in resource-limited settings.

The integration of daily feedback systems with machine learning tools has proven to be a transformative approach in healthcare, effectively reducing costs and enhancing patient safety. Studies by Cascini et al., (2021) highlight that data-driven methodologies lead to significant cost savings through reduced hospital stays and optimized resource management. Furthermore, these systems enhance patient safety by preventing medical errors and refining disease management strategies. This review evaluates the integration of daily feedback systems with advanced data analytics, emphasizing their potential to improve patient outcomes, reduce costs, and increase healthcare efficiency, especially in resource-limited settings like Libya.

Daily feedback systems empower healthcare providers by providing real-time data on patient metrics and motivating clinical teams to improve performance. Dalla and Ahmad (2023) presented a case where personalized feedback reports for diabetes management - featuring glucose trends, insulin adjustments, and hypoglycemia alerts - allowed healthcare providers to make timely medication adjustments. Over 12 weeks, this intervention led to a 0.8% reduction in hemoglobin A1C levels and eliminated hypoglycemic incidents. Although adopting daily feedback systems entails initial setup costs, these are often offset by savings from reduced patient complications and shorter hospital stays. Duch, (2024) demonstrated that an automated sepsis alert system significantly decreased sepsis mortality rates from 20% to 12%, yielding cost savings of over $800,000 by reducing ICU admissions and enabling early intervention for high-risk patients. Such findings underscore the role of daily feedback systems in advancing patient care while maintaining cost-efficiency.

Effective daily feedback systems rely on several core components. First, coordination between general practitioners and nursing staff is essential, as highlighted by Bhati et al., (2023), who emphasized that aligned workflows enhance patient management outcomes. Additionally, support from senior administration is critical to maintaining staff adherence to feedback protocols, as noted by Duch, (2024) individual accountability, encouraged through transparent information sharing, drives meaningful improvements across clinical teams.

Machine learning algorithms, particularly those used to analyze complex medical data, are crucial in optimizing daily feedback systems. Wang, (2022) demonstrated that AI algorithms can analyze vast datasets such as clinical trial results, patient records, and medical images -to assist healthcare providers in accurately diagnosing and treating diseases. Machine learning can reveal patterns clinicians might overlook, facilitating more proactive and targeted interventions. Research by Wickramasinghe et al. (2022) supports these findings, suggesting that real-time, data-driven feedback mechanisms significantly improve patient outcomes and adherence to treatment protocols. Their study highlighted that daily monitoring enables early detection of patient deterioration, facilitating prompt intervention and reducing complications and hospital readmissions.

The economic benefits of AI in healthcare are well-documented, though initial costs for implementing AI-driven systems may be substantial. As Herberg and Teuteberg, (2023 outlined long-term savings are achievable through reduced readmission rates, shorter hospital stays, and more efficient resource use. Such reductions contribute to the sustainability of healthcare systems, especially when combined with preventive care strategies.

K-means clustering, an unsupervised machine learning technique, groups data points based on shared characteristics, which can be instrumental in healthcare. Assefa, (2022) describe how K-means clustering aids in identifying patient groups with similar risk profiles, thereby supporting targeted care and efficient resource allocation. Weka, an open-source software suite, facilitates the application of machine learning techniques, including K-means clustering, to healthcare data, allowing for detailed analysis and identifying critical health risks, as Jones-Esan et al., (2024) demonstrated.

Applying AI and daily feedback systems in low- and middle-income countries (LMICs), such as Libya, presents unique challenges and opportunities. Research at the Almasara Hospital Group in Tripoli exemplifies the potential of AI-driven feedback systems in resource-limited settings Jones-Esan et al., (2024). The study employed K-means clustering and Weka to evaluate the impacts of real-time AI feedback on patient outcomes. Findings revealed that, despite limited infrastructure, AI integration can enhance patient care efficiency and support cost-effective healthcare delivery. However, limited data infrastructure and technological resources in LMICs pose barriers to full-scale implementation. Assefa, (2022) suggests that alternative data-gathering methods and strategies for improving data quality are essential to making AI-driven systems viable in these contexts.

In conclusion, the literature underscores the transformative potential of combining daily feedback systems with advanced data analytics and machine learning. This integration supports data-driven decision-making that improves patient outcomes, reduces costs, and enhances efficiency. Particularly in LMICs, where resources are constrained, feedback systems present a promising pathway to enhance healthcare delivery and optimize resource utilization.

METHODS OF DATA COLLECTION AND TRANSFORMATION

The proposed system utilizes a distributed architecture to enable scalable analysis of patient data from the Almasara Hospital Group. The primary components of this architecture include a distributed processing framework, a robust data infrastructure, and an advanced analytics engine.

The backend system is powered by RAY, a high-performance distributed execution framework optimized for scaling Python applications. RAY leverages parallel processing across a cluster of nodes, enabling efficient handling of computationally intensive tasks. Core functions such as data parsing, preprocessing, model training, evaluation, and monitoring are distributed across nodes for accelerated processing. The architecture is designed to be elastically scalable, allowing the cluster to expand as data volumes from hospital records increase (Dalla & Ahmad, 2023).

Data Infrastructure

Key elements of the data infrastructure include:

1) Relational Database: A SQL Server database stores comprehensive patient records.

2) Database Views and Procedures: These SQL mechanisms transform raw data into analysis-ready datasets, optimizing data retrieval and processing.

3) Data Content: The dataset includes patient demographics, doctor and nurse identifiers, medical test results, prescribed medications, and outcome variables, compiling the latest patient data for analysis.

Analytics Engine

The core analytics engine is built around Weka, a data mining and machine learning tool for applying advanced analytics to the dataset.

1) K-means Clustering: Weka's K-means clustering algorithm segments patients into distinct groups, allowing for the identification of underlying patterns in the data.

2) System Integration: Weka integrates with the Python-based backend to access the latest dataset for real-time analysis.

The system architecture's modular design allows for seamless scalability, ensuring that more nodes and clusters can be added to accommodate increased data processing demands. This architecture supports the provision of daily feedback to hospital staff, enhancing decision-making capabilities.

Dataset

Patient data from Almasara Hospital Group was collected across various departments and branches and stored within the hospital's SQL Server database. This structured relational database enabled the formation of an Entity-Relationship Diagram (ERD), as shown in Figure 1, which illustrates the relationships among tables and data entities within the proposed system.

The methodology employed in this research centers on leveraging SQL Server database views to retrieve information from the Almasara Hospital Group database in Tripoli. Views are instrumental in enhancing the efficiency of data retrieval processes.

