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OrthoMortPred: Predicting one-year mortality following orthopedic hospitalization

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ABSTRACT

Objective: Predicting mortality risk following orthopedic surgery is crucial for informed decision-making and patient care. This study aims to develop and validate a machine learning model for predicting one-year mortality risk after orthopedic hospitalization and to create a personalized risk prediction tool for clinical use.
Methods: We analyzed data from 3,132 patients who underwent orthopedic procedures at the Central Lisbon University Hospital Center from 2021 to 2023. Using the LightGBM algorithm, we developed a predictive model incorporating various clinical and administrative variables. We employed SHAP (SHapley Additive exPlanations) values for model interpretation and created a personalized risk prediction tool for individual patient assessment.
Results: Our model achieved an accuracy of 93% and an area under the ROC curve of 0.93 for predicting one-year mortality. Notably, 'EMERGENCY ADMISSION DATE TIME' emerged as the most influential predictor, followed by age and pre-operative days. The model demonstrated robust performance across different patient subgroups and outperformed traditional statistical methods. The personalized risk prediction tool provides clinicians with real-time, patient-specific risk assessments and insights into contributing factors.
Conclusion: Our study presents a highly accurate model for predicting one-year mortality following orthopedic hospitalization. The significance of 'EMERGENCY ADMISSION DATE TIME' as the primary predictor highlights the importance of admission timing in patient outcomes. The accompanying personalized risk prediction tool offers a practical means of implementing this model in clinical settings, potentially improving risk stratification and patient care in orthopedic practice.

1. Introduction

Predicting the risk of decease is a critical aspect of patient care across various medical disciplines. Early identification of high-risk patients can inform clinical decision-making, resource allocation, and targeted interventions to improve patient outcomes [1]. In recent years, disease prediction models have increasingly incorporated machine learning techniques, nomograms, and electronic health record data. These approaches are now recognized as powerful tools for assessing the predictive value of clinical models [2,3].

Machine learning techniques have increasingly been applied to healthcare data, offering new possibilities for predicting patient outcomes and informing clinical decision-making. In the field of orthopedics, these methods have shown promise in predicting various outcomes, including mortality risk following surgery. For instance, Angraal et al. [4] demonstrated the efficacy of machine learning models in predicting mortality and hospitalization in heart failure patients.

The application of artificial intelligence (AI) in healthcare has expanded rapidly, especially in the context of the COVID-19 pandemic. Vaishya et al. [5] highlighted seven significant applications of AI in addressing the pandemic, including early detection and diagnosis, monitoring treatment, contact tracing, and projection of cases and mortality.

While numerous studies have explored predictive models for mortality followed hospitalization in various medical settings [6,7], such as infectious diseases [8], COVID-19 [9], cardiovascular diseases [3,10,11], and intensive care units [10,12], there is a paucity of research specifically focused on the orthopaedic department [13,14].

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Orthopaedic patients often present with unique challenges and comorbidities, including musculoskeletal injuries, degenerative conditions, and postoperative complications [13]. The development of a robust and accurate prediction model for mortality within one year of orthopedic hospitalization could have significant implications for patient care [13]. Early identification of high-risk patients could prompt timely interventions, such as enhanced monitoring, targeted treatment strategies, or referral to higher levels of care. Additionally, such a model could aid in resource allocation, ensuring that appropriate medical resources are directed toward high-risk patients, potentially improving overall patient outcomes and optimizing healthcare resource utilization [15]. This research aims to address the gap in predicting one-year mortality following orthopedic hospitalization by developing and validating a predictive model tailored to this patient population. By leveraging relevant clinical data and advanced modelling techniques, this study seeks to provide a valuable tool to aid clinicians in identifying high-risk orthopaedic patients and implementing appropriate measures prior to surgery to mitigate the risk of orthopedic hospitalization decease.

2. Methods

2.1. Study design and data source

This retrospective cohort study utilized data from the "CRI_Orthopedic_Traumatology_21_22_23.csv" dataset, which contains records from the Central Lisbon University Hospital Center's CRI-Orthopaedic Traumatology department spanning from 2021 to 2023. The study population comprised 3,132 individuals, consisting of 1,960 males (62.6 %) with a mean age of 76.33 years (SD = 17.64 years) and 1,172 females (37.4 %) with a mean age of 57.35 years (SD = 21.53 years). Mortality was observed in 161 males (8.2 % of the male) and 85 females (7.3 % of the female) (Fig. 1).

