Volume 10, Issue 4, April – 2025 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

Develop an Automated Patient Arrival Predictor for Enhanced Overall Operational Efficiency at Rwanda Charity Eye Hospital

Aime Piati Nsengiyumva[1]; Dr. Wilson Musoni2 (Phd)[2]

[1,2] Masters of Science with Honors in Information Technology at University of Kigali, Rwanda

Publication Date: 2025/04/17

Abstract: This research focuses on improving patient flow, resource utilization, and operational efficiency by developing a machine learning-based model to predict patient arrivals in healthcare facilities. The model analyzes historical patient data, such as timestamps, demographic details, and external factors like public holidays and weather conditions, to forecast future arrival trends. The primary objectives are to reduce patient wait times, optimize staffing, equipment distribution, and facility use, improve appointment scheduling, ensure timely care, and minimize patient backlogs. The methodology involves data collection, preprocessing, exploratory analysis, and training the model using statistical, deep learning, and machine learning techniques. The best-performing model will be integrated into hospital systems for real-time predictions. The expected outcomes include enhanced scheduling, resource management, and patient flow, leading to improved service quality. The study's findings suggest that preventive actions based on patient arrival predictions can significantly boost operational efficiency. The insights gained from this study offer valuable guidance for decision-makers in healthcare settings, highlighting the importance of data-driven approaches in healthcare management. Introduction of research.

How To Cite: Aime Piati Nsengiyumva; Dr. Wilson Musoni2 (Phd) (2025) Develop An Automated Patient Arrival Predictor For Enhanced Overall Operational Efficiency At Rwanda Charity Eye Hospital *International Journal Of Innovative Science And Research Technology*, 10(4), 377-390. Https://Doi.Org/10.38124/Ijisrt/25apr226

I. INTRODUCTION

Healthcare facilities worldwide face a continuous challenge in ensuring the optimal utilization of resources while providing timely access to care. Efficiently managing patient arrivals is a crucial aspect of achieving this balance. Like many hospitals, the Royal City Eye Hospital (RCEH) experiences fluctuations in patient numbers that can lead to inefficient resource management, extended wait times, and ultimately, compromised patient care. Traditional methods of managing patient flow often rely on reactive strategies, which tend to exacerbate issues such as overcrowding, prolonged waiting times, and suboptimal resource allocation.

To address these challenges, this research introduces a proactive solution in the form of a machine learning-based patient arrival predictor. By leveraging historical patient data and incorporating various influencing factors such as demographic information and external variables, the proposed system aims to forecastn future patient arrival trends with high accuracy. The implementation of this predictive model will not only streamline the hospital's operations but also ensure more efficient use of resources, reduce congestion, and enhance patient satisfaction. This study explores the potential of machine learning techniques to optimize patient flow and contribute to more effective healthcare management practices.

➢ *Statement Of The Problem*

Like many other healthcare facilities across the world RCEH has a difficult time effectively controlling patient arrivals which impacts negatively both operational effectiveness and the standard of patient care. The hospital struggles with a range of patient volumes which leads to inefficient use of resources, high wait times and restricted access to necessary eye care treatments. In a report on how it operates of Rwanda's health system the World Health Organization expressed concerns about lengthy wait times and delays in receiving medical care.

The hospital still finds it difficult to adequately meet patient demand even after making steps to solve these problems using traditional methods like manual scheduling and adaptive resource allocation. There is still a major research gap concerning eye care services especially when it comes to RCEH. A few studies have looked at the use of patient arrival predictor in healthcare environment to enhance resource allocation and patient flow management.

As a result, the main issue this study seeks to address is the RCEH's inability to handle patient arrivals in an efficient way, which leads to wasteful use of resources, too much wait times, and poor patient treatment. This study aims to close this gap and enhance operational effectiveness in the hospital environment by creating a patient arrival predictor using machine learning techniques. The research aims to offer

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

useful findings that guide strategic decision-making and improve the general standard of care for patients seeking eye care services at RCEH by utilizing historical patient data and predictive analytics.

II. A REVIEW OF THE LITERATURE

➢ *Artificial Intelligence (AI)*

The technology called "AI" allows machines, computers by imitating human intelligence, allowing them to carry out tasks that involve problem-solving skills (IBM, 2024b).

➢ *Machine Learning (ML)*

ML refers to a field of AI that centers on leveraging information and models to replicate human learning processes by humans and continuously increasing their precision (ML, n.d.).

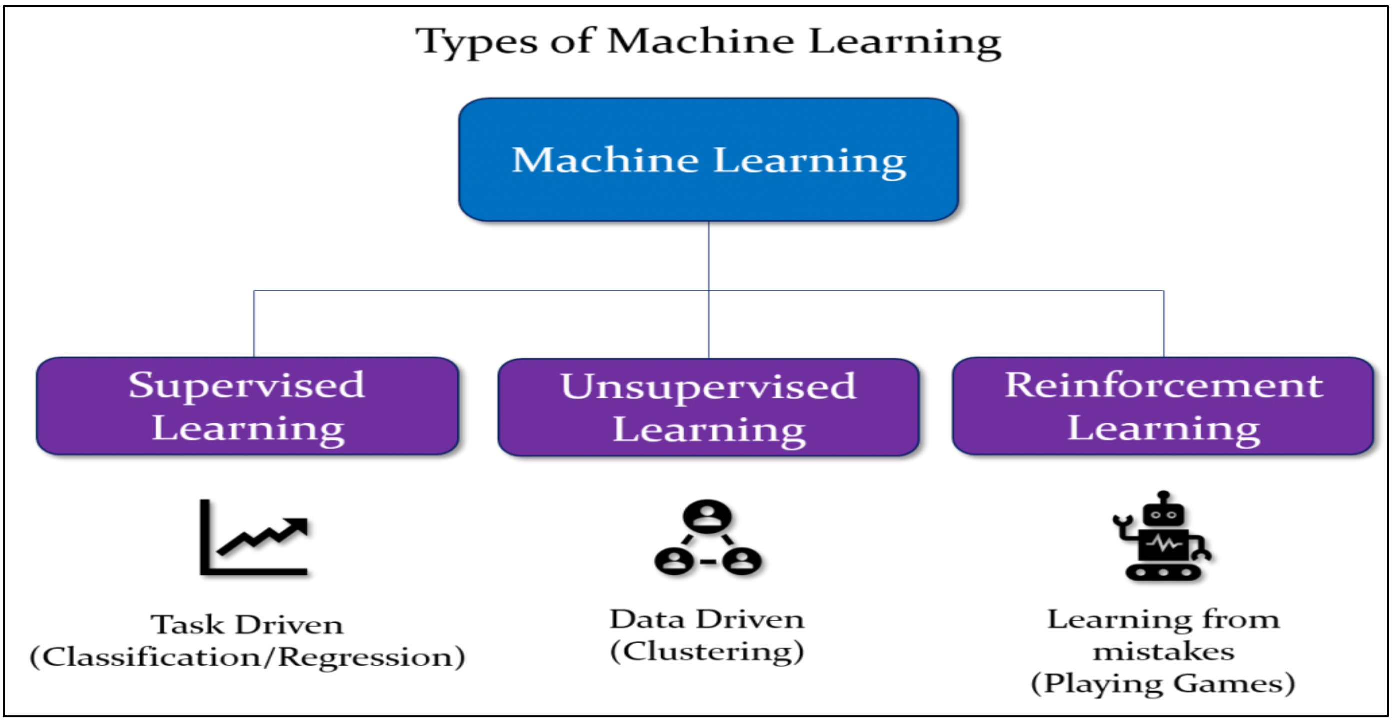


Fig 1 Types of ML (Rishabh, 2020).

➢ *Supervised Learning (Sl)*

• *Linear Regression Evaluation Metrics*

A linear regression model performance can be evaluated by several number of metrics. They reveal how well the model forecasts results:

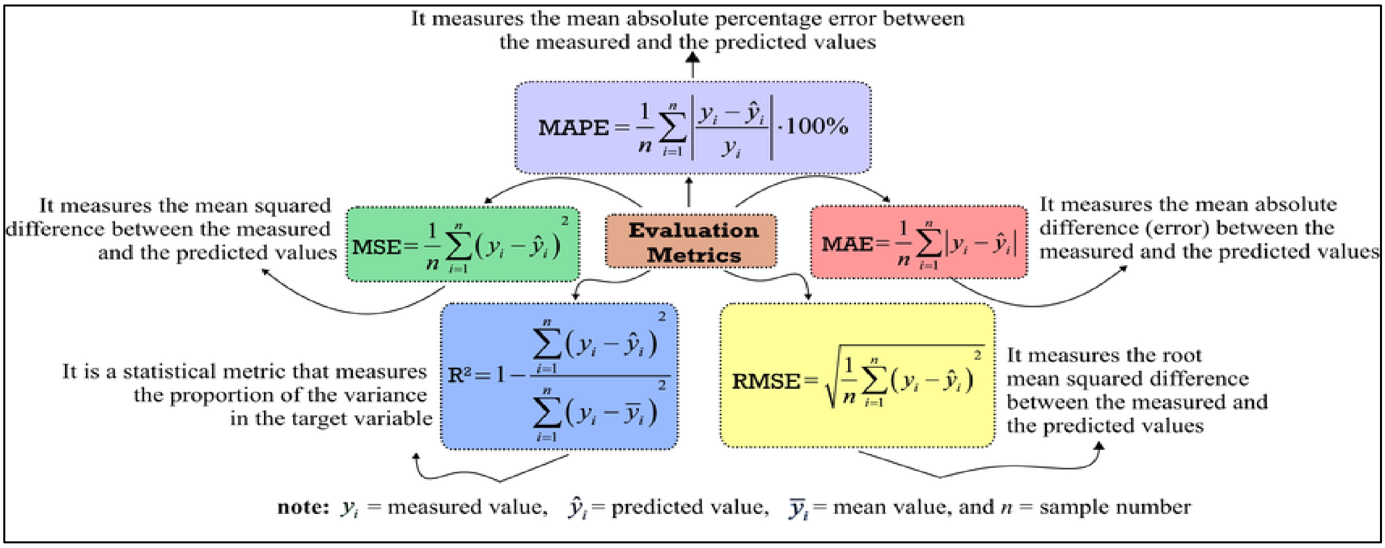


Fig 2 Evaluation metrics.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

- *Predictive Research For Hospital Admissions Based On Emergency Department Triage Information*