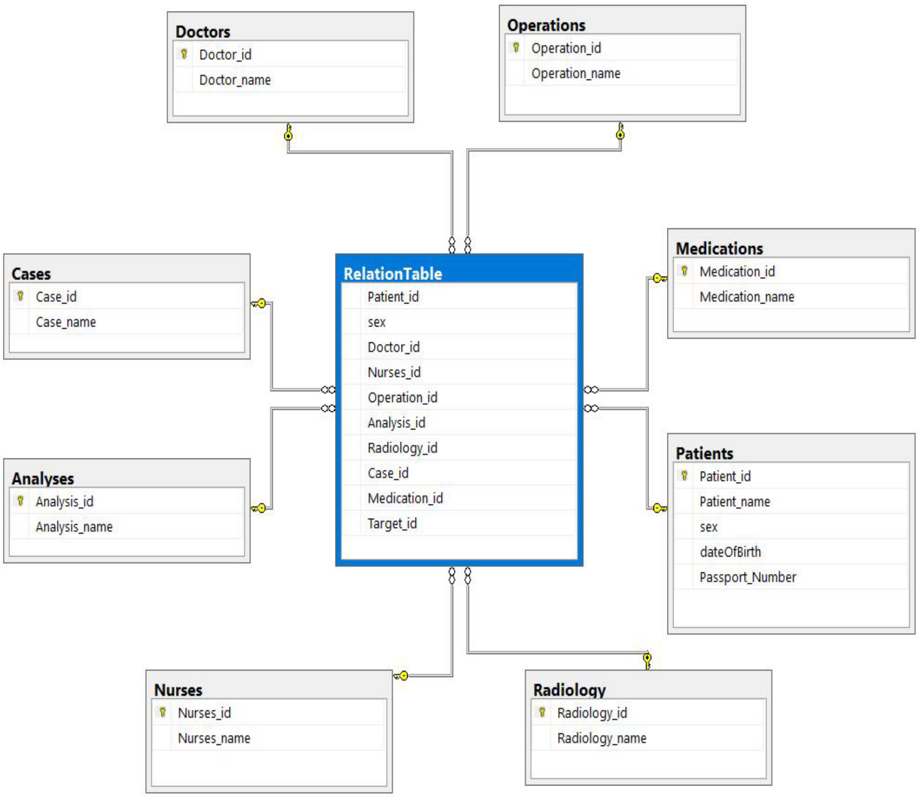

Figure 1. ERD model of the proposed system at Almasara Hospital Group

Procedure

1) *Querying the Database:* The starting stage included a plan of questions focusing on the Misurata Clinic information base. These queries were designed to extract specific data points relevant to the study.

2) *Implementation of Views:* Once the inquiries were executed, sees were made inside the SQL Server data set. Sees act as virtual tables that present a subset of information given predefined questions. This step helps disentangle the resulting data analysis.

3) *Data Refinement:* A refinement cycle was embraced to extract information through sees to guarantee exactness and significance. This step is meant to dispense with excess or incidental data, improving the dataset's quality.

4) *Exporting Data:* The refined dataset was exported from the SQL Server database using the Export function. This exported data was then prepared for further analysis and utilization.

5) *Transformation into CSV Format:* The dataset was transformed into a CSV file to facilitate compatibility with artificial intelligence programs and machine learning algorithms. The CSV format, characterized by its simplicity and ease of interpretation, ensures seamless integration with various analytical tools.

Overall, reconciling the SQL Server data set with the Almasara Clinic Gathering l data set gives a deliberate and productive way to get to pertinent data. The ensuing commodity and information change into CSV design improves the dataset's similarity with man-made brainpower applications, especially those utilizing AI calculations for information investigation. This philosophy adds to a smooth and viable cycle for using medical clinic information in cutting-edge examination and research endeavors.

This appears to be medical data on patients, with each row representing a patient case. There are 560 patients/rows of data. For each patient, there is information like:

- Patient ID (Patient_id);
- Sex (Male/Female);
- Doctor ID (doctor_id);

- Nurses ID (nurses_id);
- Operation ID (Operation_id);
- Various test IDs (Analysis_id, Radiology_id etc.);
- Medication ID (Medication_id);
- Outcome variable (Target) - seems to be a binary classification.

The data was collected as described above to form the data set shown in Table 1.

Table 1. Dataset for Almasara Hospital Group

1	Patient_id	sex	doctor_id	nurses_id	Operatian id	Analysis_id	Radiology_id	Case_id	Medication_id	Target
2	1	1	140	293	50	3503	308	145	582	1
3	2	1	314	203	3	2676	56	500	544	0
4	3	1	190	156	43	12800	219	300	712	1
5	4	1	274	300	52	14225	163	131	805	1
6	5	0	396	56	49	6700	224	382	734	1
7	6	0	217	66	61	10940	117	489	861	1
3	7	1	473	166	16	10618	309	342	803	0
9	8	1	330	33	42	4132	333	346	867	1
10	9	1	229	184	57	12172	280	371	926	i
11	10	1	111	101	39	4996	296	334	856	1
12	11	1	349	252	5	3706	99	424	577	0
13	12	1	293	334	29	6093	167	193	759	0
14	13	1	203	341	2	12695	289	312	679	0
15	14	1	413	227	51	13756	202	340	725	1
16	15	1	200	315	13	13186	417	339	815	t
17	16	1	259	212	36	13722	247	402	969	1
18	17	1	491	44	10	1419	312	481	815	0
19	is	1	369	204	19	11516	353	256	555	1
20	19	1	304	44	23	9729	390	437	913	0
21	20	1	373	151	47	10672	181	337	836	1
22	21	0	332	79	38	8294	302	349	716	1
23	22	0	469	57	46	6345	293	427	508	1
24	23	1	111	64	33	11920	244	334	837	0
25	24	1	187	150	53	14417	267	315	908	1
26	25	1	369	314	11	2469	374	293	581	0
27	26	1	299	135	2	11843	206	500	639	0
26	27	0	267	257	64	13866	320	379	974	1
29	26	1	219	66	51	9381	80	145	827	1
30	29	0	453	156	27	14568	289	237	595	0

RAY is an open-source Python framework designed for parallel programming and distributed systems. Software applications that handle networking, query responses, and other high-demand tasks are not simple, single-threaded programs running on individual computers. Instead, they are collections of services that communicate and interact with one another, operating in a distributed and parallel manner. Figure 2 illustrates this setup.