2.2. Outcome variable definition

The primary outcome of interest, defined as the target variable, was the risk of decease (Fig. 1). This variable was operationalized to include:

All cases of one-year mortality following orthopedic procedures (one-year follow-up).
All patients with age belonging to the 83th percentile or above.

The inclusion of the latter group in our target variable is justified by the observation that this age group accounted for 18.9 % of all decease cases, representing the highest risk factor among all variables analyzed (Fig. 2).

2.3. Data preprocessing and quality assurance

Columns with almost 100 % null values were identified and removed and with > 50 % null values were manually curated and nan were filled with zeros, while columns with 50 % to 20 % null values were filled with either zeros for object columns or the mean value for numerical columns. For columns with 20 % to 1 % null values, we used the KNNImputer from scikit-learn to impute missing values in numerical columns, and the SimpleImputer was used to impute missing values in categorical columns using the most frequent category. Summary of the original dataset can be accessed in supplementary material (Table S1).

2.4. Feature correlation analysis

To understand which variables are more related to decease, we plotted the correlation of the different variables with the decease variable using seaborn and matplotlib for visualization. We considered variables of interest those that presented a correlation higher or lower than 0.1 or −0.1 (Fig. 4).

2.5. Machine learning model development and evaluation

To ensure a robust evaluation, the data was split into training and test sets with a 70:30 split ratio, utilizing sklearn's train_test_split function with a fixed random state for reproducibility. Furthermore, the SMOTE (Synthetic Minority Over-sampling Technique) algorithm from imblearn package was applied to balance the class distribution in the training set, and data was normalized using sklearn's MinMaxScaler function (Fig. 5).

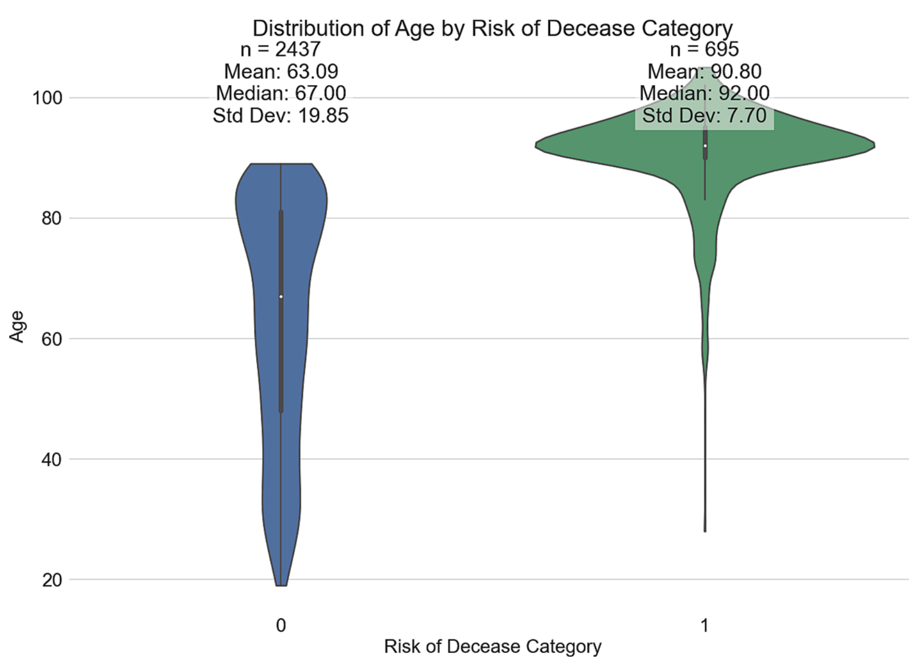


Fig. 1. Figure 1. Distribution of Age by Risk of Decease Category. Violin plot shows the age distribution across risk categories (0 low risk, 1 high risk), with inner boxplots indicating central measures. Descriptive statistics are annotated above each category.