Research on predicting hospital admissions based on emergency department (ED) triage data plays a crucial role in enhancing healthcare delivery. By analyzing key data—such as patient demographics, vital signs, and presenting symptoms—prediction models can forecast whether a patient will require hospitalization. This helps healthcare providers better allocate resources and improve patient care. However, challenges such as patient privacy, data quality, and ethical concerns must be carefully addressed to ensure effective and ethical application of such predictive analytics. Despite these hurdles, the potential to optimize emergency care and improve patient outcomes highlights the importance of this research area (Araz et al., 2019).

- *ML Risk Prediction Models For Assessing Undifferentiated Patients' Acuity Upon ED Admission*

Machine learning (ML) risk prediction models are becoming a key tool in assessing the severity of undifferentiated patients upon entering the emergency room (ER). These models use advanced algorithms to analyze patient data and predict the severity of their condition, allowing healthcare providers to prioritize care and allocate resources more effectively. The theoretical basis for this approach lies in understanding the complex relationships between a patient's characteristics, clinical symptoms, and their medical outcomes. Key challenges include selecting appropriate data features, validating models against actual clinical outcomes, and integrating these models into real-time clinical practices. Ethical concerns, such as patient privacy and fairness, must also be considered in the deployment of ML-based triage systems. Despite these challenges, enhancing triage accuracy and reducing treatment delays present significant benefits (Miles et al., 2020).

- *Predicting Emergency Room Delays Using An Integrated ML And Systems Thinking Approach*

An integrated approach that combines machine learning with systems thinking offers a comprehensive method for predicting delays in emergency rooms. This approach integrates predictive analytics to estimate waiting times based on historical and real-time data, while systems thinking provides a broader view of the interdependencies in the ED, such as patient flow, staffing, and resource use. This holistic approach helps identify inefficiencies and anticipate bottlenecks, ultimately improving patient outcomes and optimizing service delivery. While this method shows promise, challenges related to data quality, algorithm transparency, and the complexity of healthcare systems need to be overcome. Furthermore, the ethical implications of algorithmic decision-making, as well as the need for collaboration among stakeholders, are crucial to the effective use of this integrated approach (Kuo et al., 2020).

- *Predictive Research For Hospital Admissions Using ED Triage Data*

Recent studies in predictive research for hospital admissions from ED visits have led to the development of more accurate prediction models that incorporate a wide range of data from triage. Machine learning techniques such as decision trees, logistic regression, and neural networks are commonly used to predict the likelihood of hospital admission based on key triage indicators, such as vital signs and comorbidities. Decision support systems that integrate these predictive models into clinical practice have shown positive results in improving patient outcomes and optimizing resource allocation. However, challenges like data quality and model interpretability remain, underscoring the need for further research and interdisciplinary collaboration (Araz et al., 2019).

- *ML Risk Prediction Models For Assessing Undifferentiated Patients' Acuity In The ED*

Recent empirical studies have explored the use of ML techniques to predict the acuity of undifferentiated patients in the emergency department. These models use diverse patient data and algorithms such as regression and gradient boosting to accurately classify the severity of patient conditions. Validation studies show that these ML models perform well in terms of sensitivity, specificity, and other metrics across various patient groups and settings. Implementing such systems has been shown to improve resource allocation, decrease treatment delays, and enhance overall patient outcomes. Despite these advantages, issues such as model interpretability, data quality, and generalizability remain, requiring further research to maximize the potential of ML in emergency care (Miles et al., 2020).

- *Predicting Emergency Room Delays With ML And Systems Thinking*

Empirical research has also applied machine learning in conjunction with systems thinking principles to predict waiting times in emergency departments. Various ML algorithms, such as regression models and neural networks, have been used to analyze data on patient arrival patterns, staffing levels, and other factors that affect ED operations. These models provide valuable insights into patient flow dynamics and process bottlenecks. Integrating machine learning with systems thinking enhances the ability to interpret and apply waiting time predictions effectively. This combination of approaches has proven beneficial for improving ED efficiency, optimizing resource allocation, and ultimately enhancing patient care outcomes (Kuo et al., 2020).

III. METHODOLOGY OVERVIEW

The methodology for this study is outlined in the accompanying work plan, which focuses on key steps including the use of an iterative process to build a patient arrival forecasting model that enhances operational efficiency, along with data collection techniques.

- *Research Design*

This study adopts a quantitative research design to create a patient arrival prediction model tailored to the unique conditions of RCEH. The process begins with gathering historical patient data, which includes arrival times as well as pertinent medical and demographic information. The next step involves data preprocessing, such as removing missing values and outliers, and performing feature engineering to

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

extract meaningful insights. Exploratory Data Analysis (EDA) follows to identify patterns, trends, and correlations within the data. EDA is crucial as it lays the foundation for model development by offering a comprehensive understanding of the variables, including identifying any gaps in the data and assessing relationships between independent and dependent variables (IV and DV). During the initial phase of EDA, a univariate approach is employed to focus on the target variable first, followed by numerical and categorical variables, which are visualized using pie charts and line graphs. For forecasting patient arrivals, machine learning techniques such as regression and time series analysis are used to train the model based on past data.

➢ *Research Participants*

The participants for this study will include patients who have visited RCEH within a specified time frame and required various eye care services. This group will encompass a wide range of patients with different demographic backgrounds, medical conditions related to eye care, and various age groups and genders. Additionally, healthcare practitioners and staff members involved in patient care will be included in the study population due to their impact on overall hospital operations and patient flow.

➢ *Data Collection Methods, Tools, and Instruments*

- *Data Collection Methods*

✓ *Secondary Data:*

Historical data from previous patient visits, available in Excel format from 2024, will be utilized for analysis. This data will provide critical insights into patient arrival trends, supporting the evaluation of patient flow.

- *Documentation:*

Documentation will involve referencing and citing sources of information not originally created by the researcher. This includes information from external sources such as books, articles, journals, and online resources. Proper documentation ensures clarity between original ideas and those sourced from literature.

- *Instruments Used*

✓ *Agile Methodology:*

This methodology, widely used in software development, is characterized by its flexibility and adaptability. Agile is suitable for projects with changing needs and fast-paced development, as it focuses on incremental software delivery throughout the project rather than waiting until the end to release the full product.

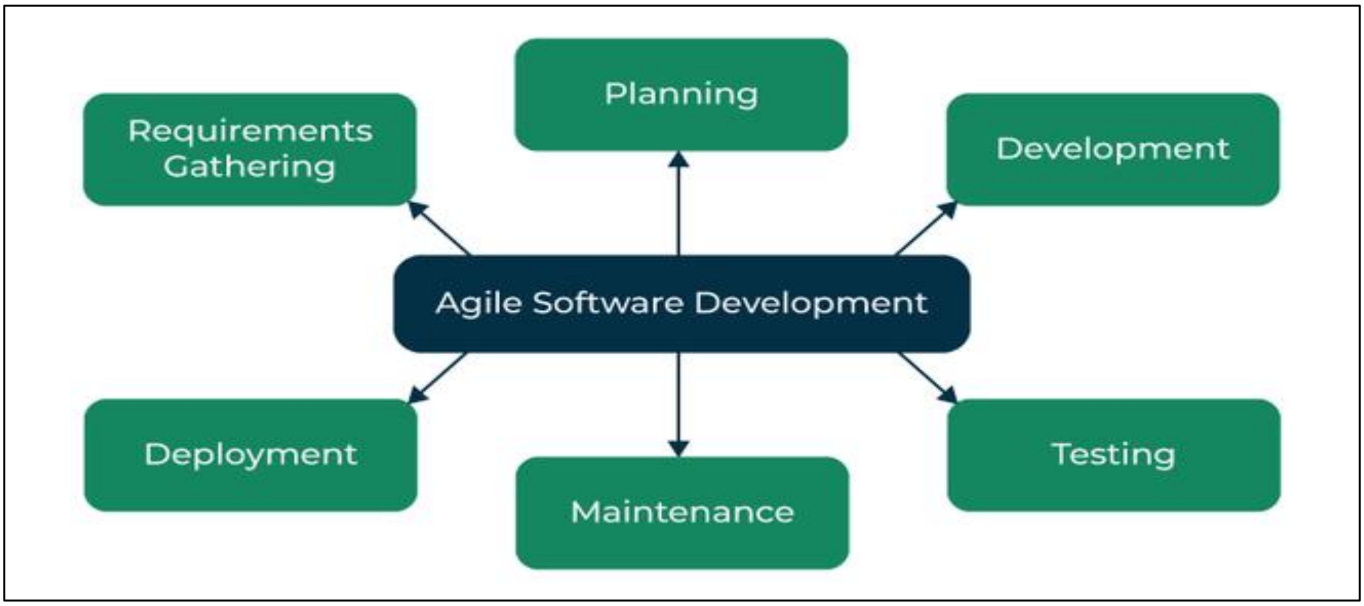


Fig 3 Agile Methodology

▪ *Planning*:

Developers create a strategy for software delivery, specifying which features will be completed in each iteration.

