Data-Driven Safety Protocol: Machine Learning Applications in Post-Surgical Care

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Publication Date: 2026/08/10

Abstract:

- ***Background:***

Post-surgical complications play a major role in causing patient morbidity, prolonged hospital stay, and increased healthcare costs. Traditional monitoring systems tend to miss cases of early clinical deterioration because of their dependence on pre-set cut-off values and periodic assessment. On the other hand, machine learning (ML) offers an evidence-based method of increasing the efficiency of postoperative risks prediction and improving patient outcomes.

- ***Objective:***

Machine learning models development and evaluation for predicting post-operative adverse events and proposal of a data driven safety protocol.

- ***Methods:***

A retrospective cohort study that involved the use of clinical, demographic, laboratory, and surgical information related to post-surgery patients hospitalized in Government Cuddalore Medical College and Hospital was conducted. The data were processed and analyzed using Orange Data Mining software. Three classification models based on logistic regression, random forest, and gradient boosting (XGBoost) techniques were constructed and assessed by classification measures (accuracy, precision, recall, F1-score), and ROC curves.

- ***Results:***

ML algorithms proved their ability to detect the presence of adverse events following surgery. Moreover, the ensemble algorithms showed better predictive performance than traditional models. The main predictors included demographic, laboratory, surgical, and comorbidity factors. The predictive models were able to differentiate patients according to their risk of developing complications after surgery.

- ***Conclusion:***

Machine learning algorithms can be used to increase postoperative patient safety by detecting complications before their occurrence and helping clinicians make informed decisions about patient management.

Keywords: *Machine Learning, Post-Surgical Care, Patient Safety, Predictive Analytics, Postoperative Complications, Risk Stratification.*

How to Cite: Lakshminarayanan S.; Gopika Shri G. S.; Dr. Gopalakrishnan G.; Dr. Junior Sundresh N. (2026) Data-Driven Safety Protocol: Machine Learning Applications in Post-Surgical Care . *International Journal of Innovative Science and Research Technology,* 11(7), 3428-3437. https://doi.org/10.38124/ijisrt/26jul1868

I. INTRODUCTION

Postoperative complications continue to be a significant global healthcare challenge, driving up patient morbidity, mortality, hospital stays, and overall medical costs. Even with major leaps in surgical techniques, anesthesia, and perioperative care, a large number of surgical patients worldwide still experience adverse events. With over 313 million surgeries performed every year, it is estimated that complications affect roughly 10–15% of patients—a figure

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

that is often higher in low- and middle-income countries where medical resources are stretched thin [1,2]. Common issues like surgical site infections, respiratory problems, blood clots, acute kidney injury, and unexpected ICU admissions can severely diminish a patient's quality of life and clinical outcomes [3].

To improve patient safety and prevent avoidable harm, it is vital to identify those at risk of deteriorating early on. Traditionally, postoperative monitoring has leaned on standardized observation charts, clinical intuition, and early warning systems like the Modified Early Warning Score (MEWS) or the National Early Warning Score (NEWS) [4]. While these systems are widely used to flag clinical decline and trigger faster care, they have clear drawbacks. They rely on periodic checks rather than continuous monitoring, often fail to account for a patient's unique baseline, and can lack the sensitivity needed to catch the subtle physiological shifts that happen before a crisis [5,6]. As a result, many complications aren't recognized until a patient has already significantly declined.

The shift toward digital healthcare has created a massive influx of data through electronic health records (EHRs), lab systems, bedside monitors, and hospital databases [7]. This wealth of information offers a chance to use advanced analytics to spot complex patterns and predict outcomes. Recently, machine learning (ML)—a subset of artificial intelligence (AI)—has emerged as a powerful tool for clinical prediction and decision support [8]. Unlike standard statistical models, ML algorithms can sift through massive, multi-dimensional datasets, identify non-linear relationships between variables, and get better over time through continuous learning [9].

Research has already shown that machine learning models often outperform traditional risk assessment methods in clinical settings. Techniques such as Logistic Regression, Random Forests, Support Vector Machines, Gradient Boosting, and Artificial Neural Networks have been used successfully to predict mortality, hospital readmissions, long stays, and various postoperative complications [10–12]. For instance, Rajkomar et al. found that deep learning models trained on extensive EHR data could predict mortality and readmission with high accuracy [13]. Similarly, Futoma et al. showed that ML algorithms could detect early signs of sepsis and clinical decline even before traditional monitoring systems flagged them [14].

In the context of surgical patients, machine learning shows great promise in forecasting issues like infections, pulmonary complications, kidney injury, and the need for ICU transfer [15]. Algorithms like Random Forest and Gradient Boosting are particularly useful here because they can manage complex interactions between different clinical variables [16]. Additionally, modern interpretability tools, such as SHapley Additive exPlanations (SHAP), have made these models more transparent by showing exactly how much each predictor influences a result, which helps build clinician trust and encourages real-world use [17].