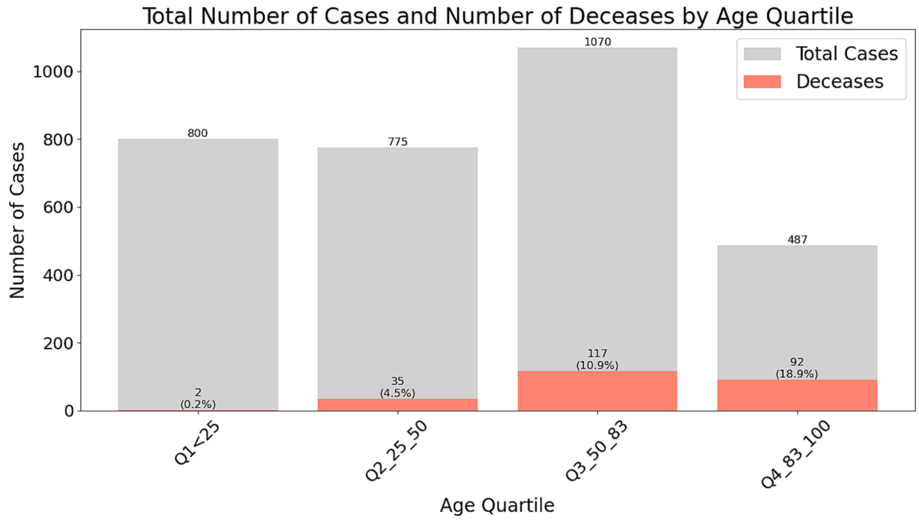


Fig. 2. Figure 2. Total Number of Cases and Number of decease by Age Quartile. The bar chart shows the total number of cases (light grey) and the number of deceases (salmon) within each age quartile. Percentages and number of deceases are annotated above the respective bars.

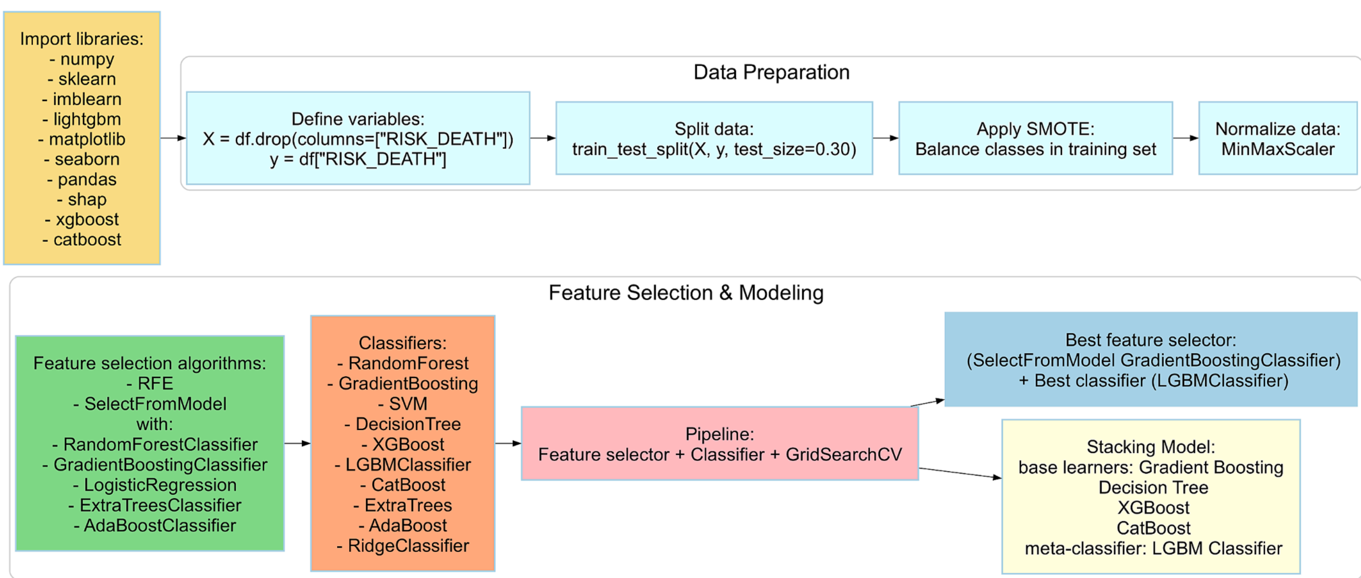


Fig. 3. Figure 3. Data Preparation Flowchart: Steps involved in preparing data for machine learning. Importing necessary libraries, defining variables, splitting the data into training and testing sets, applying SMOTE to balance classes in the training set, and normalizing the data using MinMaxScaler. **Feature Selection & Modeling Flowchart:** flowchart outlines the process of feature selection and model training. Feature selection algorithms (RFE, SelectFromModel with various classifiers), training classifiers, creating a pipeline with feature selectors and classifiers using GridSearchCV, constructing a stacking model with base learners and a meta-classifier, and selecting the best feature selector and classifier.

2.6. *Feature selection and algorithm comparison*

For each combination of feature selector and classifier, we constructed a pipeline using sklearn that first applies the feature selection method and then trains the classifier on the selected features. We found that a model using 11 specific variables achieved comparable accuracy to models with more variables. This finding allowed us to prioritize model simplicity and interpretability without sacrificing performance.