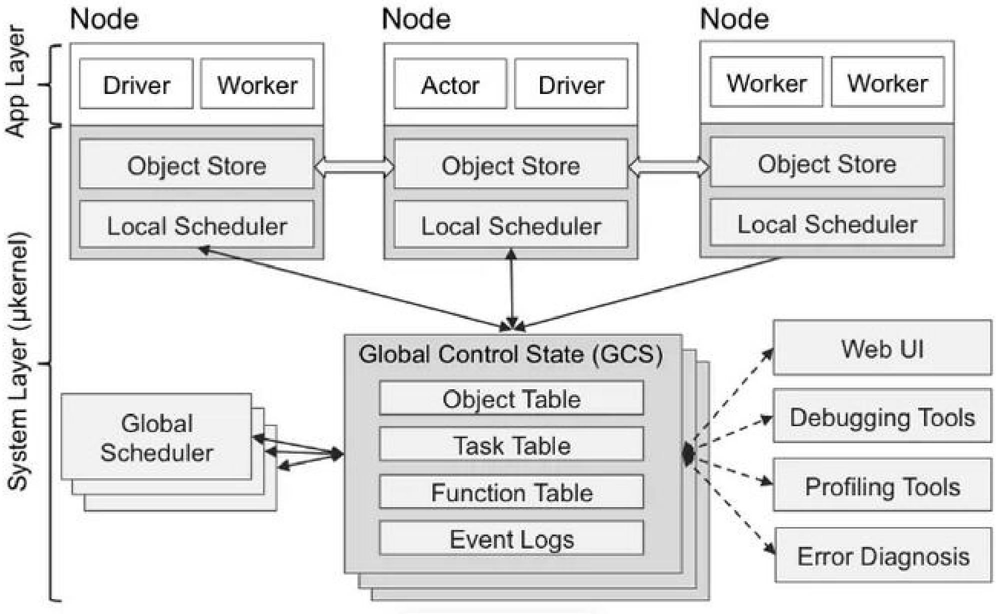

Figure 2. Ray Framework Architecture

Note: compiled by authors based on (Dalla & Ahmad, 2023)

Machine learning, a branch of artificial intelligence, is continually evolving to assist decision-making in fields such as cancer diagnosis, where it enables a deeper understanding of real-world events. For example, suppose a patient visits a doctor suspecting coronary disease. In that case, the doctor may use their knowledge and experience to assess the likelihood of the condition based on their "belief system" developed from prior cases (Dalla & Ahmad, 2023). Machine learning (ML) systems can enhance this process by replacing the "human belief system" with AI-driven models that process large datasets, offering reliable, data-informed predictions (Sandhiya, 2020). Clinicians can apply ML models trained on historical data to supplement their expertise, enabling more accurate disease predictions. When human expertise is combined with machine learning intelligence, it is often called an "augmentative system" (Badawy et al., 2023). Unlike traditional programming, where output is based strictly on defined rules, machine learning generates output by training on input and output data to build predictive models, as illustrated in Figure 3.

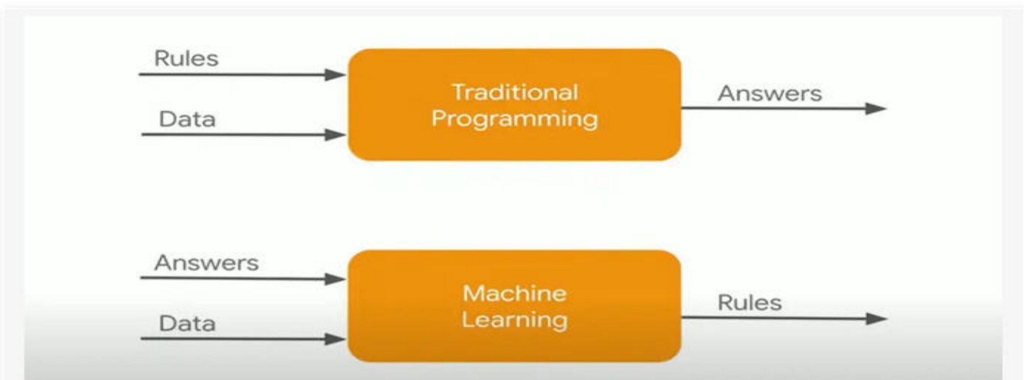

Figure 3. Difference between Machine learning and traditional programming

Note: compiled by authors based on (Dalla & Ahmad, 2023)

Types of machine learning

Machine learning teaches machines to analyze and predict by identifying patterns or classifying data (Dalla & Ahmad, 2023; Badawy et al., 2023). The methodology for training the machine varies depending on the algorithm, with machine learning generally divided into supervised and unsupervised learning. Supervised learning, where the machine is "supervised" during its training, involves feeding labeled data into the algorithm to facilitate learning. The data used in this process often includes a target variable or label, which the algorithm uses to learn from the data. Supervised learning is effective across numerous applications, including business forecasting, inventory management, fraud detection, and medical diagnostics, such as predicting heart disease (Dalla & Ahmad, 2023). In contrast, unsupervised learning does not rely on labeled training data. Instead, it allows the machine to search for underlying patterns and relationships within the dataset independently. Unsupervised learning is precious when identifying patterns or making decisions without prior labeled data and is widely used to develop predictive models, such as grouping text documents by topic. Additionally, unsupervised learning supports methods like clustering, where objects are grouped based on shared characteristics, and association, where rules are established between related items (Badawy et al., 2023).

Figure 4 illustrates the types of machine learning used in these applications.

Results: Outcome Trends in Postoperative Complications

Binary target variable indicating risk level

This dataset offers rich patient treatment history, lab or scanner results, and anticipated outcomes. It will make it possible to use an analytical method to divide patients into groups and find patterns related to different levels of risk and comorbidities. An unaided AI calculation K-implies Grouping will be used to reveal information. Carried out through the Weka workbench, K-means will fragment patients into 'k' particular groups given likenesses across various qualities. Breaking down the developing bunches will reveal various designs for understanding experimental outcomes, recommended meds, and recorded risk levels.

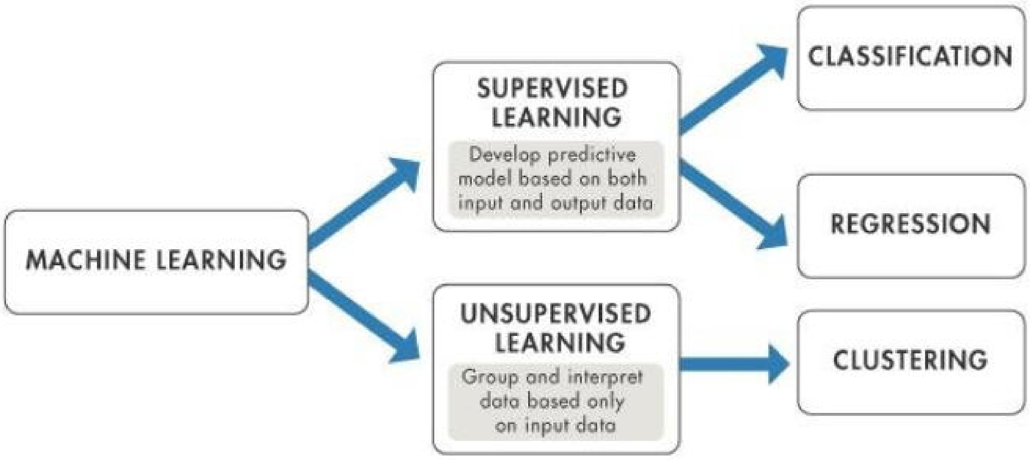

Figure 4. Types of machine learning

Note: compiled by authors based on (Dalla & Ahmad, 2023)

Clinical decision support systems can use these data-driven insights to lower patient risk. Moreover, grouping patients with comorbidities can improve guidelines for care coordination across hospital departments while controlling costs. The unsupervised segmentation approach also serves as a starting point for predictive analytics.