Moving beyond just accuracy, integrating machine learning into clinical decision support systems (CDSS) allows for the creation of data-driven safety protocols. These protocols pair predictive insights with specific clinical actions, helping providers intervene with high-risk patients before a complication actually occurs [18]. Rather than using a "one-size-fits-all" method, these data-driven approaches allow for personalized risk assessment and adaptive monitoring tailored to each patient's evolving condition. This shift reflects the broader move toward precision medicine and patient-centered care [19].

Government Cuddalore Medical College and Hospital (GCMCH), a tertiary care teaching hospital serving both rural and semi-urban populations in Tamil Nadu, serves as an ideal setting to test these machine learning applications. The hospital handles a high volume of surgical cases and maintains detailed clinical records, including demographics, lab results, surgical details, and postoperative outcomes. This data provides a unique opportunity to build predictive models that are relevant to the specific challenges found in resource-limited healthcare settings.

Consequently, this study aims to develop a data-driven safety protocol for postoperative care by applying machine learning to retrospective clinical and laboratory data from surgical patients at GCMCH. The goal is to evaluate how well these algorithms perform, pinpoint the key risk factors for postoperative complications, and propose a practical framework for risk-based monitoring and clinical intervention. These findings could help enhance patient safety, make better use of available resources, and provide stronger evidence for decision-making in postoperative care.

II. METHODOLOGY

- Study Design: Retrospective cohort Study
- Study site: Government Cuddalore Medical College and Hospital (GCMCH), Chidambaram, Tamil Nadu, India, a tertiary care teaching hospital providing surgical care to a large rural and semi-urban population.
- Study Period: 6 months (November 2024 - April 2025)
- Study tools: Data preprocessing, analysis, and machine learning model development were performed using Orange Data Mining software. Machine learning algorithms including Logistic Regression, Random Forest, and Gradient Boosting Machine (XGBoost) were utilized for predictive modeling.
- Source of data: Data were collected retrospectively from hospital records, including patient demographic information, clinical characteristics, laboratory investigations, surgical details, and postoperative outcomes documented in the surgical wards of GCMCH.

- Study Population: 100 patients

- *Inclusion Criteria:*

✓ Patients admitted to the surgical inpatient wards of GCMCH during the study period.
✓ Age ≥ 18 years.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

- ✓ Surgical patients who have had surgeries within a specified time frame.

- *Exclusion Criteria*

- ✓ Patients admitted solely for outpatient procedures or discharged from the Emergency Department without ward admission.
- ✓ Patients with hospital stays < 24 hours.
- ✓ Records with excessive missing data deemed critical for analysis (e.g., missing outcome variable, majority of predictors missing).
- ✓ Duplicate entries (based on IP number and admission date).

- *Data Collection:*

The primary source of data for this study was a structured dataset provided in a spreadsheet format (Patient Information Form.xlsx), reflecting information typically captured in patient case records or Medical Health Records (MHRs) within the Department of Surgery, GCMCH.

➢ *Data Management and Preprocessing*

The collected data underwent preprocessing before statistical and machine learning analyses. We cleaned the data to fix formatting issues, remove duplicate records, and change variables into the right numerical or categorical formats.

- ✓ Availability of essential data points, including outcome variable (Adverse Events) and key predictors (e.g., age, sex, vitals, basic labs).

We handled missing values using appropriate imputation methods and excluded records with too many missing details from the analysis. We applied feature engineering techniques to create clinically relevant variables, such as the length of hospital stay. Categorical variables were encoded, and we standardized numerical variables as needed to improve model performance. Finally, we split the dataset into training and testing subsets to support model development and evaluation.

➢ *Statistical Analysis*

Descriptive statistics summarized the demographic, clinical, laboratory, and surgical characteristics of the study population. Continuous variables were shown as mean ± standard deviation or median with interquartile range. Categorical variables appeared as frequencies and percentages. To compare patients with and without adverse events, we used independent t-tests or Mann-Whitney U tests for continuous variables and Chi-square or Fisher's exact tests for categorical variables. We conducted binary logistic regression analysis to identify independent predictors of postoperative adverse events. We evaluated the performance of machine learning models using accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) metrics. We carried out statistical analyses using Python (version 3.9) and Orange Data Mining software, considering a p-value <0.05 to be statistically significant.