▪ *Development*:

Software is built through fast, frequent development cycles.

▪ *Testing*:

The application is rigorously tested to ensure it meets client requirements and maintains high quality.

▪ *Deployment*:

The application is released and made accessible for use.

▪ *Maintenance*:

Continuous updates and support are provided to ensure the software continues to meet the client's evolving needs.

➢ *Conceptual Model*

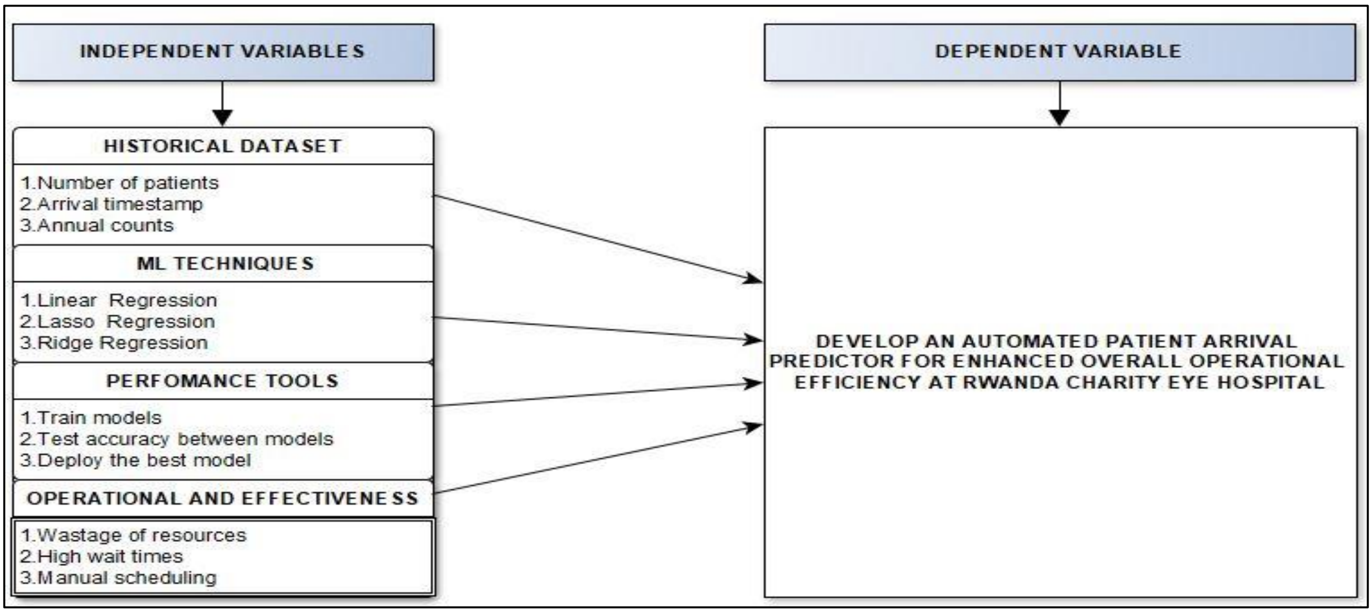


Fig 4 Conceptual Model

IV. RESULTS PRESENTATION, ANALYSIS, AND INTERPRETATION

➢ *Overview*

This section presents and analyzes the findings from research on forecasting patient arrivals at RCEH. The data collected were examined in alignment with the research objectives, serving as a tool to assess the outcomes from the field study. It also includes an overview of the technologies used in the application, its operations, testing procedures, limitations of the current system, and compatibility requirements for both software and hardware.

- *Automated Machine Learning Workflow*

The machine learning (ML) workflow typically involves repetitive tasks and experimentation. For example, during development, various algorithms and hyperparameters must be tested to identify the optimal model. In traditional training, specific code is written to train the model, which is then adjusted to experiment with different configurations. While this process is manageable for smaller projects, it can become inefficient for larger ones. Automated Machine Learning (AutoML) simplifies this by handling tasks like feature selection, hyperparameter tuning, and algorithm choice, allowing the focus to remain on the core ML problem and data ("Automated Machine Learning (AutoML)," n.d.).

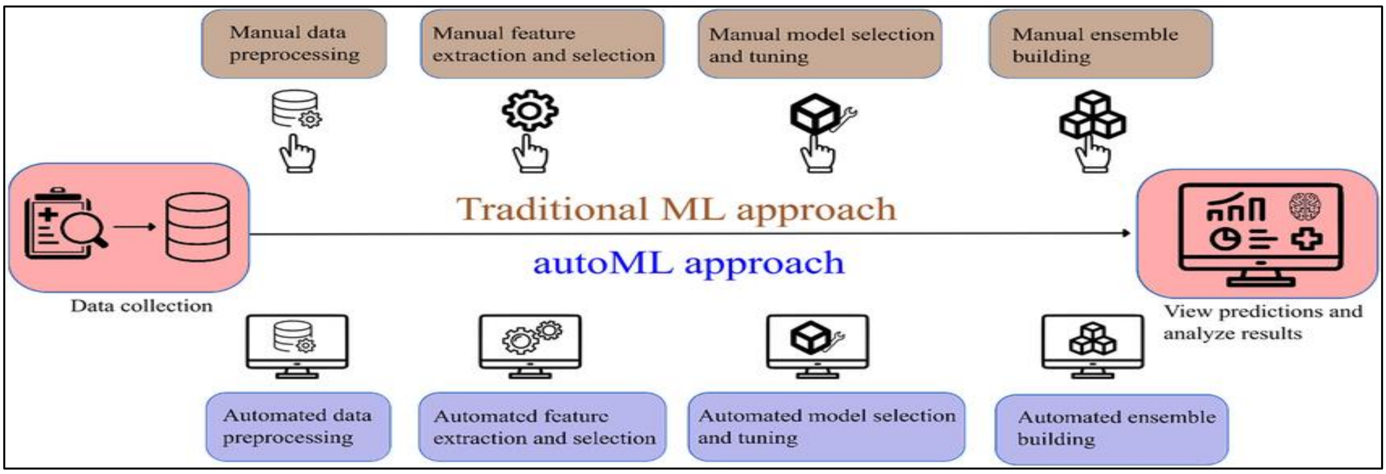


Fig 5 Automated Machine Learning Workflow

Systems can automate various steps in building a machine learning model, including:

- ✓ Preparing data (handling missing values, encoding variables, scaling, and splitting).
- ✓ Creating relevant features from raw data.
- ✓ Selecting and training the appropriate model.
- ✓ Fine-tuning model settings for improved performance.
- ✓ Combining multiple models to boost results.
- ✓ Deploying the model in a production environment.
- ✓ Monitoring and maintaining the model with new data.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