The LightGBM classifier consistently demonstrated superior performance in our specific use case, even outperforming ensemble methods. Detailed comparative analysis of their performance can be found in supplementary table S2. Code used for determining the best combination of feature selector and classifier can be accessed at https://github.com/frpcarvalho/OrthoMortPred/blob/main/OrthoMortPred/code_estimator_classifier.ipynb.

2.7. *Hyperparameter optimization*

For hyperparameter tuning, we employed a grid search approach using sklearn's GridSearchCV. The hyperparameter grid included various combinations of learning_rate (0.01 to 0.2), max_depth (3 to 10), n_estimators (50 to 130), min_child_weight (1 to 4), and num_leaves (10 to 50). The optimal configuration was determined based on the best ROC-AUC score achieved through 5-fold cross-validation. The final hyperparameters selected were learning_rate = 0.8, max_depth = 6, n_estimators = 25, and num_leaves = 20.

Code used for hyperparameter tuning can be found in https://github.com/frpcarvalho/OrthoMortPred/blob/main/OrthoMortPred/Hyperparameter_tuning .ipynb.

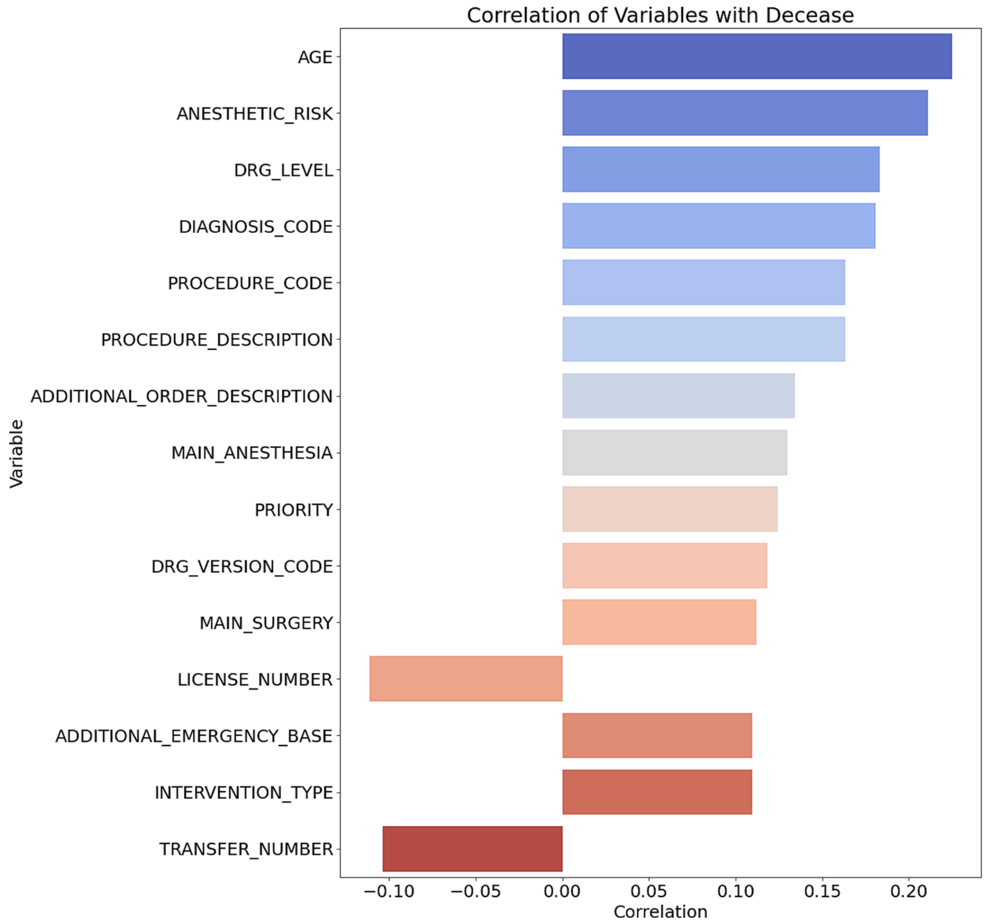


Fig. 4. Figure 4. Correlation of Variables with Decease. Horizontal bar chart illustrates the correlation values between various medical and procedural variables and the outcome of being deceased. Only variables with a correlation coefficient greater than 0.1 or less than -0.1 are included.