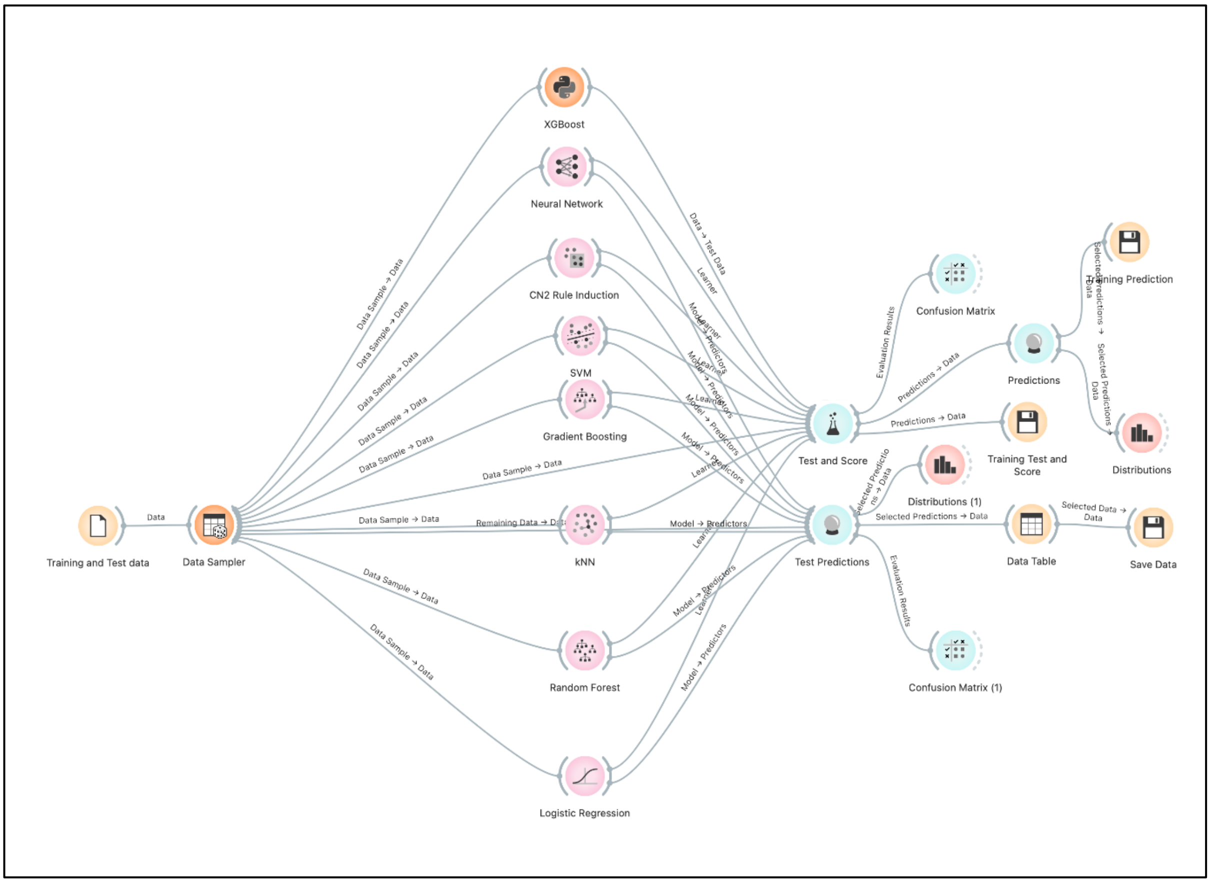

Fig 1 Orange Mining Workflow of Data Cleaning, ML Training and Test for the Surgical Ward Patient Data.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

III. OBSERVATIONS AND RESULTS

➢ *Surgical Patient Data Analysis and ML Prediction Report*

- *Patient Admission and Discharge Trends*

The line chart illustrates monthly admissions and discharges from December 2014 to February 2025. Key observations:

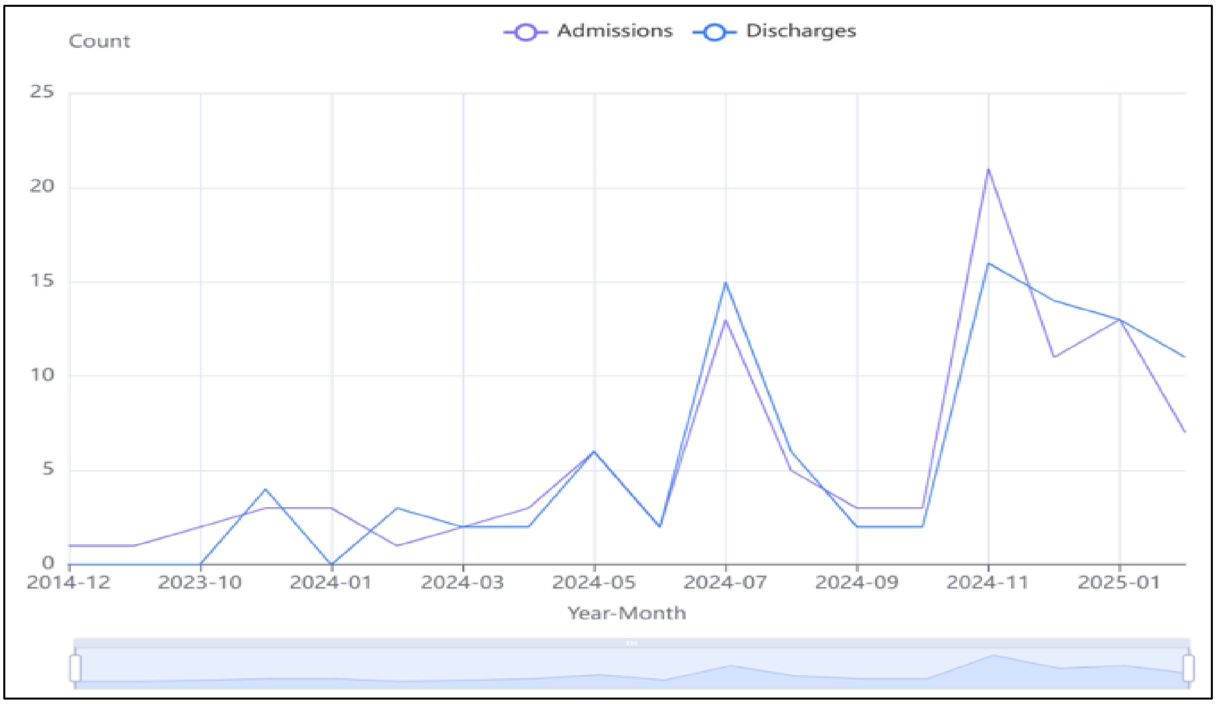

Fig 2 Representation of Patient Admission and Discharge Trends

✓ Seasonal patterns with peaks in both admissions and discharges around July 2024, followed by another significant peak in November 2024
✓ Anomalies in December 2014 and early 2023 showing very low admission and discharge rates
✓ Notably higher peak in November 2024 for admissions compared to other months

- *Age Correlations with Blood Test Results*

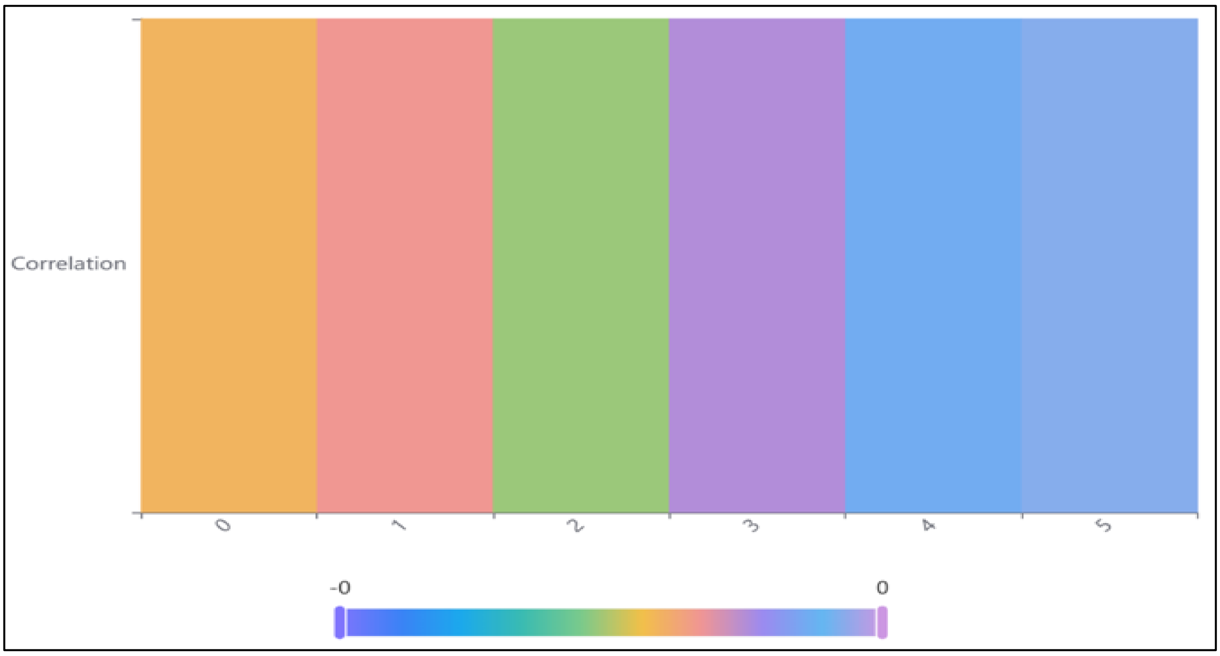

Fig 3 Age vs Blood Test Correlation Heatmap

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

Table 1 Correlation Between Age and Selected Laboratory Parameters

Laboratory parameter	Correlation coefficient(r)	Interpretation
Hemoglobin	0.071	Weak positive
Total count	0.127	Weak positive
Platelet count	-0.024	Very weak negative
Random blood sugar	0.204	Positive
Blood urea	0.288	Positive
Serum creatinine	0.340	Positive

Correlation analysis revealed different correlation levels between age of patients and laboratory values. Serum creatinine had the highest positive correlation coefficient with age (r=0.340), then came blood urea (r=0.288) and random blood sugar (r=0.204). Total count correlated positively with age (r=0.127), whereas hemoglobin correlated poorly positively with age (r=0.071). Platelet count had a slight