➢ *The System Study*

- *Weaknesses Observed in the Current System*

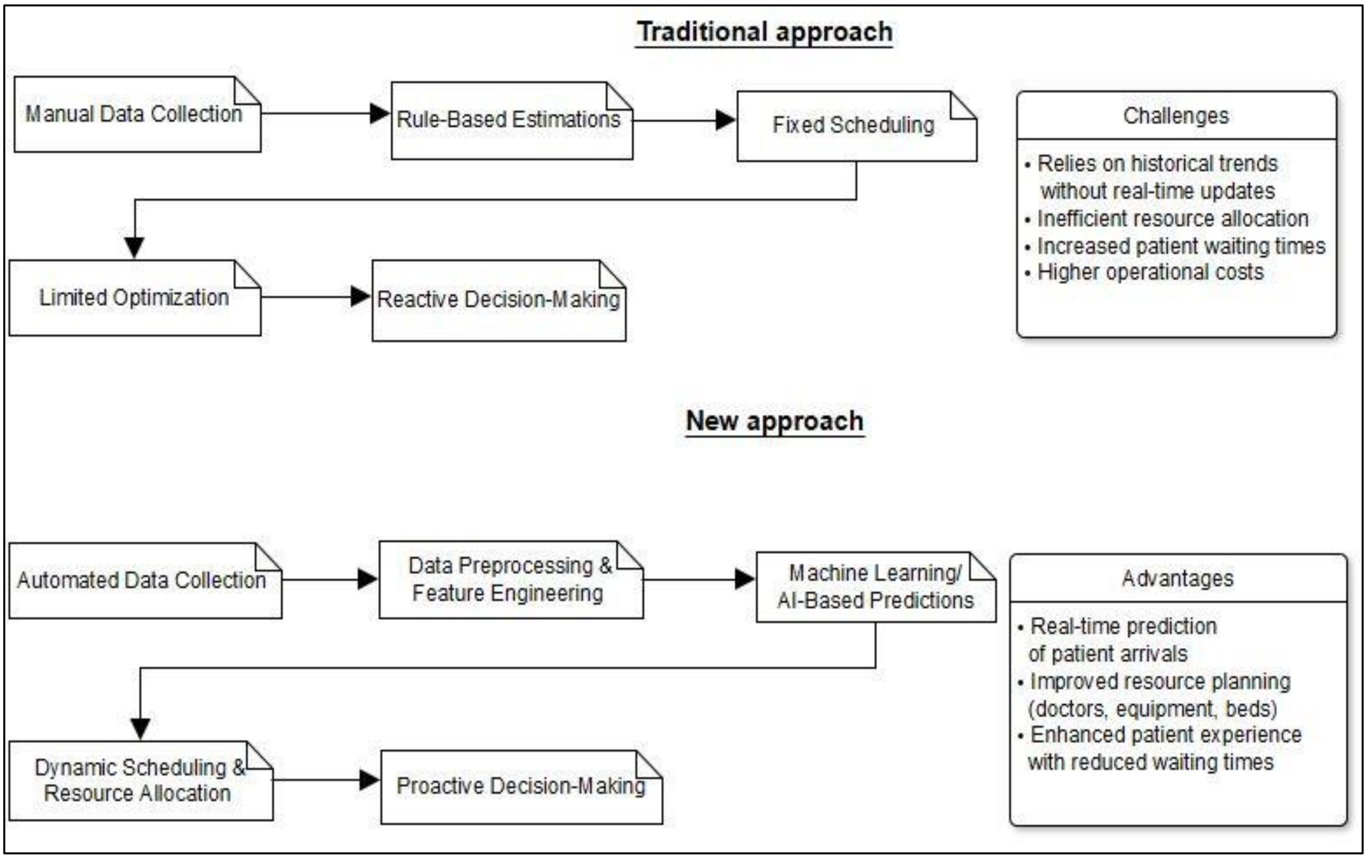


Fig 6 Weaknesses Observed in the Current System

- *Modeling Activity Diagram*

With the Diagrams below, we describe the major activities of the model.

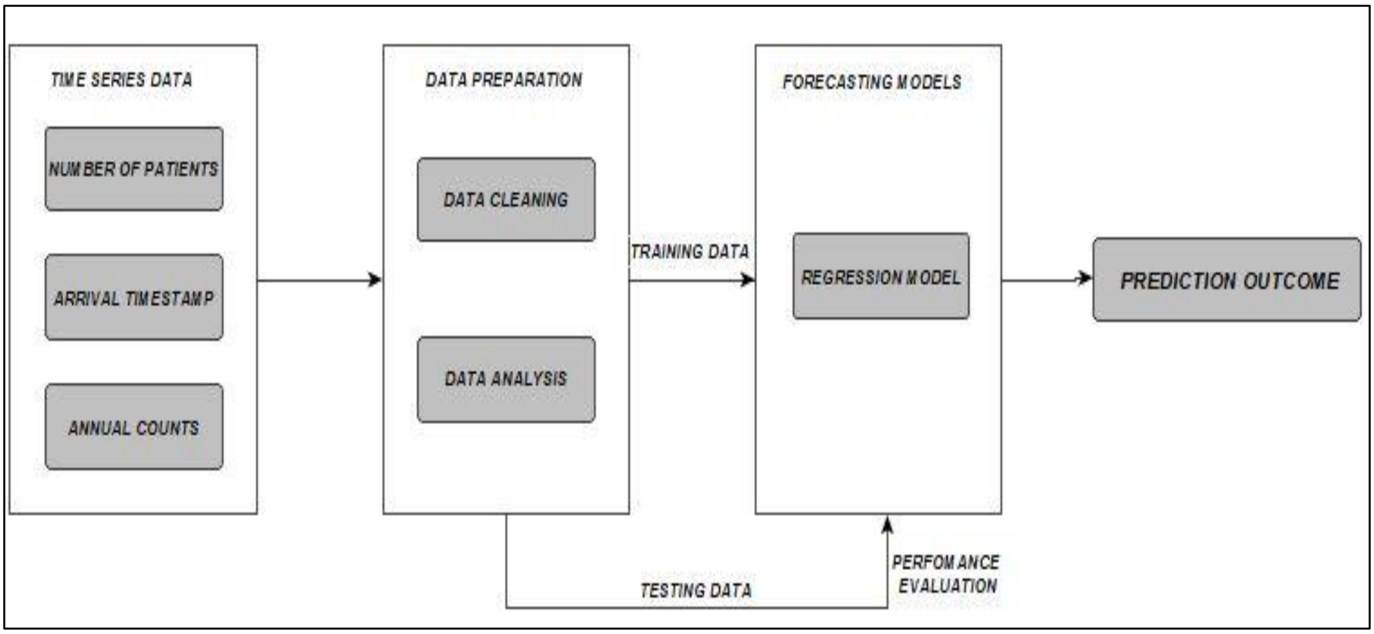


Fig 7 Modeling Activity Diagram

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

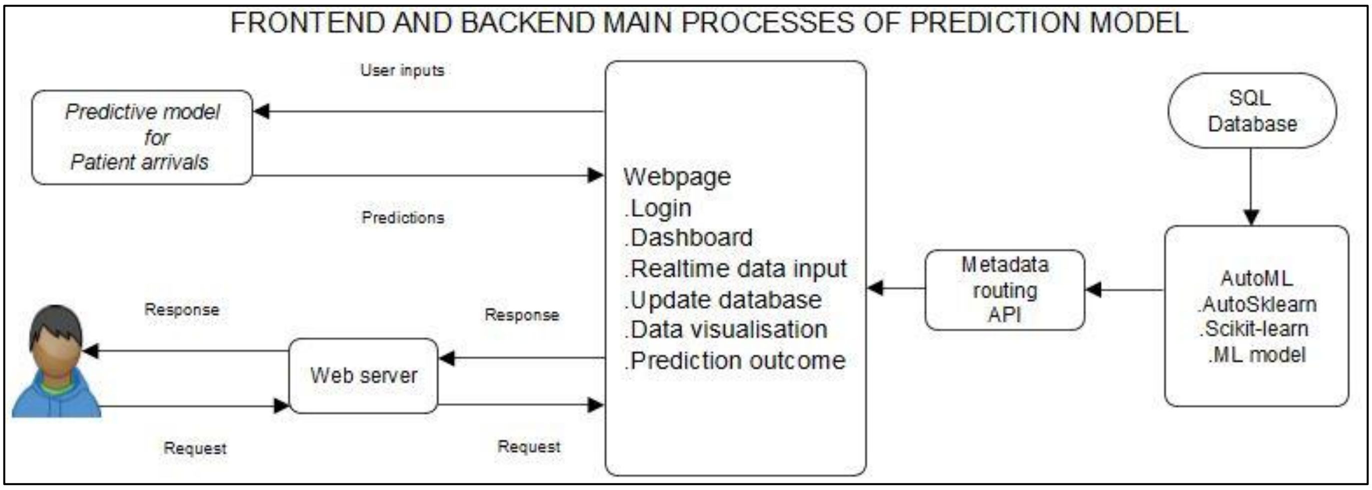


Fig 8 Main Processes of Prediction Model

A **context diagram** in software engineering shows how entities interact with a system, representing the system's top-level process (Level 0). It typically includes labeled boxes for entities and lines to show their relationships. The diagram highlights how each entity influences the system, whether directly or indirectly.

- ✓ **Process**: A rounded rectangle that transforms incoming data into outgoing data.
- ✓ **Data Store**: Temporarily holds data between processes.
- ✓ **External Entity**: Represents sources of incoming or outgoing data (e.g., people, systems).
- ✓ **Data Flow**: Indicates how data moves between entities and processes.

➢ *Data Visualization*

Data visualization involves representing information and data through graphical formats. By utilizing elements like maps, charts and graphs these tools offer an intuitive way to identify patterns, anomalies and trends in the data. Visualization tools are crucial for analyzing a lot of information and making data-driven decisions. The analysis with different visualizations can help an organization understand everything about patient arrivals dataset. Therefore, the Because of the flexibility of the distinct values of the numeric columns, an organization can work with the data and apply various filters to view different data characteristics of the data set.

Table 1 Input dataset format in excel file

code	type	begindate	enddate	gender	age	code_service	insurer	label	certainty
1_329048	Admission	3/1/2024	3/5/2024	M	45	SMT_OPT	RSSB	Hypertension	OLD
1_509284	Visit	5/12/2024	5/12/2024	F	28	CONS_TSO	MMI	Asthma	NEW
1_804729	Visit	7/14/2024	7/14/2024	M	32	HOS_COM	FARG	Malaria	NEW
1_729031	Admission	2/9/2024	2/15/2024	F	65	SMT_OPT	PRIVATE	Diabetes	OLD
1_394857	Visit	6/21/2024	6/21/2024	M	20	CONS_TSO	EDEN CARE	Fracture	NEW
1_582301	Admission	1/3/2024	1/10/2024	F	50	HOS_COM	RSSB	Pneumonia	OLD
1_402985	Visit	4/25/2024	4/25/2024	F	36	SMT_OPT	MMI	Gastroenteritis	NEW
1_809245	Admission	3/17/2024	3/22/2024	M	71	HOS_COM	FARG	Heart Failure	OLD
1_623948	Visit	6/9/2024	6/9/2024	F	41	CONS_TSO	PRIVATE	Migraine	NEW
1_972340	Visit	7/20/2024	7/20/2024	M	18	SMT_OPT	EDEN CARE	Allergic Reaction	NEW
1_184720	Admission	2/13/2024	2/19/2024	F	56	HOS_COM	RSSB	Kidney Stones	OLD
1_598341	Visit	5/2/2024	5/2/2024	M	23	CONS_TSO	MMI	Skin Rash	NEW
1_749023	Admission	1/15/2024	1/21/2024	F	60	SMT_OPT	FARG	Stroke	OLD
1_809436	Visit	3/30/2024	3/30/2024	F	12	HOS_COM	PRIVATE	Ear Infection	NEW
1_729348	Admission	2/25/2024	3/2/2024	M	49	SMT_OPT	EDEN CARE	Appendicitis	OLD
1_598734	Visit	7/18/2024	7/18/2024	F	22	CONS_TSO	RSSB	Sinusitis	NEW
1_739028	Admission	4/12/2024	4/18/2024	M	65	HOS_COM	MMI	Anemia	OLD
1_982743	Visit	5/27/2024	5/27/2024	F	14	SMT_OPT	FARG	Tonsillitis	NEW
1_830492	Admission	6/5/2024	6/10/2024	M	53	CONS_TSO	PRIVATE	COPD	OLD
1_940283	Visit	2/22/2024	2/22/2024	F	34	SMT_OPT	EDEN CARE	Back Pain	NEW
1_502834	Admission	3/8/2024	3/13/2024	M	67	HOS_COM	RSSB	Cataract Surgery	OLD
1_674839	Visit	7/7/2024	7/7/2024	F	40	SMT_OPT	MMI	Urinary Tract Infection	NEW
1_839401	Admission	1/27/2024	2/2/2024	M	58	HOS_COM	FARG	Gallstones	OLD