2.8. Ensemble modeling: Stacking approach

This ensemble approach combined base learners, such as Gradient Boosting Classifier, Decision Tree Classifier, XGBoost Classifier, and CatBoost Classifier, with a LightGBM Classifier serving as the *meta*-classifier (Fig. 3). Code used for the stacking model can be found in https://github.com/frpcarvalho/OrthoMortPred/blob/main/OrthoMortPred/stacking_model.ipynb.

2.9. Performance metrics and cross-validation

The study employed a comprehensive set of evaluation metrics from sklearn to assess the performance of the developed models. These metrics included the classification report, confusion matrix, and ROC-AUC score. Additionally, 5-fold cross-validation scores were computed to ensure the robustness and generalizability of the models. We used matplotlib and seaborn for visualizing these evaluation metrics (Fig. 5).

2.10. Model interpretation and feature importance analysis

To gain insights into the model's decision-making process, we employed SHAP (SHapley Additive exPlanations) values. The shap library was used to compute and visualize the impact of each feature on the model's predictions, providing a deeper understanding of the factors influencing the risk of decease within one year of orthopaedic surgery (Fig. 7).

2.11. Development of a personalized risk prediction tool

To facilitate the practical application of our predictive model, we developed an interactive risk assessment tool. This tool, implemented as a Python script, allows clinicians to input patient-specific data and obtain a personalized prediction of post-operative mortality risk.

The tool utilizes the trained machine learning model (LightGBM) to calculate a risk score for each patient. Additionally, it employs the SHAP technique to provide a transparent interpretation of the model's predictions. Script for accessing personalized risk prediction tool can be accessed in

https://github.com/frpcarvalho/OrthoMortPred/blob/main/Patient%20Risk%20Prediction_using_SHAP_Values.ipynb.

3. Computational efficiency analysis

In addition to evaluating the predictive performance of our models, we conducted a comprehensive analysis of their computational efficiency. The measurements were conducted over multiple runs to ensure reliability. All experiments were performed on a Mac with an Apple M1 chip and average training, and prediction times can be accessed on supplementary material (table S3).

3.1. Availability of resources

All code used for data preprocessing, analysis, and model development, as well as the anonymized dataset, are available on GitHub at the following repository: https://github.com/frpcarvalho/OrthoMortPred.