- *Blood Test Distribution and Outliers*

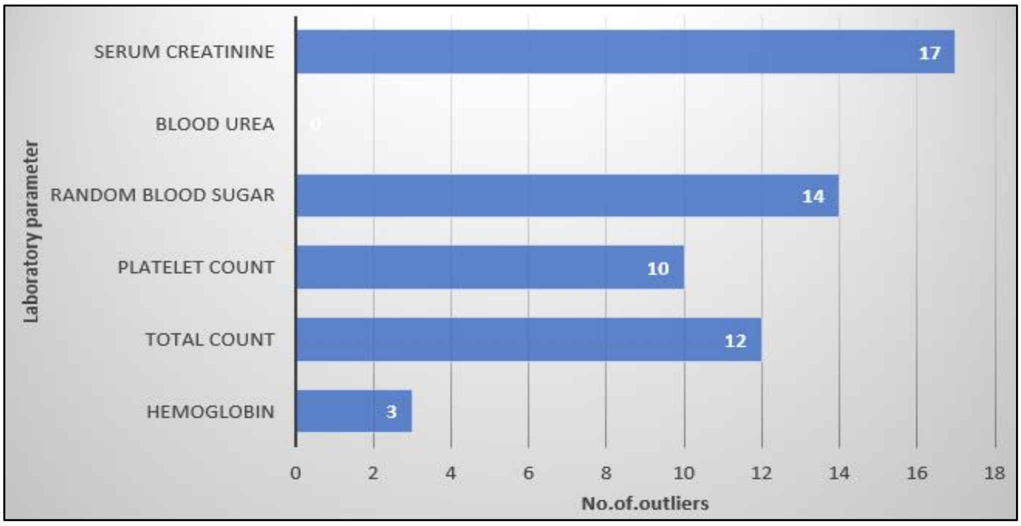

Fig 4 Blood Test Distribution and Outliers

On examination of the laboratory parameters, there was found a lot of variation in the laboratory parameters in the study subjects. The most number of outliers were observed in serum creatinine (n=17) followed by random blood sugar (n=14), total count (n=12), and platelets count (n=10). Hemoglobin had the smallest number of outliers (n=3) and no outliers were seen in blood urea.

➢ *Patient Demographics Distribution*

- *Age Distribution:*

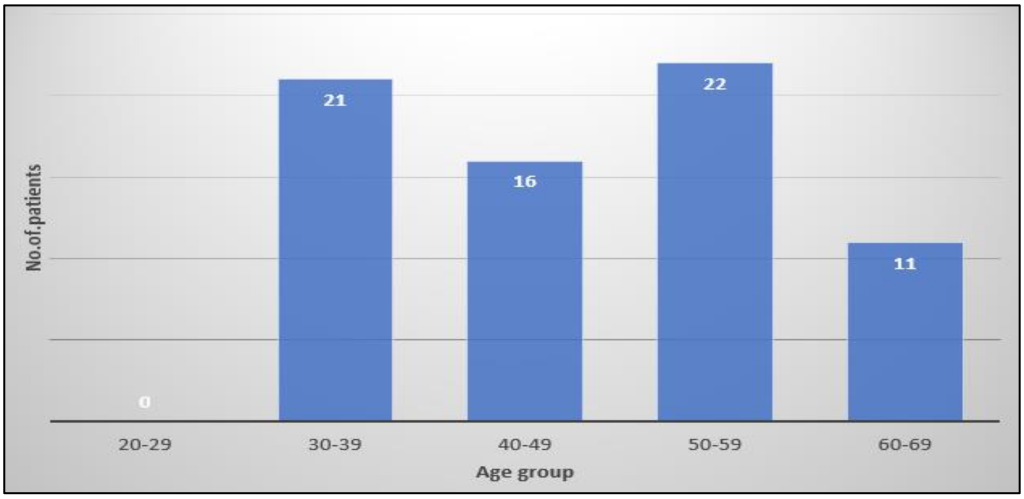

Fig 5 Age-Wise Distribution of the Study Population.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

Age structure of the studied patients revealed that most of the subjects fell within the age bracket of 50-59 years (n=22), followed by those between ages 30-39 (n=21), 40-49 (n=16), and 60-69 (n=11). There were no patients in the age brackets of 0-9, 80-89, and 90-99 years. This indicates higher presence of middle aged patients in the study population.

- *Sex Distribution:*

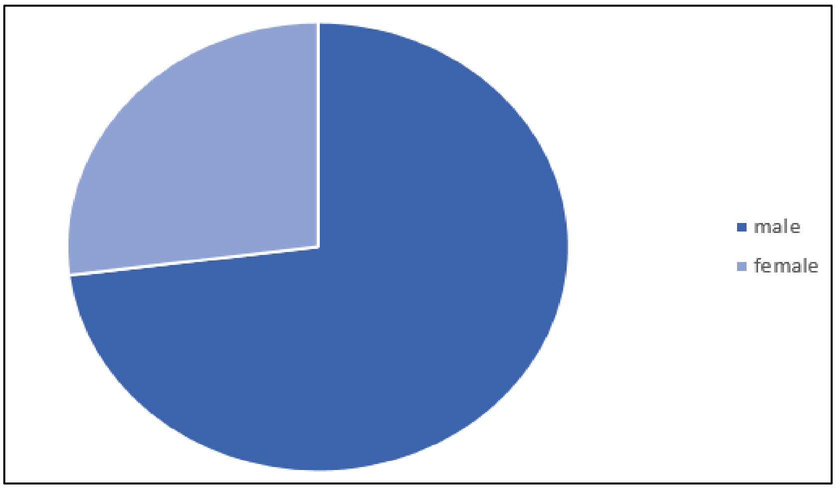

Fig 6 Sex Distribution of the Study Population (n=100).