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

➢ *An Automated Patient Arrival Predictor for Enhanced Overall Operational Efficiency System Presentation*

This presentation describe the whole process of an online-based On-Field Verification system for the RCEH. This is an intuitive online interface enabling real-time monitoring and including activity recording tools. The model acts as a resource for healthcare professionals to foresee upcoming patient need, allowing them to strategize staffing, distribute resources, and possibly recognize times of increased or decreased demand for proactive actions.

- *Login*

Fig 9 Login Page

- *Menu*

This menu indicates that MediTrack is an all-inclusive healthcare system that facilitates data input, reporting, analysis, and also prediction modeling to enhance operations and patient care.

This menu grants entry to different functions in the MediTrack system:

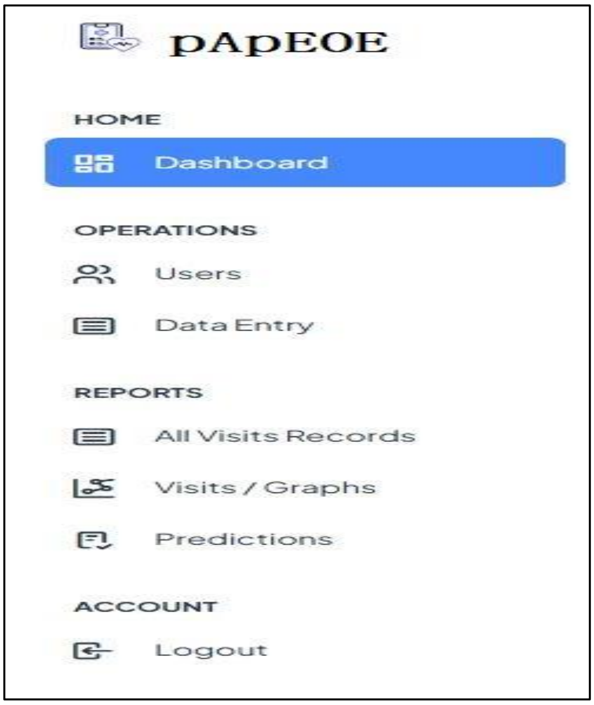
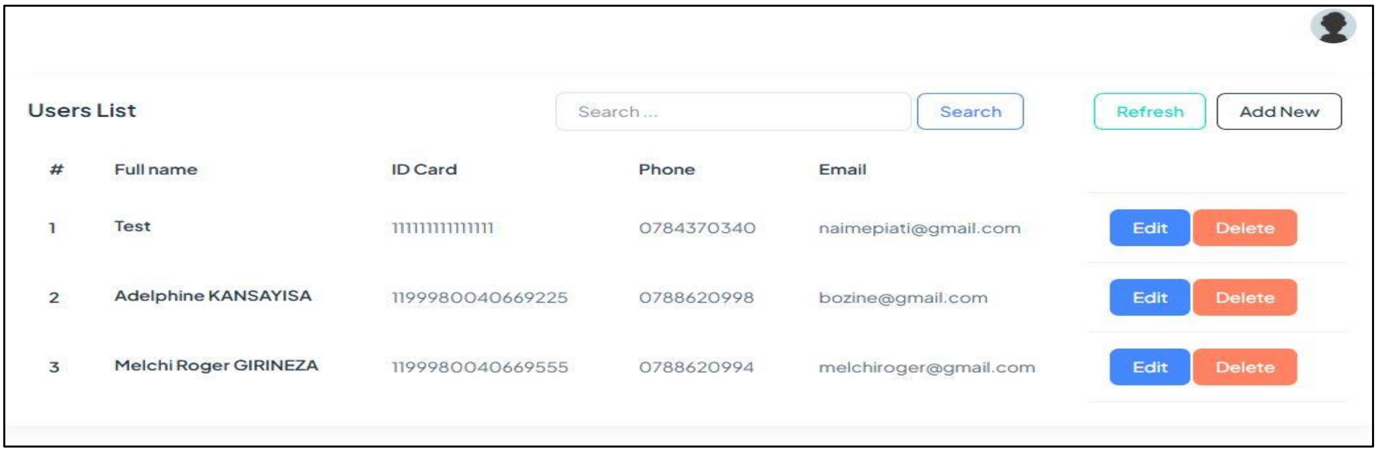


Fig 10 Menu

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

- *Users*

  Users page oversees user accounts and privileges.



#	Full name	ID Card	Phone	Email	
1	Test	11111111111111	0784370340	naimepiati@gmail.com	Edit Delete
2	Adelphine KANSAYISA	1199980040669225	0788620998	bozine@gmail.com	Edit Delete
3	Melchi Roger GIRINEZA	1199980040669555	0788620994	melchiroger@gmail.com	Edit Delete

Fig 11 Users Page

- *Add dataset*

  Data Entry or Input page enables the entry of patient information (dataset).

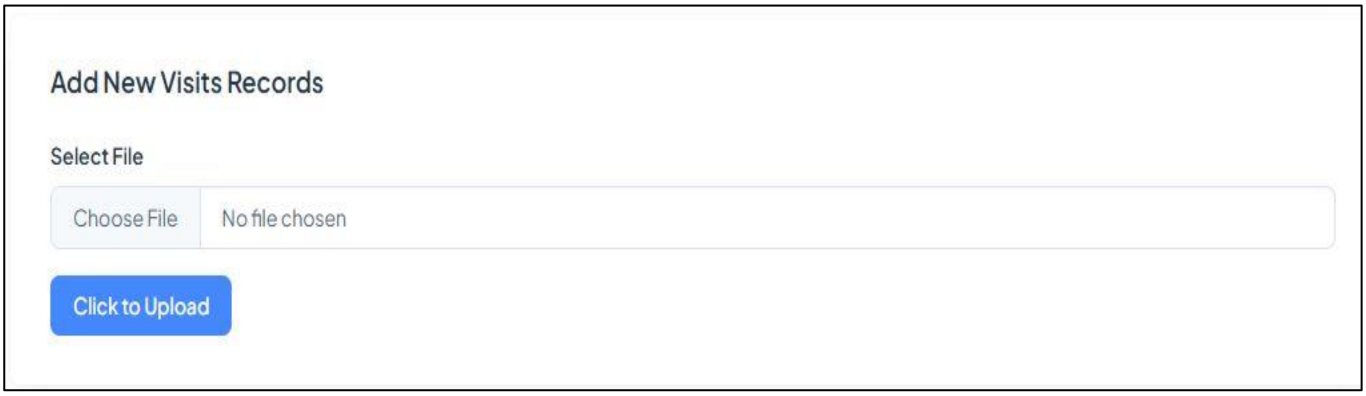
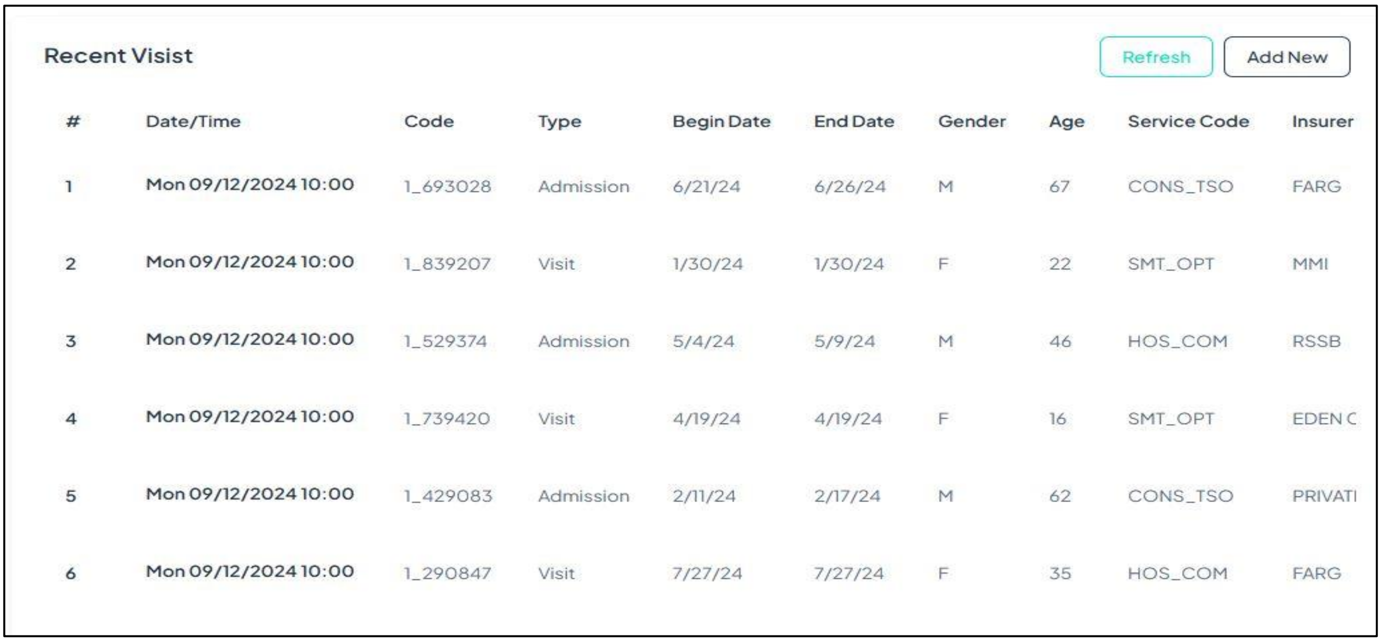