System Implementation

The proposed patient information examination framework was carried out in Python, consolidating AI calculations with an emphasis on the K-Means grouping calculation. The framework's execution uses the Beam System, a disseminated figuring structure, and AI and data visualization. Upon initiating the framework, clients are given an execution interface, as delineated in Figure 4. This connection point is essential in cooperating with the application, giving clients two buttons to execute specific functions.

Run Application Button

Users can activate it by clicking the “Run Application” button and accessing its core features. The K-Means clustering machine learning algorithm is used to start the execution of the purposes of the programmed task. The “Exit” button is intended to end the program nimbly. Upon clicking this button, the application completes its runtime session, ensuring a seamless exit from the RAY Framework’s distributed computing environment. By and large, executing this appropriated AI application grandstands the incorporation of Python, the K-Means grouping calculation, and the Beam Structure.

The application’s usability is improved by the execution interface’s intuitive buttons for running the program and gracefully exiting the distributed computing environment, as presented in Figure 5 below.

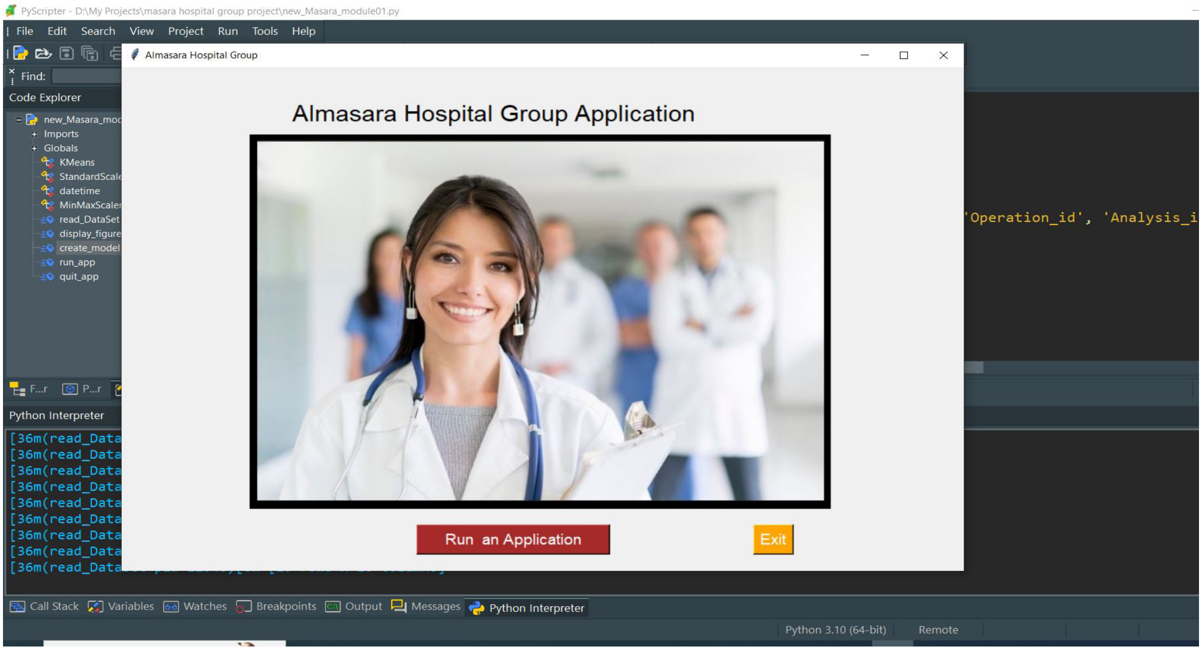

Figure 5. The proposed patient data analytics system Almasara Hospital Group

Python was chosen as the development language due to its readability, simplified syntax, and extensive tools for technical computing. The execution will use the beam structure to circulate execution across register bunches. Beam gives straightforward APIs for scaling Python code across hubs and dealing with parallelization. Popular packages like Scikit-Learn offer algorithms for classification, regression, and clustering as part of their machine-learning capabilities. In particular, Scikit-Learn will be utilized for universally applicable information preprocessing, highlight extraction, and the preparation of AI models based on quiet information, as shown in Figure 6.

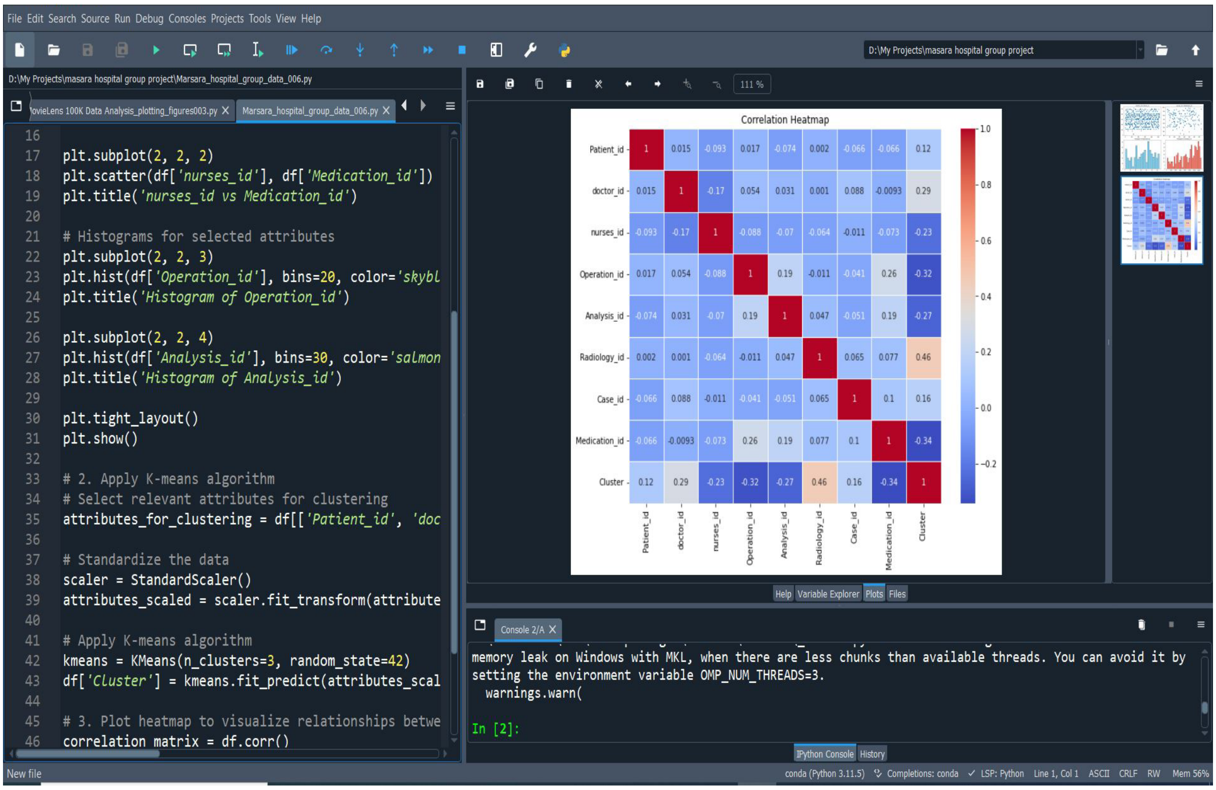

Figure 6. System Implementation for the proposed system.