In the current study, 73 patients out of 100 (73%) were men while 27 patients out of 100 (27%) were women, implying a higher proportion of men in the sample population.

- *Alcohol Consumption and Smoking Habits:*

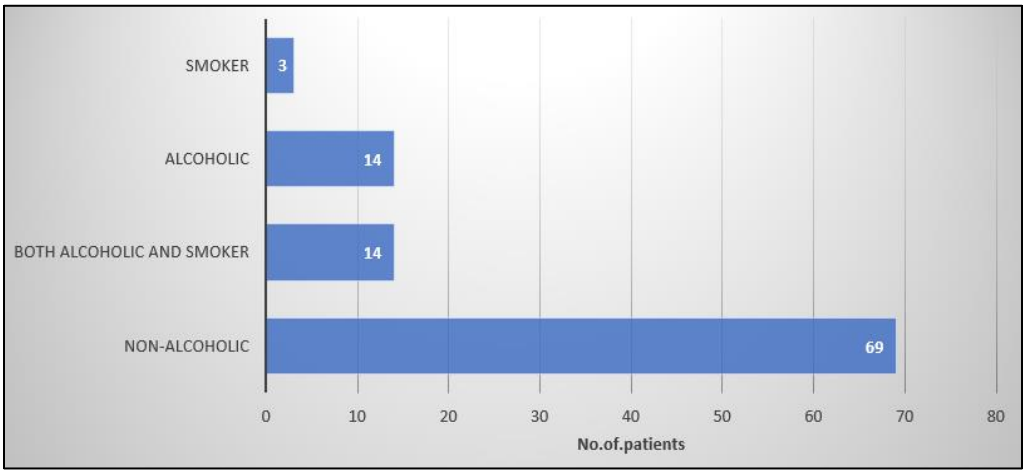

Fig 7 Distribution of Alcohol Consumption and Smoking Habits Among the Study Population (n=100).

Of all the 100 participants, 69 (69%) were non-alcoholics; 14 (14%) were alcoholics; 14 (14%) were both alcoholics and smokers, while 3 (3%) were smokers. Therefore, most of the population under investigation were non-alcoholics.

- *Disease Code Prevalence:*

Table 2 Most Frequently Recorded Disease Codes in the Study Population

Disease code	**Frequency, n**
K40.9	11
K35.8	5
K40.2	4
K35	4

The most common disease code observed was K40.9 (n=11), with the second being K35.8 (n=5). K40.2 and K35 had an equal number of four patients each. The rest of the disease codes were observed with lower frequency, thus illustrating diversity in surgical diagnoses among the subjects.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

➢ *Adverse Events and Post-Surgical Complications*

Table 3 Mean Frequency of Adverse Events and Post-Surgical Complications

Outcome	Status	Mean frequency
Adverse event	False (Absent)	1.94
Adverse event	True (Present)	0.91
Post-surgical complications	False (Absent)	2.54
Post-surgical complications	True (Present)	0.31

When there was an analysis of adverse events and post-operative complications, it was observed that the mean frequency for the absence of post-operative complications (2.54) was higher than the mean frequency for the presence of post-operative complications (0.31). In the same way, the mean frequency for the absence of adverse events (1.94) was higher than the mean frequency for the presence of adverse events (0.91).

➢ *Surgery Trends*

The analysis of the surgical activity carried out every month revealed the presence of variation in terms of the number of operations conducted within this period. The highest number of operations was done in November 2024 when there were 20 operations while the lowest number of operations was done in January with just one operation. Some of the commonly conducted operations include emergency open appendectomy, right inguinal hernioplasty, excision and biopsy, bilateral inguinal hernioplasty, and incision and drainage. This shows that there is diversity in the types of cases operated and most of them are emergency cases and hernia cases.

➢ *Adverse Events and Complications by Sex and Blood Group*

Overall, the mean percentage of adverse event was 19.39% (SD 31.47%), whereas the mean percentage of post-surgery complications was 7.33% (SD 11.91%). The maximum percentage of adverse events was seen in female patients of B +Ve blood group. Also, there was a relatively high percentage of post-surgery complications in female patients of AB +Ve blood group, and there was a good percentage of adverse events in male patients of O +Ve blood group.