Fig 12 Add Dataset Page

- *Loaded Dataset in the System*



#	Date/Time	Code	Type	Begin Date	End Date	Gender	Age	Service Code	Insurer
1	Mon 09/12/2024 10:00	1_693028	Admission	6/21/24	6/26/24	M	67	CONS_TSO	FARG
2	Mon 09/12/2024 10:00	1_839207	Visit	1/30/24	1/30/24	F	22	SMT_OPT	MMI
3	Mon 09/12/2024 10:00	1_529374	Admission	5/4/24	5/9/24	M	46	HOS_COM	RSSB
4	Mon 09/12/2024 10:00	1_739420	Visit	4/19/24	4/19/24	F	16	SMT_OPT	EDEN C
5	Mon 09/12/2024 10:00	1_429083	Admission	2/11/24	2/17/24	M	62	CONS_TSO	PRIVATI
6	Mon 09/12/2024 10:00	1_290847	Visit	7/27/24	7/27/24	F	35	HOS_COM	FARG

Fig 13 Loaded Dataset in the System

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

- *All Added Visits/Records Page*

  This page illustrates an extensive catalog of patient visits.

Recent Visist

#	Date/Time	Code	Type	Begin Date	End Date	Gender	Age	Service Code	Insurer
1	Mon 09/12/2024 10:00	1_693028	Admission	6/21/24	6/26/24	M	67	CONS_TSO	FARG
2	Mon 09/12/2024 10:00	1_839207	Visit	1/30/24	1/30/24	F	22	SMT_OPT	MMI
3	Mon 09/12/2024 10:00	1_529374	Admission	5/4/24	5/9/24	M	46	HOS_COM	RSSB
4	Mon 09/12/2024 10:00	1_739420	Visit	4/19/24	4/19/24	F	16	SMT_OPT	EDEN C
5	Mon 09/12/2024 10:00	1_429083	Admission	2/11/24	2/17/24	M	62	CONS_TSO	PRIVATI
6	Mon 09/12/2024 10:00	1_290847	Visit	7/27/24	7/27/24	F	35	HOS_COM	FARG
7	Mon 09/12/2024 10:00	1_804729	Admission	6/14/24	6/19/24	M	55	SMT_OPT	MMI
8	Mon 09/12/2024 10:00	1_583729	Visit	5/23/24	5/23/24	F	31	CONS_TSO	RSSB

Fig 14 All Added Visits/Records Page

- *Graphical Representation Of All Added Visits/Records*

  Visits/Graphs page displays patient visit information using charts and graphs.

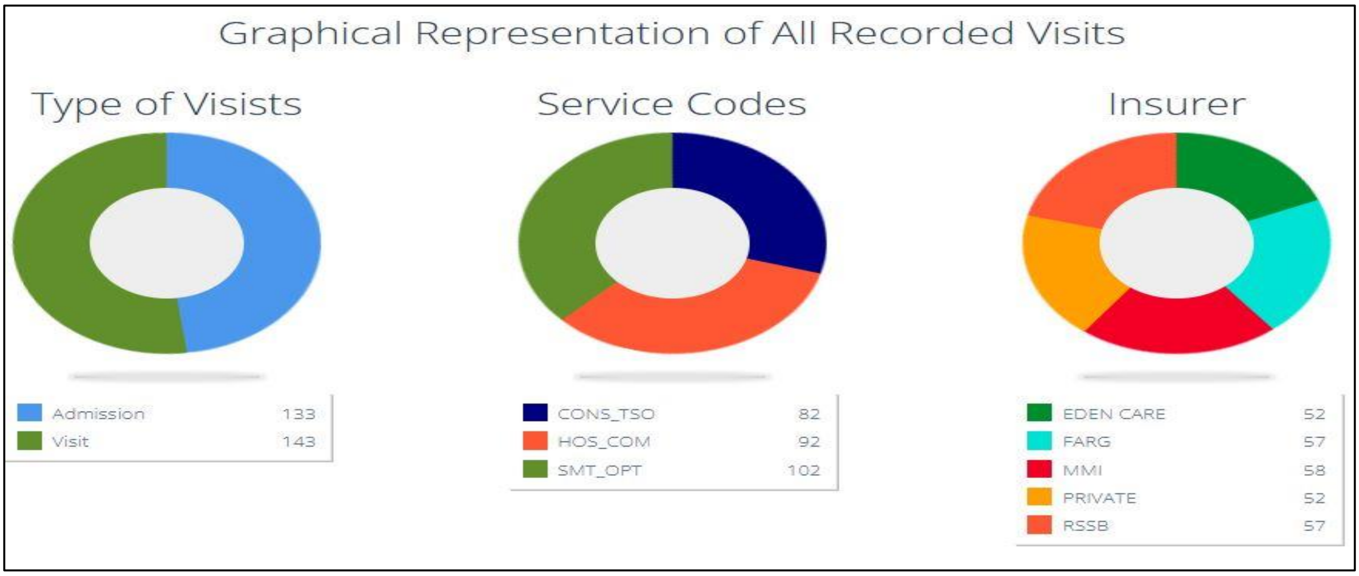


Fig 15 Graphical Representation of All Added Visits/Records

V. RESULTS AND FINDINGS

This page displays anticipated patient arrival trends.

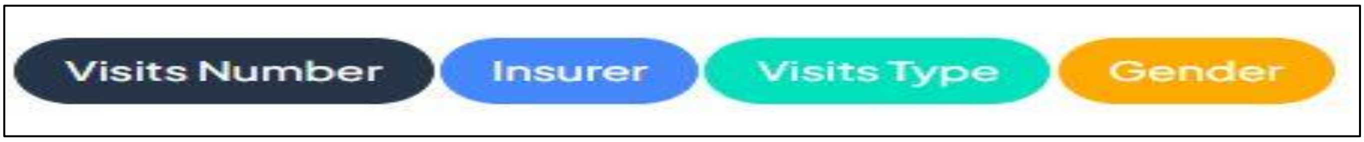


Fig 16 Anticipated Patient Arrival Trends

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

➢ *Prediction By Visit Numbers*

The "Predictions / Visit Numbers" chart shows expected patient visit patterns from 2025 to 2031. The y-axis represents visit counts, and the x-axis shows the years. Visits are projected to increase from 2025 to 2027, peak in 2027, decline until 2029, rise slightly in 2030, and then decrease again in 2031.