Additionally, Python Plots, graphs, and multi-dimensional representations of key patient dataset variables will be created using visualization libraries like Matplotlib and Seaborn. Picturing patient gatherings, risk levels, and results can uncover bits of knowledge and impart patterns. Clinicians are empowered to explore interactive visualizations of clinical decision-support systems, as shown in Figure 7, and the relationship between operations and medication attributes in the proposed system, as illustrated in Figure 8.

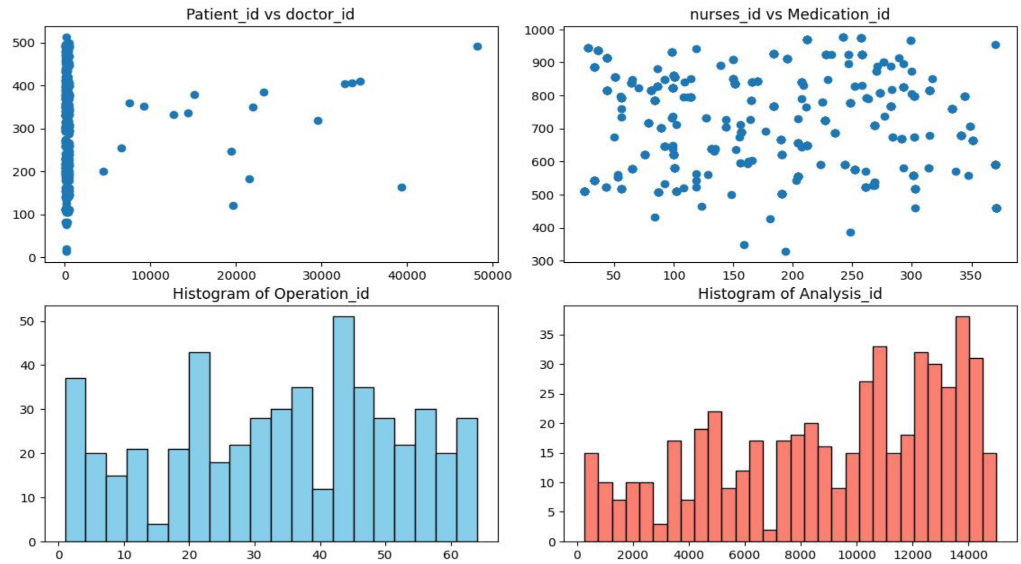

Figure 7. Visualizes some relationships between attributes in a dataset in the proposed system

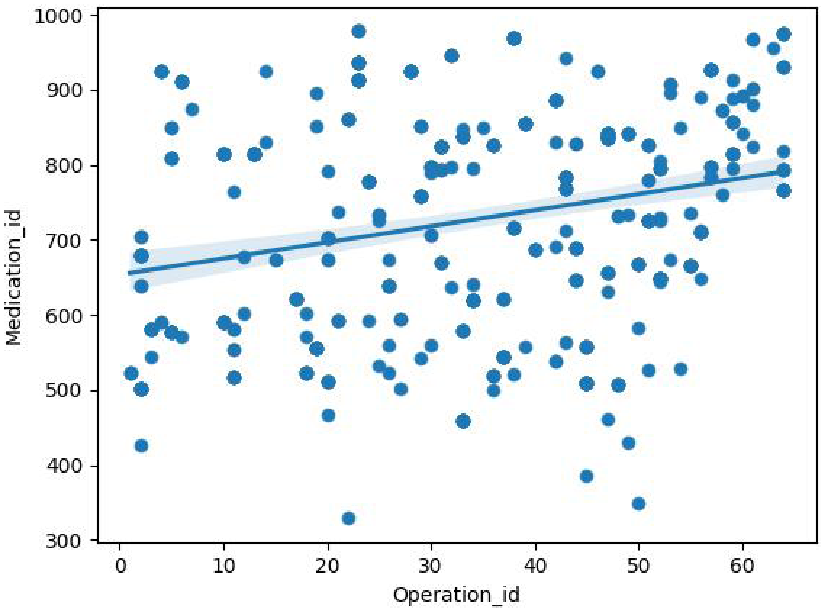

Figure 8. The relationship between operations and medication attributes in the proposed system

Python is a versatile language for integrating data processing, AI, and visualization, coordinating processes such as extracting insights from patient data and delivering feedback through automated dashboards for clinical staff. This integration enhances model interpretability for hospital administrators while leveraging advanced analytics. The K-Means clustering algorithm was applied to the dataset after presenting visual representations that outline the data analysis process within the Almasara Hospital Group framework. The clustering process, which identifies data points around specific centroids, suggests the potential presence of particular phenomena or recurring patterns at certain times and locations. These observations enable a deeper examination of underlying conditions, such as detecting issues and risks associated with specific medications, assessing the likelihood of an epidemic outbreak, or analyzing clusters of patients who present with the same illness and symptoms within a given timeframe. Data analysis, mainly through clustering, clarifies necessary actions for decision-makers at the Almasara Hospital Group. This analytical approach is designed to anticipate potential future issues, implement cost-saving measures, and maintain high standards in medical service delivery.

Importance of Data Analysis (Data Clustering)

Data analysis, especially clustering, is important because it can guide decision-makers at the Almasara Hospital Group. This scientific approach enables the hospital to take proactive measures by uncovering patterns and potential risks, mitigating future issues, and minimizing associated costs. Key areas of consideration include identifying medication-related issues, predicting possible epidemic outbreaks, and managing cases where multiple patients exhibit similar illnesses and symptoms within a specific period (Figure 9).

The application of the K-Means algorithm for, on the other hand, information examination in the Almasara Clinic Gathering is an essential device for distinguishing information groups and examples. When carefully analyzed, this data engages chiefs to address possible issues proactively, decrease expenses, and improve the conveyance of clinical benefits. The meaning of information examination, especially about information bunching, underlines its job in directing vital choices for the hospital's future.