➢ *Relationship Between Age, Disease Code, and Length of Stay*

Table 4 Relationship Between Age and Length of Hospital Stay Across Disease Codes

Parameter	Result
Mean correlation coefficient (r)	0.39
SD of correlation coefficient	0.59
Range of correlation coefficients	−0.41 to 1.00
Mean p-value	0.64
SD of p-value	0.33
Range of p-values	0.10 to 1.00

Duration of hospitalization was measured using the difference between the admission date and discharge date. With regards to the different disease codes, there was an average correlation coefficient of $r = 0.39$ (SD = 0.59) between the age of patients and duration of stay. This correlation coefficient varied from −0.41 to 1.00. The average p-value was 0.64 (SD = 0.33). This varied from 0.10 to 1.00. There were no statistically significant relationships, based on the $p<0.05$ criterion.

➢ *Distribution of Patient Length of Stay*

The average number of days spent in the hospital was 6.0 days, while the 25th percentile, 50th percentile, and 75th percentile were all equal to 6.0 days. There were no outliers based on either IQR or 3σ rule criteria. In the subset of individuals where admission and discharge dates were available, the length-of-stay distribution was concentrated at 6 days.

➢ *Machine Learning Model Performance*

- *Model Accuracy*

Table 5 Accuracy Comparison of Machine Learning Models

Model	Accuracy
KNN	0.75
Logistic Regression	0.75
Gradient Boost	0.70
SVM	0.75

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

Model predictions were ranked on the basis of accuracy scores. Accuracy of 0.75 (75%) was obtained from the K-Nearest Neighbors (KNN), Logistic Regression, and Support Vector Machine (SVM) algorithms, which is the best accuracy score recorded among the models evaluated. Accuracy for the Gradient Boosting algorithm was slightly lower at 0.70 (70%). While KNN, Logistic Regression, and SVM had identical overall accuracy scores, this may not sufficiently assess model performance especially in light of imbalanced classes. Consequently, other metrics including precision, recall, and F1 score were taken into consideration to select the most appropriate model for predicting adverse events.

- *Classification Metrics (Positive Class)*

Table 6 Classifications Metrics for Positive Class

Model	Precision	Recall	F1-score
KNN	0.50	0.20	0.29
Logistic Regression	0.50	0.60	0.55
Gradient Boost	0.40	0.40	0.40
SVM	0.00	0.00	0.00

Moreover, the classification ability of the machine learning algorithms was assessed based on precision, recall, and F1-score for the positive class. The best results were achieved by Logistic Regression, which obtained a precision of 0.50, recall of 0.60, and an F1-score of 0.55. KNN achieved the same level of precision (0.50) but had low recall (0.20) and F1-score (0.29). The precision and recall of Gradient Boosting were balanced and amounted to 0.40 each, while its F1-score was equal to 0.40. At the same time, SVM showed precision, recall, and F1-score values equal to 0.00. This means that the algorithm did not recognize positive cases in the data split under consideration.

IV. DISCUSSIONS

The present study aimed to assess the usefulness of machine learning (ML) in terms of establishing post-surgery safety measures based on survey results from 100 patients who underwent surgeries at Government Cuddalore Medical College and Hospital (GCMCH). The study has revealed that the sampled population included a variety of patients in terms of their demographics, laboratory results, type of surgery, and outcomes. It was also found that it is possible to utilize the collected data to build predictive models for identifying potential adverse events. Such information is critical to ensure that post-surgery health outcomes are not compromised as adverse events can lead to significant morbidity, lengthened hospital stays, and overall increased healthcare costs, which is why there is a need to improve the early recognition of such occurrences [1]. The ability to do so is especially crucial for post-surgery patients in low-resource settings where appropriate treatment for adverse events in a timely manner might be unavailable [2].

The sampled population comprised 73% of male and 27% of female patients. The majority of patients were between the ages of 30 – 69, with the highest number falling under the banner of 50 – 59 years. In terms of lifestyle, most patients were ‘non-alcoholic’ (69%), while 14% were ‘alcoholic,’ 14% – ‘tobacco + alcoholic,’ and 3% – ‘tobacco,’ and 3% – ‘alcoholic,’. In terms of diseases, ‘K40.9’ was diagnosed most commonly among the study participants, which can be explained by the fact that the majority of surgeries were performed to treat an inguinal hernia. It is essential to highlight that the demographic data of the patients can affect their likelihood of experiencing a complication, as well as the overall outcome of surgery, while health conditions and the type of interventions also play an important role in this relationship [3]. While conventional methods of early warning score detection are still applicable and effective at recognizing critical events, the complexity of post-surgery care requires further improvements to ensure that patient-specific factors identified by algorithms are also considered [4].

Laboratory results suggested a number of variables, positively related to age, including serum creatinine (r=0.340), blood urea (r=0.288), and random blood sugar (r=0.204). Other parameters, including hemoglobin (r=0.071) and total count (r=0.127), were only weakly correlated, while platelet count, indeed, showed a negative correlation (r=−.024). Therefore, it is essential to consider a combination of factors for a comprehensive understanding of post-surgery recovery. Indeed, a great number of variables can interact in complex ways, making the task of evaluation challenging. Thus, multivariable analysis aiming to take multiple variables into account is more likely to provide accurate prediction of post-surgery outcomes than a single variable analysis [7]. In particular, ML methods seem especially relevant for such tasks due to their ability to identify complex and potentially non-linear patterns in data [8].