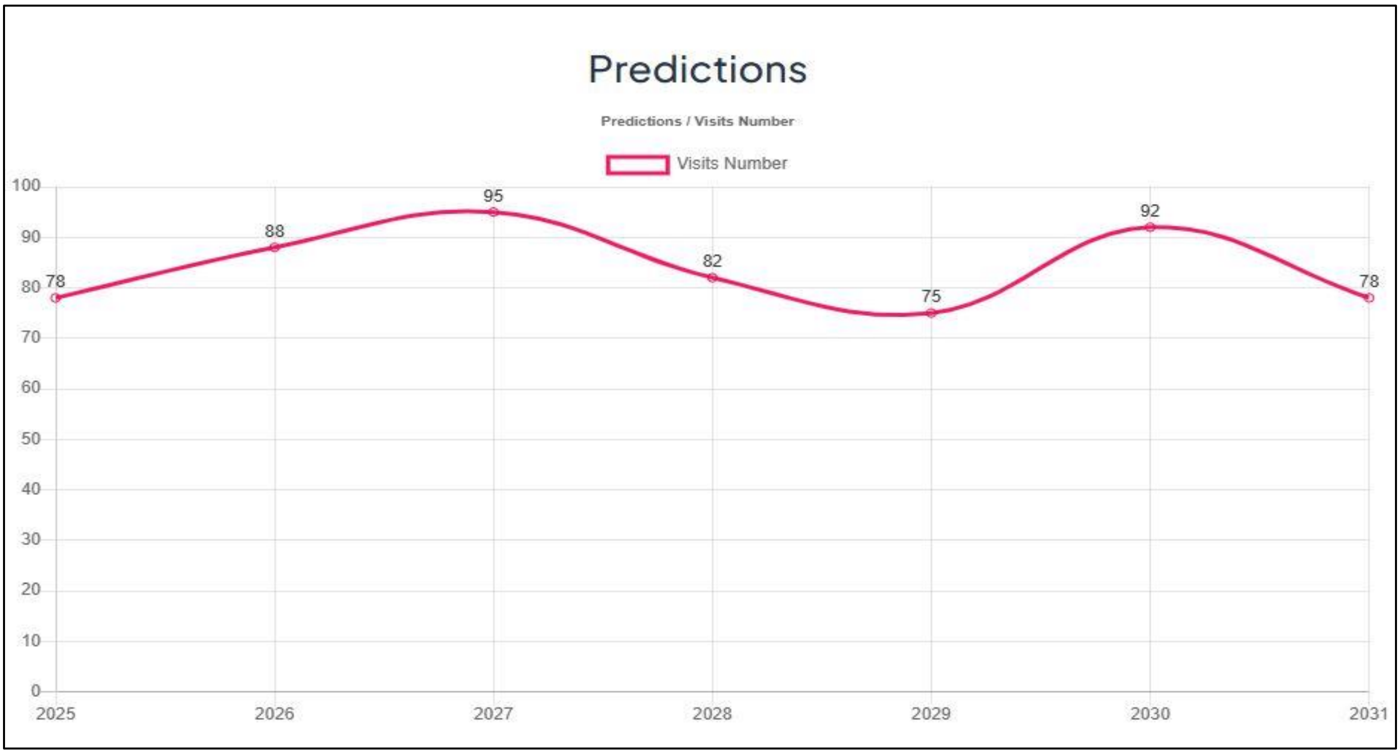


Fig 17 Prediction by Visit Numbers

➢ *Prediction by Insurer*

he "Predictions / Insurer" chart shows projected patient visits from 2025 to 2031, categorized by insurers (FARG, MMI, RSSB, EDEN CARE, and PRIVATE). The y-axis represents visit counts, and the x-axis shows the years. Each line reflects the predicted visit trend for a specific insurer, with varying visit counts and fluctuations. Some insurers predict higher visit numbers, and the lines intersect at different points, indicating distinct growth or decline trends. This chart helps healthcare professionals anticipate patient needs from different insurers.

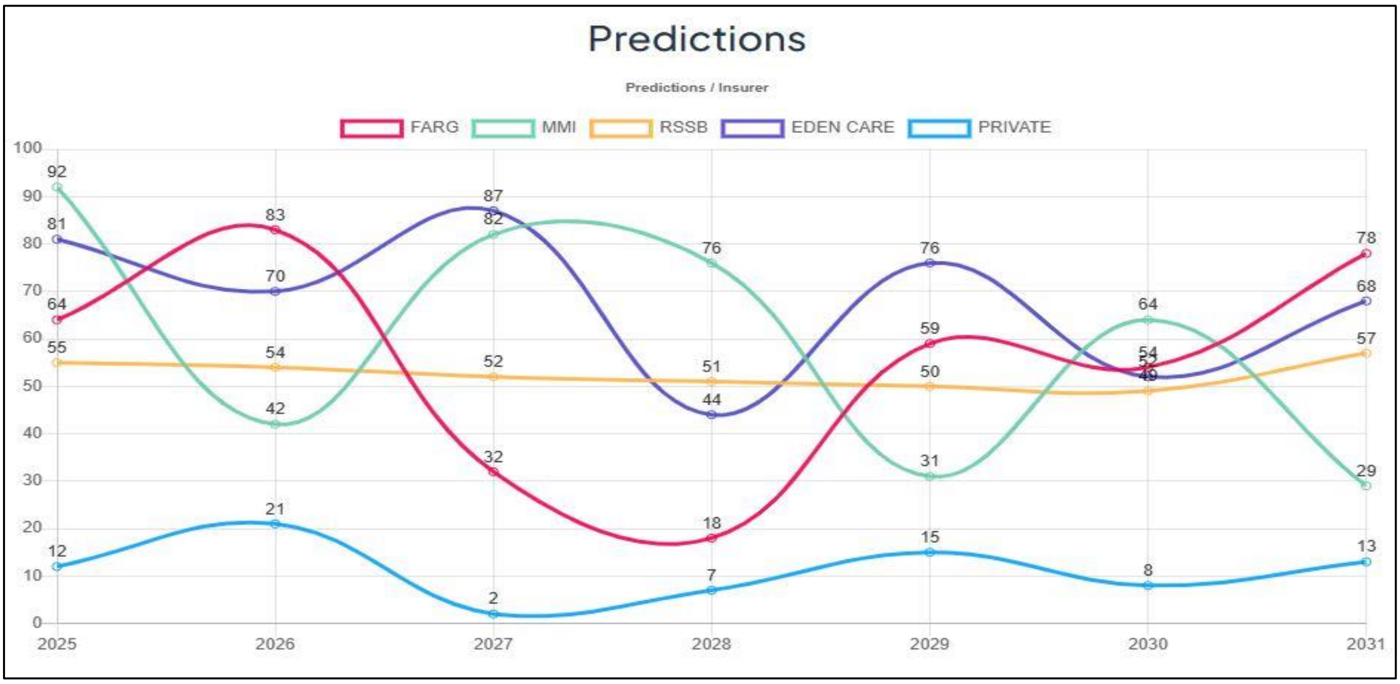


Fig 18 Prediction by Insurer

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

➢ *Prediction by Visit Type*

The "Predictions / Visit Type" chart shows projected patient visits and admissions from 2025 to 2031. The y-axis represents visit counts, and the x-axis shows the years. Each line represents the predicted visit trend, with fluctuations indicating periods of increased or decreased visits. The lines intersect and separate at various points, reflecting changes in visit patterns. This chart helps healthcare professionals forecast future patient visit needs.

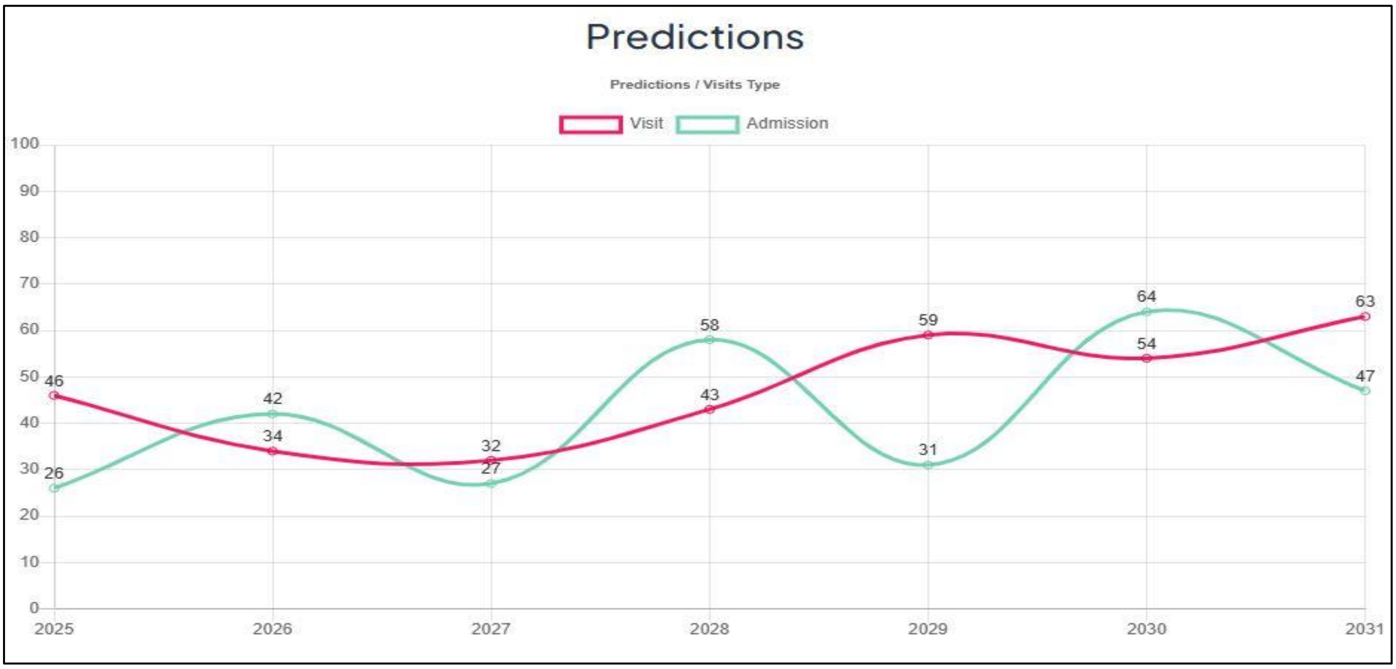


Fig 19 Prediction by Visit Type

➢ *Prediction by Gender*

The "Predictions / Gender" chart shows projected patient visits from 2025 to 2031, separated by gender (Male and Female). The y-axis represents visit counts, and the x-axis shows the years. Each line depicts the forecasted trend for each gender, with female visits generally higher than male visits. The lines fluctuate over time, indicating periods of varying gender-based disparities in visits. This chart helps healthcare providers anticipate future patient needs by gender.