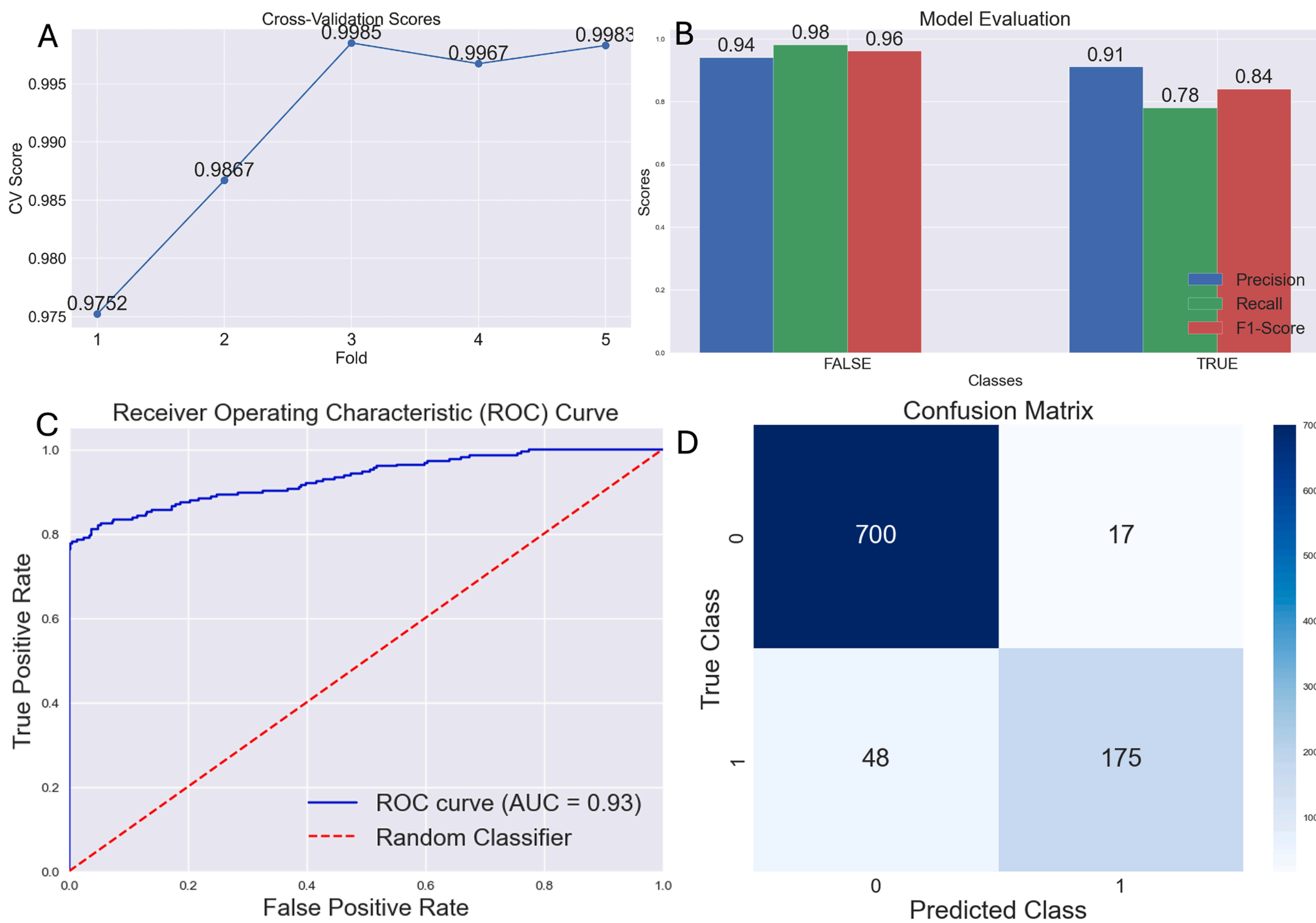


Fig. 5. Figure 5.A Cross-Validation Scores: cross-validation scores across five folds for the classifier ranging from approximately 0.975 to 0.998, indicating stable model performance across different subsets of the data. **B Model Evaluation:** Precision, recall, and F1-score for class 0 (non-deceased) are 0.94, 0.98, and 0.96 and for class 1 (deceased) are 0.91, 0.78, and 0.84, respectively. **C Receiver Operating Characteristic (ROC) Curve:** The AUC-ROC score is 0.93, indicating a high ability of the classifier to distinguish between the positive and negative classes. **D Confusion Matrix:** Heatmap displays the confusion matrix for the classifier LGBMClassifier with the feature selector SelectFromModel_GB. True Negatives (700), False Positives (17), False Negatives (48) and True Positives (175). The overall accuracy of the model is 93%.

4. Results

The study aimed to develop and validate a clinical prediction model for decease within one year of surgery among orthopaedic patients. The cohort characteristics revealed a gender distribution of 62.6 % males and 37.4 % females, with mean ages of 76.33 and 57.35 years, respectively. Mortality rates were similar between genders, with 8.2 % for males and 7.3 % for females. In the feature correlation analysis, age emerged as the strongest predictor of mortality, with a correlation of 0.22. Other variables showing correlations included anaesthesia risk (0.21), GDH level (0.18), and diagnostic code (0.18).

The combination of selector and classifier that produced the best results in this pipeline was the combination of GradientBoostingClassifier and LGBMClassifier. The process of choosing the number of features to be selected and sent to the classifier was done manually, which involved many experiments to determine the best number of features to provide to the classifier. After several attempts, the number of max_features were set to 11. The grid search explored various options for key parameters of our chosen algorithm. After a comprehensive evaluation, the best-performing configuration was identified with the following hyperparameters: learning_rate: 0.8, max_depth: 6, n_estimators: 20, num_leaves: 20. This combination of hyperparameters resulted in the most effective model performance based on our evaluation metrics. The stacking model, which combined multiple base learners including GradientBoostingClassifier, DecisionTreeClassifier, XGBClassifier, and CatBoostClassifier, with LGBMClassifier as the *meta*-classifier, was implemented to potentially improve predictive performance. Despite this sophisticated approach, the stacking model did not outperform the simpler combination of the feature selector (SelectFromModel with GradientBoostingClassifier) and the standalone LGBMClassifier. The LightGBM Classifier, used as an individual model, emerged as the best-performing model, demonstrating high accuracy and stability. The model achieved an overall accuracy of 0.93, with precision and recall of 0.94 and 0.98 for survival (class 0), and 0.91 and 0.78 for mortality (class 1), respectively. These metrics indicate a strong predictive performance, particularly in identifying patients likely to survive. The confusion matrix provided a detailed breakdown of the model's predictions, correctly identifying 700 survival cases and 175 mortality cases, while misclassifying 17 cases as false positives and 48 as false negatives (Fig. 5).