The number of surgeries varied greatly between months with the highest number of procedures in November of 2024. In particular, emergency open appendectomy, right inguinal hernioplasty, excision and biopsy, bilateral inguinal hernioplasty, and incision and drainage were the most frequent surgeries. Overall, adverse events averaged 19.39%, compared to 7.33% of complications. The rates differed between male and female patients as well as different blood-group categories. At the same time, it is essential to note that the sample sizes were limited for some categories. Therefore, these findings should be considered preliminary with insufficient data for making any specific conclusions about the influence of sex or blood groups on post-surgery outcomes. Finally, failure-to-rescue research highlights the need for further investigation into the relationship between post-surgery complications and the ability of hospitals to manage them [3]. Individual patient risk assessment, including the analysis of variables mentioned above, may help take timely action.

Length of Stay analysis resulted in a peculiar observation with a mean equal to 6.0 days, while the 25th, 50th, and 75th percentiles also were six days. Besides, the data set did not contain any outliers according to the IQR and 3σ criteria. The mean correlation between age and length of stay for disease codes was 0.39, but individual codes showed a wide range from -0.41 to 1.00, and the mean p-value was 0.64. Thus, there was no significant association between age and length of stay overall. The uniform LOS distribution could indicate a specific pattern of release or the absence of necessary data for more detailed analysis. This point is essential because ML-based methods applied to electronic health records (EHRs) allow to predict length of stay if sufficient data are available [13].

The initial analysis of the predictive models showed that they demonstrated good performance, with KNN, Logistic Regression, and SVM having an accuracy of 75%, while Gradient Boost had an accuracy of 70%. At the same time, considering only accuracy was not enough to choose the best-performing model. Indeed, Logistic Regression showed the best performance in terms of positive-case identification with a precision of 0.50, recall of 0.60, and, consequently, an F1-score of 0.55. Gradient Boost had an F1-score of 0.40, while KNN, despite having a precision of 0.50, had a recall of only 0.20, which resulted in a low F1-score of 0.29. Finally, SVM had accuracy of 75%, but precision, recall, and F1-score were equal to zero. Thus, a model with reasonably good accuracy could have very poor performance in terms of positive-case identification.

The discussed results emphasize the importance of evaluating ML models using various metrics and choosing the best-performing model depending on the task. In this case, Logistic Regression was the best option due to its overall good performance. It is worth noting that the application of ML to EHR data has already demonstrated the ability to identify predictive markers of relevant clinical outcomes [13]. Moreover, the early prediction of critical conditions such as sepsis was also found to be possible using ML technologies [14]. Nevertheless, despite the obvious advantages of ML models, their clinical implementation requires careful consideration and optimization. Thus, predictive models should not burden clinicians with excessive notifications and ensure the accuracy of predictions [17]. Therefore, clinicians' needs should be considered during the development of ML models [19]. Indeed, predictive analytics technologies should be implemented and tested in clinical settings [19], and their performance should be evaluated in terms of clinical outcomes [17].

From an analytical standpoint, the results of the study are compelling because they demonstrate that the appropriate use of data mining can help design a safety protocol that utilizes readily available data to identify patients who require additional post-surgery oversight. The results can be integrated into the existing framework of physician-led protocols. It is essential for the field to remember that AI algorithms should operate as an aid to clinical decision-making [18] and that responsible healthcare ML requires attention to downstream impacts such as patient safety, fairness, transparency, and generalizability [20].

The study has multiple limitations, including the small sample size that was used for model training and testing, a single-center design, and limited variance in the outcome of interest. These factors reduce the study's capacity to generalize its findings to broader populations. Additionally, there is a possibility that the data set lacks crucial predictive features and that the time-dependent nature of the data introduces confounding factors. With these limitations in mind, the results of the study should be considered preliminary proof-of-concept results. Further research should employ multi-center studies, seek to validate the findings in an external and prospective manner, utilize more features and focus on interpretability, and evaluate the performance of the model in real-world settings. These steps are critical before ML-driven predictions can be used as part of a post-surgery safety protocol [19] [20].

V. CONCLUSION

This study highlights the importance of implementing Machine Learning-based data-driven safety mechanisms in order to ensure the best post-surgery patient outcome. The study showed that the best-performing model, which was Logistic Regression, had an accuracy of 75% and the highest F1-score (55%), thus, balancing the precision and recall rates. The analysis also revealed the presence of several influential variables, including patient demographics, laboratory test results, and surgery-related parameters, which may impact the post-surgery outcome. Therefore, despite the limitations of this study, including a small sample size and single-centre design, the analysis can be used as a foundation for future research and development of post-surgery risk prediction systems to improve patient safety.

ABBREVIATION

- AI - Artificial Intelligence
- ML -Machine Learning
- KNN - K-Nearest Neighbors
- SVM - Support Vector Machine
- LR- Logistic Regression
- LOS - Length of Stay
- GCMCH - Government Cuddalore Medical College and Hospital

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ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1868

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