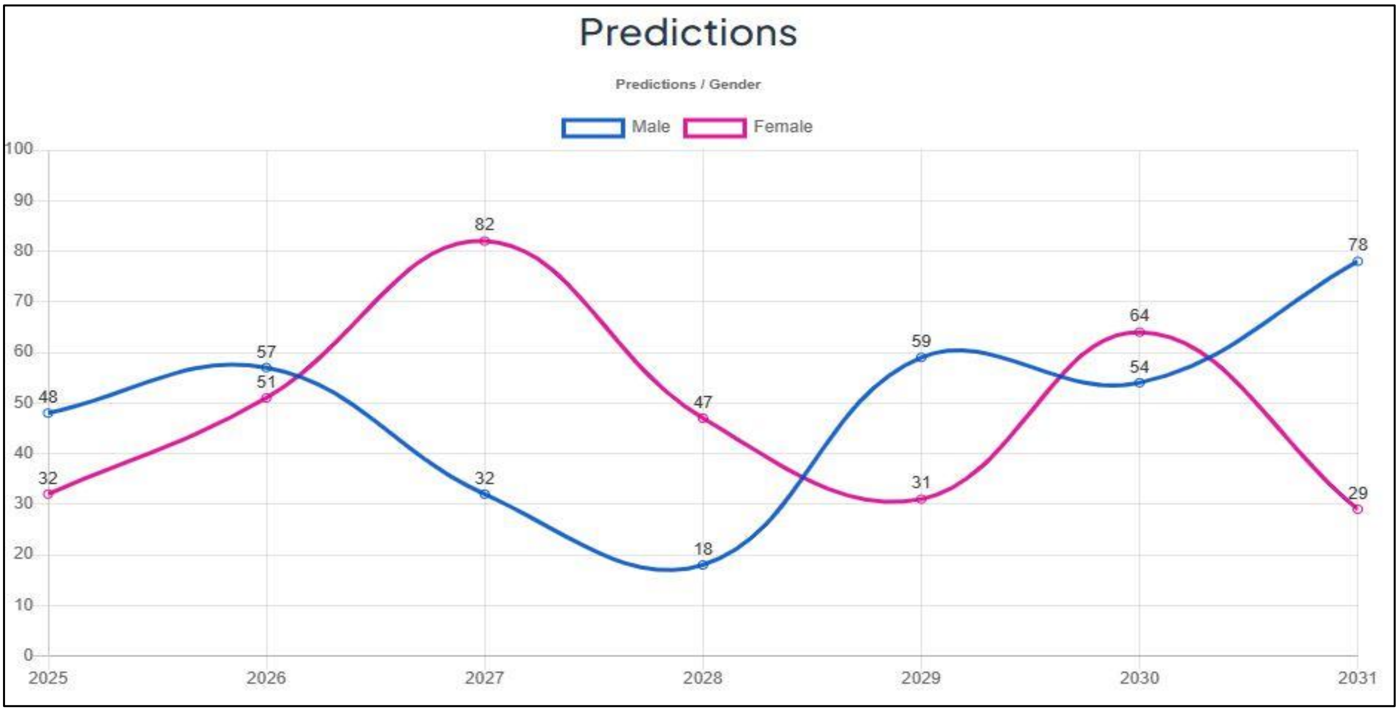


Fig 20 Prediction by Gender

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

➢ *Analysis of Findings*

The charts highlight factors influencing patient trends at RCEH, such as holidays, referral patterns, public health campaigns, new treatments, specialist visits, outbreaks, and weather.

Capacity Planning: Adjust staffing for peak times and reallocate staff during off-peak hours for administrative tasks.

Resource Distribution: Allocate resources based on demand, considering insurer needs, gender-specific services, and visit types (e.g., ICU vs. outpatient).

Workforce Management: Use adaptable workforce strategies and provide staff training to handle diverse patient needs.

Financial Strategy: Budget according to anticipated demand (e.g., flu season) and predict revenue based on historical data to adjust resource allocation.

These strategies help RCEH optimize operations, improve patient care, and make informed decisions for future healthcare demands.

VI. CONCLUSION

The investigation revealed that machine learning techniques can accurately predict patient arrivals at RCEH. Time-based factors, such as season, month, and day of the week, along with special events like holidays and weather, significantly influence patient patterns. By utilizing this predictive model, the hospital can optimize staffing, resource allocation, and overall efficiency.

RECOMMENDATIONS

To enhance the patient arrival predictor, the following suggestions are made:

Data Quality and Quantity: Ensure data accuracy and continuously update it to reflect patient behavior and external factors. Collect more data, including demographics and appointment schedules, to improve accuracy.

Model Refinement: Explore advanced techniques like neural networks and deep learning, and regularly update the model to adapt to new trends and include external factors like economic and public health events.

Model Integration: Develop a user-friendly interface for visualizing predictions and integrate the model into hospital decision-making processes, such as staff scheduling and resource allocation. Regularly assess the model's performance and make necessary adjustments

REFERENCE

[1]. Adobe. (n.d.). *Photoshop: Image editing and design*. Retrieved from https://www.adobe.com/products/photoshop

[2]. Apache Friends. (n.d.). *XAMPP: Apache distribution made easy*. Retrieved from https://www.apachefriends.org

[3]. Araz, O. M., Olson, D., & Ramirez-Nafarrate, A. (2019). Predictive analytics for hospital admissions from the emergency department using triage information. International Journal of Production Economics, 208, 199–207. https://doi.org/10.1016/J.IJPE.2018.11.024

[4]. Automated Machine Learning (AUtOML). (n.d.). Retrieved from https://developers.google.com/machine-learning/crash-course/automl

[5]. Belcic, I., & Stryker, C. (2024b, December 26). Supervised Learning. Retrieved from https://www.ibm.com/think/topics/supervised-learning

[6]. ECMA International. (n.d.). *JSON: JavaScript Object Notation for data exchange*. Retrieved from https://www.ecma-international.org

[7]. GeeksforGeeks. (2024b, March 27). Machine Learning Lifecycle. Retrieved from https://www.geeksforgeeks.org/machine-learning-lifecycle/

[8]. GeeksforGeeks. (2024c, September 4). Reinforcement learning. Retrieved from https://www.geeksforgeeks.org/what-is-reinforcement-learning/

[9]. GeeksforGeeks. (2024h, December 16). Linear Regression in Machine learning. Retrieved from https://www.geeksforgeeks.org/ml-linear-regression/?ref=gcse_outind

[10]. GeeksforGeeks. (n.d.). What is AutoML in Machine Learning? Retrieved from https://www.geeksforgeeks.org/what-is-automl-in-machine-learning/

[11]. Getting Started. (n.d.). Retrieved from https://scikit-learn.org/stable/getting_started.html

[12]. Ibm. (2024b, December 19). Artificial Intelligence. Retrieved from https://www.ibm.com/think/topics/artificial-intelligence

[13]. Ibm. (2024d, December 19). Linear Regression. Retrieved from https://www.ibm.com/think/topics/linear-regression

[14]. Ibm. (2024e, December 19). Unsupervised Learning. Retrieved from https://www.ibm.com/think/topics/unsupervised-learning

[15]. Ibm. (2024h, December 27). Exploratory Data Analysis. Retrieved from https://www.ibm.com/think/topics/exploratory-data-analysis

[16]. Induraj. (2023, February 23). How does L1, and L2 regularization prevent overfitting? *Medium*. Retrieved from https://induraj2020.medium.com

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr226

[17]. International Organization for Standardization (ISO). (n.d.). *Structured Query Language (SQL): A programming language for relational databases*. Retrieved from https://www.iso.org

[18]. Kuo, Y. H., Chan, N. B., Leung, J. M. Y., Meng, H., So, A. M. C., Tsoi, K. K. F., & Graham, C. A. (2020). An Integrated Approach of Machine Learning and Systems Thinking for Waiting Time Prediction in an Emergency Department. International Journal of Medical Informatics, 139, 104143. https://doi.org/10.1016/J.IJMEDINF.2020.104143

[19]. Machine learning. (n.d.). Retrieved from https://www.ibm.com/design/ai/basics/ml/

[20]. Microsoft Corporation. (n.d.). *Microsoft Office*. Retrieved from https://www.microsoft.com

[21]. Miles, J., Turner, J., Jacques, R., Williams, J., & Mason, S. (2020). Using machine-learning risk prediction models to triage the acuity of undifferentiated patients entering the emergency care system: a systematic review. Diagnostic and Prognostic Research 2020 4:1, 4(1), 1–12. https://doi.org/10.1186/S41512-020-00084-1

[22]. Notepad++. (n.d.). *Notepad++: A free source code editor*. Retrieved from https://notepad-plus-plus.org

[23]. Oracle. (n.d.). *JavaScript: The programming language for dynamic web content*. Retrieved from https://www.oracle.com/javascript

[24]. Oracle. (n.d.). *MySQL: The world's most popular open-source database*. Retrieved from https://www.mysql.com

[25]. Performance evaluation metrics for regression models. (n.d.). Retrieved from https://www.researchgate.net/figure/Performance-evaluation-metrics-for-regression-models_fig5_381401914

[26]. Rishabh, P. &. (2020, June 23). 3 types of machine learning. Retrieved from https://www.newtechdojo.com/3-types-of-machine-learning/

[27]. Simplified flowchart describing the difference in traditional ML and autoML approaches. (n.d.). Retrieved January 9, 2025, from https://www.researchgate.net/figure/Simplified-flowchart-describing-the-difference-in-traditional-ML-and-autoML-approaches_fig1_374323075

[28]. The PHP Group. (n.d.). *PHP: A general-purpose scripting language for web development*. Retrieved from https://www.php.net

[29]. Twitter. (n.d.). *Bootstrap: The most popular CSS framework for developing responsive websites*. Retrieved from https://getbootstrap.com