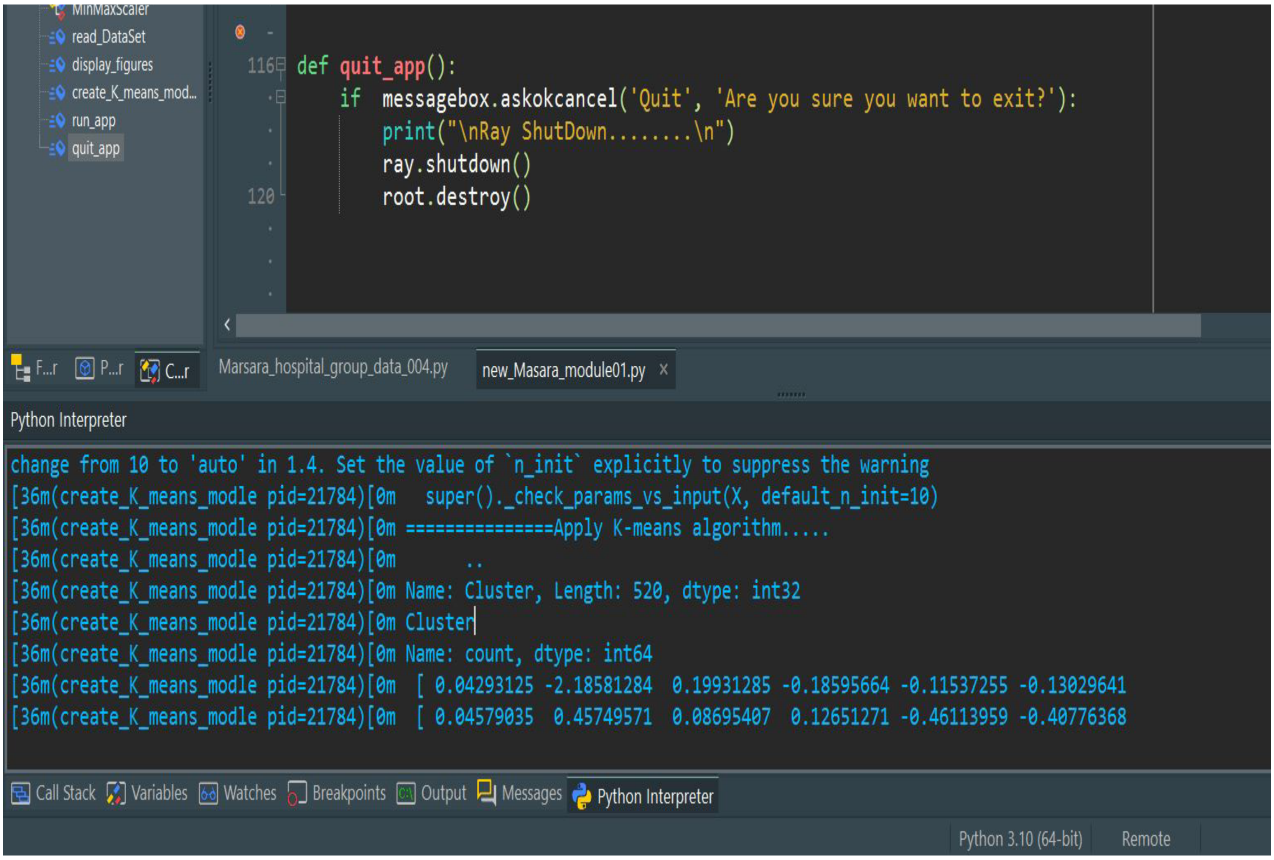

Figure 9. Application of the K-Means algorithm for data analysis in the Almasara Hospital Group

Over the past 10 years, the total number of annual surgeries at Almasara Emergency Clinic steadily increased from 1,500 procedures in 2013 to 2,000 in 2022. As the surgical volume expanded, the rate of postoperative complications consistently declined from 20% to 10% over the same timeframe. The most significant reduction, 6%, occurred between 2015 and 2017. Following the pandemic's onset in 2020, the complication rate continued to decline, reaching its lowest level, as shown in Figure 10.

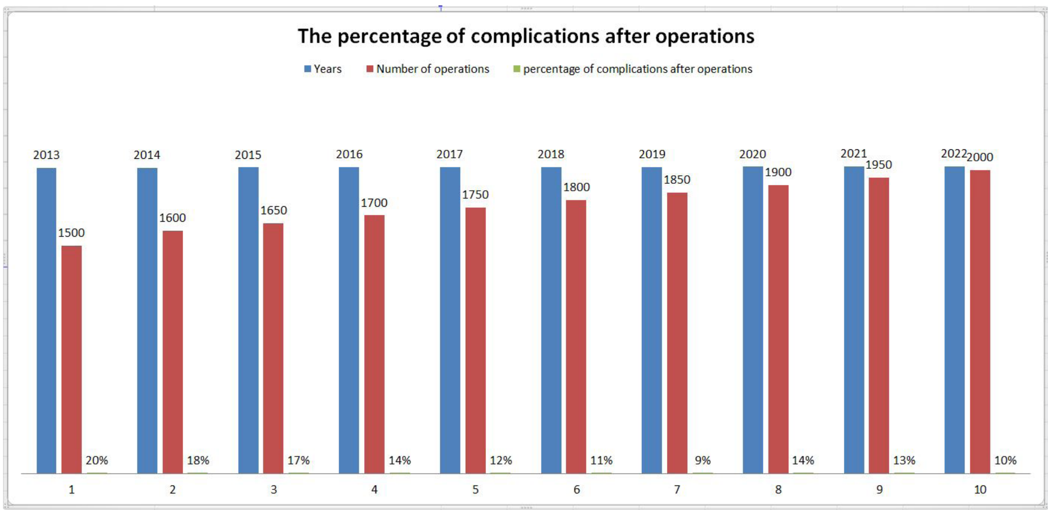

Figure 10. Percentage of complications after operations

A correlation analysis of the dataset indicates a strong relationship between the variables. As the years progress, there is a notable increase in the number of surgeries performed, shown by a very high positive correlation of approximately 0.996. This trend of rising surgical volumes is accompanied by a significant reduction in the rate of complications, with a strong negative correlation of about -0.799 between the years and the complication rate. Additionally, an increase in the number of surgeries is associated with a decrease in the complication rate, demonstrated by a negative correlation of approximately -0.815. These relationships suggest that as the volume of surgeries has grown over time, the rate of complications has decreased, indicating improvements in procedural safety and outcomes.

A correlation coefficient close to 1 indicates a strong positive relationship, while a coefficient near -1 reflects a robust negative relationship. A coefficient close to 0 implies no linear correlation. These correlations provide valuable insights into the interdependence of variables within the dataset, as illustrated in the heatmap correlation matrix in Figure 11.