Cross-validation results further supported the model's robustness, with scores ranging from 0.97 to 0.99 across five folds, with a mean CV score of 0.99. This high score suggests that the model's performance is consistent across different subsets of the data, enhancing its generalizability to new patients (Fig. 5).

Feature importance represents the relative contribution of each feature to the performance of a machine learning model. The importance values indicate how influential each feature is for the model's predictions. 'EMERGENCY ADMISSION DATE TIME' with a score of 87 was the most important feature, in the prediction of high and low risk of decease meaning that splits using this feature resulted in substantial improvements. 'AGE' had a score of 82, indicating it is also highly influential in our model prediction. 'PRE OP DAYS' add a score of 54, showing its crucial for the model. The importance score reflects the cumulative contribution of these splits across all trees in the ensemble (Fig. 6).

SHAP values offer in-depth insights into model predictions by quantifying the impact of each feature. The summary plot visualizes this impact, with the color representing the feature value and the x-axis displaying the SHAP value (Fig. 7.B). For instance, the feature "AGE" shows the highest mean SHAP value, highlighting its significant influence on the model's predictions. Fig. 7.A illustrates the SHAP values for a specific instance, revealing how individual features contribute to that prediction. This method aids in interpreting and validating model behavior. In the given example, a 105-year-old patient's high SHAP value for "AGE" indicates that this feature has a strong effect on the prediction of a high risk of death.

Further analysis of mortality rates across various factors in surgical cases revealed some of the patterns cashed by our model (Fig. 8). The distribution of deaths by hour of admission (Fig. 8.A) and total cases by pre-operative days (Fig. 8.C), different surgical procedures (Fig. 8.B), and month of admission (Fig. 8.D) provided additional insights into how these factors correlate with mortality rates.

LightGBM (LGBM) demonstrated a good balance between efficiency and performance. Its training times ranged from 0.23 to 1.60 s depending on the feature selection method, which is competitive considering its high predictive performance (supplementary material S3).

5. Discussion

The present study aimed to develop and validate a clinical prediction model for decease within one year of orthopedic surgery, addressing a significant gap in the literature. Our findings demonstrate that machine learning techniques [16], specifically the LightGBM Classifier, can effectively predict the risk of decease using a set of readily available clinical variables [11]. LightGBM's balance of efficiency and performance supports our decision to focus on this model in our final analysis. Its relatively fast training and prediction times. The model achieved an overall accuracy of 93 %, with an area under the ROC curve of 0.93, indicating excellent discriminative ability. This information can anticipate and contribute to a better management of high-risk patients [9], allowing for more tailored care strategies and resource allocation [17].

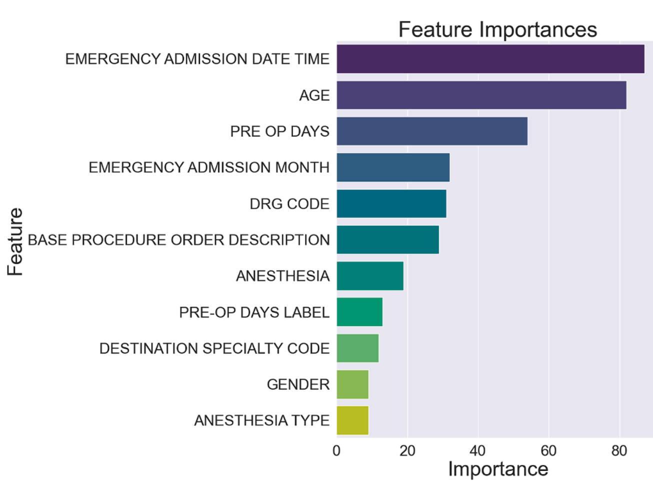
One of the most striking findings of our study is the paramount importance of 'EMERGENCY ADMISSION DATE TIME' as the strongest predictor of mortality risk. This result suggests that the timing of hospital admission may play a crucial role in patient outcomes, possibly reflecting variations in hospital resources, staffing levels, or the severity of the patient's condition upon arrival [18]. The significance of this temporal factor warrants further investigation and may have important implications for hospital resource allocation and staffing strategies[19].

Guttmann et al. [18] found that emergency department presentation during shifts with longer waiting times was associated with increased risk of short-term mortality and hospital admission. Our results suggest that the temporal aspects of admission capture important information about the patient's condition and the healthcare environment.