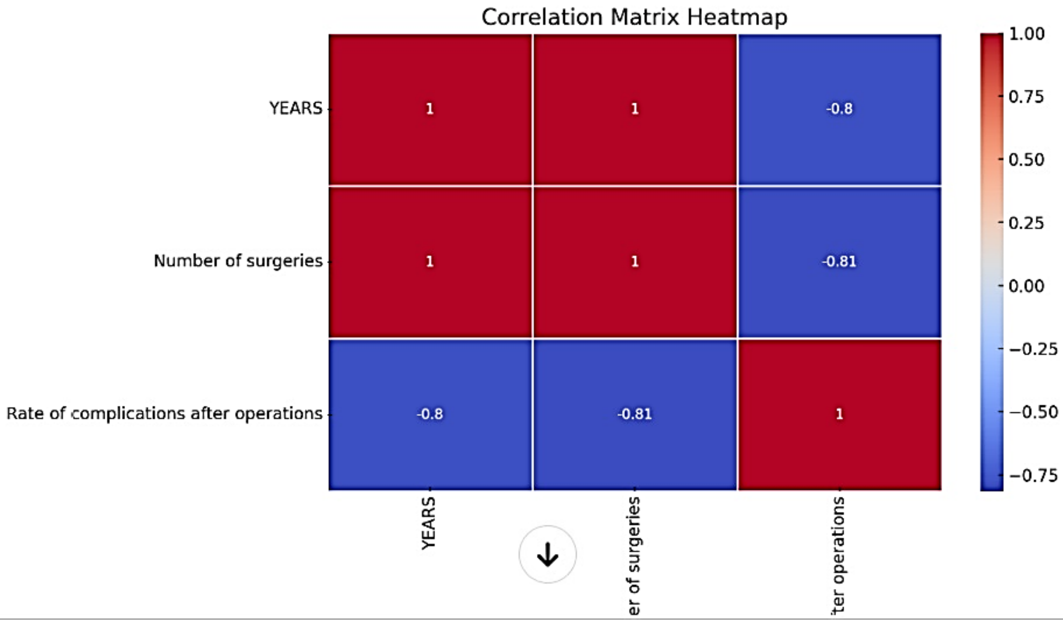

Figure 11. The correlation matrix of the required system heatmap

A regression analysis on the dataset, examining the rate of complications across different years, is visualized in a scatter plot. The plot shows actual data points alongside a red line representing the fitted linear regression model. Annotations include the R^2 Score and Mean Squared Error (MSE). The R^2 Score, at 0.95, reflects a high level of fit, indicating that the model effectively explains the data's variance. The MSE, at 0.0003, suggests a low error rate in predictions. These results indicate that the linear regression model reliably captures the trend in post-operative complication rates over the years.

The K-Means clustering algorithm was applied to the patient dataset to identify patterns in patient characteristics and clinical records. Using an initial random selection of starting points and replacing missing values with global mean or mode, the clustering was completed within 3 iterations, resulting in a Within-Cluster Sum of Squared Errors (WCSS) of 348.451. The final cluster centroids for key attributes are presented in Table 1, summarizing two clusters (Cluster 0 and Cluster 1) based on the complete data.

Table 2. K-means clustering results (Iterations = 3; WCSS = 348.451), initial starting points: random; missing values replaced with mean/mode

Attribute	Full Data (520.0)	Cluster 0(323.0)	Cluster 1(197.0)
Patient_id	260.5	258.2446	264.198
sex	0.8269	0.8328	0.8173
doctor_id	300.9731	296.2477	308.7208
nurses_id	180.3923	175.1486	188.9898
Operation_id	34.1481	43.7028	18.4822
Analysis_id	9127.0115	9344.0743	8771.1168
Radiology_id	243.8904	245.7895	240.7766
Case_id	319.1577	316.3653	323.736
Medication_id	726.8827	736.7678	710.6751
Target	0.6212	1	0
Clustered	Instances	Weight	
0	323	62%	
1	197	38%	
Total	520	100%	

Note: compiled by authors

The model identified 143 canopies, subsequently grouped into five user-defined clusters. The final cluster sizes were 108, 112, 105, 117, and 117 records, respectively. An analysis of the cluster centroid values revealed no new actionable patterns. Target complication rates and sex ratios across the five clusters displayed a distribution similar to the Simple K-Means analysis, with balanced outcomes across most clusters. Notably, Cluster 2 exhibited slightly higher adverse outcomes. The visualization plots X: Analysis_id (Num) and Y: Operation_id (Num), with color indicating the target variable. The highest values observed are X: Analysis_id = 64 and Y: Operation_id = 14999. Furthermore, illustrates the results of a canopy clustering model applied to the filtered dataset, built in 0.12 seconds.

The centroid values for each attribute across eight clusters obtained from the K-means clustering analysis represent the average values within each cluster, helping to identify unique patterns or characteristics across patient groups. The clusters show variations in critical attributes such as Patient ID, Sex, Doctor ID, and Analysis ID, among others. Cluster 0 has notably high values in Operation ID and Analysis ID, while Cluster 1 shows elevated values in Doctor ID and Analysis ID. Similarly, Cluster 5 exhibits an unusually high value for Operation ID compared to other clusters, which may indicate a distinct patient group or treatment pattern. These centroids provide a clearer understanding of the differences between clusters, enabling targeted analysis based on patient characteristics (Table 3).

Table 3. Centroid values for attributes across clusters in K-means clustering analysis

Cluster No.	Patient ID	Sex	Doctor ID	Nurse ID	Operation ID	Analysis ID
Cluster 0	350.370787	0.494382	346.044944	138.977528	44.719101	8157.370787
Cluster 1	211.730233	0.981395	276.460465	196.344186	44.888372	10290.47907
Cluster 2	276.125	0.982143	300.482143	238.294643	18.008929	8495.232143
Cluster 3	201.846154	0.974359	312.538462	72.615385	20.512821	9438.948718
Cluster 4	394.090909	0.545455	382.454545	85.454545	21.636364	10094.454545
Cluster 5	372.8,0.9	276.4,163.9	14.6,3999.6	267.5,361	633.2	1
Cluster 6	261.32	0	322.84	163.72	13.84	8514.12
Cluster 7	257.333333	1	132.333333	150.333333	47.333333	1858.333333
Clustered	Instances		Weight		-	-
0	50		10%		-	-
1	179		34%		-	-
2	87		7%		-	-
3	51		10%		-	-
4	10		2%		-	-

5	20	4%	-	-
6	28	15%	-	-
7	27	8%	-	-
Total	452	100%	-	-

Note: compiled by authors

The results presented show the values of the centroids for various attributes in eight clusters obtained using the K-means algorithm. The values of the centroids for each cluster help to identify the average characteristics of patient groups and assess how different attributes are distributed between clusters. Cluster 0 shows high values for `Patient ID` and `Analysis ID`, suggesting frequent diagnostics. In contrast, Cluster 1 has elevated values in `Doctor ID` and `Analysis ID`, indicating regular check-ups with specific doctors. Cluster 2, with high values for `Doctor ID` and `Nurse ID`, represents more intensively monitored patients. In contrast, Cluster 3 has lower values for `Nurse ID` and `Operation ID`, suggesting fewer interventions.

Illustrates the clustering results from the WEKA Explorer Hierarchical Cluster applied to the hospital dataset, where the number of clusters was set to 5.

The clustering algorithm used a centroid linkage type with Euclidean distance as the similarity metric. After building the model, cluster assignments were extracted, with doctor_id on the X-axis and Target on the Y-axis, represented by different colors for each cluster. The highest recorded values are observed at X: Medication_id = 1 and Y: Patient_id = 514, indicating key data points within the clustering analysis.

DISCUSSIONS

The cluster sizes acquired were 100, 106, 124, 111 and 118 records. Examination of the bunch centroid values did not uncover new experiences that contrasted with K-Means or covering models - procedural and clinic identifiers prevalently drove groupings. Target intricacy rates were again genuinely adjusted other than group 3 having marginally raised negatives. Sex proportions inside each bunch additionally did not show clear separation on that dimension. This research issued a goal of issues, possibly keeping minor worries from becoming severe dangers. It supports open correspondence among staff, which is fundamental for perceiving and moderating dangers in tolerant consideration. Given recent patient information, ceaseless criticism can affect care by considering prompt treatment plans and care system changes. Standard criticism circles can help recognize designs demonstrating well-being issues, prompting proactive measures to work on quiet security. Drawing in staff with day-to-day criticism can expand their mindfulness and contribute to the risk to the executives, prompting a more educated and watchful consideration group. By deliberately gathering and dissecting criticism, the emergency clinic can settle on proof-based choices that work to produce tolerant results. Day-to-day criticism gives continuous information that can be utilized to follow the exhibition of people and units inside the clinic, which is pivotal for the viable risk of the executives. Feedback mechanisms have the potential to bring to light flaws in current policies and procedures, necessitating necessary modifications to lessen risks. Distinguishing everyday dangers through criticism can illuminate designated preparation and training for medical services suppliers to forestall future occurrences. By diminishing dangers and forestalling episodes, day-to-day criticism can add to cost investment funds through superior productivity and reduced need for corrective actions. To empirically assess these impacts, a research study could be conducted using qualitative and quantitative methods to collect data before and after the implementation of daily feedback. This data could then be analyzed to identify any correlations between the feedback mechanisms and changes in risk management outcomes.

Scalability and Reliability

A defining advantage of the proposed distributed analytics system is innate scalability, achieved by leveraging the Ray framework for cluster computing. As patient data volumes from Almasara facilities grow exponentially, the system can seamlessly scale by allocating additional computational nodes. Ray's dynamic resource scheduling and cluster management handles allocation and replication for reliability. System monitoring tools track metrics like resource utilization, model accuracy, and training times. Alerting ensures high cluster uptime with failover capabilities for graceful degradation during outages. The modular design based on microservices architecture enables independent scaling of database, machine learning, and visualization containers. In conclusion, vertical and horizontal scaling capacities guarantee that the analytics pipeline can expand to meet future demands.

Trade-offs and Limitations

Several pragmatic challenges emerging in medical services frameworks warrant thought. Safeguarding delicate patient data is basic - methods like differential protection and unified learning try not to uncover crude records. Group systems administration can observe bottlenecks, initiating compromises between dispersed effectiveness and precision. Utilizing steady hashing mitigates delays. Neural networks and other "black box" models lack interpretability regarding analytics. Producing model clarifications assists heads with building trust and consistency. Overall, the system architecture tries to solve these real-world problems while providing valuable insights.

Discussion of the potential limitations and challenges

Implementing a system that relies on consistent, high-quality data can be challenging, especially in a healthcare setting where data is often fragmented across different systems. Data consistency, completeness, and accuracy are critical for practical machine-learning applications. Any discrepancies in data collection or errors in data entry can lead to flawed analyses and potentially harmful decisions. While the system is designed to be scalable, practical limitations in computational resources can pose challenges. The Ray framework supports parallel processing, but the scalability is contingent upon the available infrastructure, which might be limited in a resource-constrained setting like Libya. Additionally, handling large volumes of data in real-time requires significant processing power and efficient algorithms to prevent lag and ensure timely feedback. Implementing new technologies in healthcare settings often encounters resistance from staff who may be accustomed to traditional methods of operation. Training and convincing the staff to adopt new technologies can be a significant hurdle. The system's effectiveness depends heavily on how well the staff understands and uses it to its full potential . With the increasing use of data analytics and machine learning in healthcare, protecting patient privacy becomes more complex and critical. Ensuring the system complies with health data regulations and standards, such as HIPAA in the U.S. or equivalent standards in other countries, is essential. The system must securely handle sensitive information, preventing unauthorized access and data breaches . Machine learning models, including those using K-means clustering, can inadvertently perpetuate or even amplify biases present in the training data. This can lead to unfair treatment of specific patient groups or misdiagnoses. Regular reviews and updates of the algorithms are necessary to ensure they make equitable and accurate predictions. The system requires continuous monitoring, maintenance, and updates to ensure its effectiveness. This includes updating the software to handle new types of data, improving algorithms based on new medical research, and troubleshooting any issues during operation. Ensuring the system remains up-to-date with the latest medical guidelines and technology standards is crucial for its long-term success. Finally, the economic aspect of implementing and maintaining such advanced systems cannot be ignored. In settings like Libya, where resources might be limited, the initial and ongoing costs associated with advanced data analytics platforms can be a significant barrier. This includes hardware, software licensing, professional services, and operational costs.

CONCLUSION

In summary, this research carried out a versatile engineering exhibiting the combination of dispersed figuring, data set frameworks, and AI to convey an information-driven examination of medical clinic records. The quantitative outcomes and clinical criticism showed a huge commitment to helping medical clinic managers control expenses and chance variables through interpretable examination. As medical care frameworks wrestle with expanding information resources, such multi-faceted examination frameworks structure the fundamental and translational support point for clinical computerized change. In this manner, one can imagine a significant long-haul influence on clinical results and cycle expansion through information unification. Altogether, day-to-day criticism procedures like agendas, alarms, and execution reports show adequacy for lessening preventable mischief and reducing costs. Care consistently improves through systematic reminders of best practices and real-time data analysis. Leadership is necessary to implement such systems while building a culture of transparency and accountability. Further work on predictive models and automation can strengthen future feedback platforms.

AUTHOR CONTRIBUTION

Conceptualization and theory: LOFOBD, TM and IM; research design: LOFOBD, TM and IM; data collection: TM and MU; analysis and interpretation: LOFOBD and MU; writing draft: LOFOBD, TM and UM; supervision: TM and MU; correction of article: LOFOBD and MU; proofread and final approval of article NY. All au-

thors have read and agreed to the published version of the manuscript.

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