While not specific to orthopedics, the study by Zheng et al. [11] demonstrated the effectiveness of the LightGBM model in time-to-event prediction analysis for patients with chronic conditions, showcasing the versatility of this machine learning approach across different medical domains.

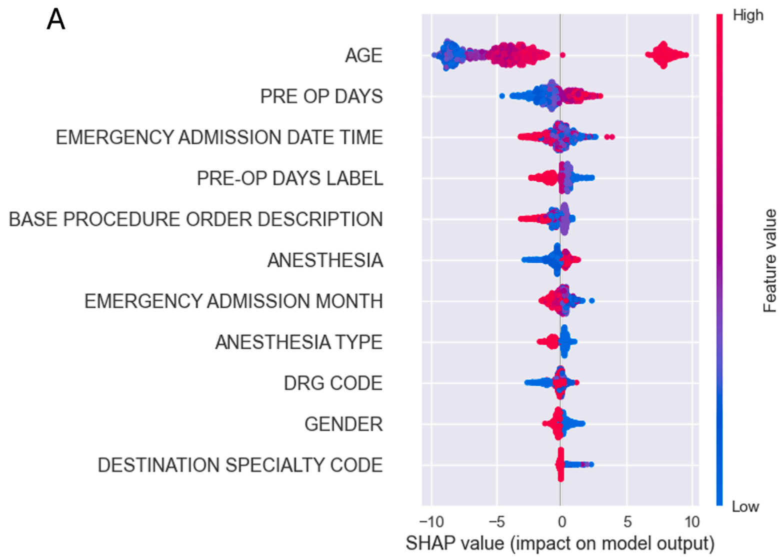
Age emerged as the second most important predictor, corroborating previous research on the impact of advanced age on orthopaedic outcomes [20]. This finding underscores the need for heightened vigilance and potentially more aggressive management strategies in elderly orthopaedic patients. Notably, in the 83rd percentile or higher, the mortality rate reaches 20 % among all patients, which motivated the inclusion of this group (percentile > 83) together with decease patients in our target population. Interestingly, the number of pre-operative days also proved to be a strong predictor of mortality risk. This suggests that delays in surgical intervention may adversely affect patient outcomes and increase mortality [21,22], highlighting the potential benefits of early surgical management in high-risk patients. The developed model has the potential to assist physicians in early identification of high-risk orthopaedic patients, allowing for timely implementation of targeted interventions. Moreover, the identification of pre-operative days as a significant risk factor suggests that strategies to reduce surgical delays could potentially improve patient outcomes.

Our study has limitations that warrant consideration. First, as a single-centre study, the generalizability of our findings to other institutions or healthcare systems may be limited. Second, while we employed advanced imputation techniques to handle missing data, this approach may have introduced some bias into our results. Third, our definition of decease within one year of orthopaedic surgery death risk, which included patients in the 83rd percentile of age or above, may have influenced the results and requires further validation.



Feature	Importance
EMERGENCY ADMISSION DATE TIME	87
AGE	82
PRE-OPERATORY DAYS	54
EMERGENCY ADMISSION MONTH	32
DRG CODE	31
BASE PROCEDURE ORDER DESCRIPTION	29
ANESTHESIA	19
PRE-OP DAYS LABEL	13
DESTINATION SPECIALTY CODE	12
GENDER	9
ANESTHESIA TYPE	9

Fig. 6. Figure 6. Feature importances for the LGBMClassifier model. The most influential features are EMERGENCY ADMISSION DATE TIME, AGE, and PRE-OPERATORY DAYS, with importance scores of 87, 82, and 54 respectively. Other notable features include EMERGENCY ADMISSION MONTH, DRG CODE, and BASE PROCEDURE ORDER DESCRIPTION.



B

Feature	Value	SHAP Value
AGE	105	9,61
PRE OP DAYS	6	-0,72
EMERGENCY ADMISSION DATE TIME	2023-10-28 19:41:21	-0,05
PRE-OP DAYS LABEL	3	-0,13
BASE PROCEDURE ORDER DESCRIPTION	3	-0,05
ANESTHESIA	General	-0,40
EMERGENCY ADMISSION MONTH	10	-0,25
DRG CODE	342	-0,39
GENDER	Male	-0,10

Fig. 7. Figure 7.A SHAP (SHapley Additive exPlanations) Summary Plot: impact of features on model predictions. Each point represents a Shapley value for a feature and an instance, with color indicating the feature value (red high, blue low). Features are ordered by the sum of SHAP value magnitudes across all samples, with the most influential features at the top. **B Individual Patient Case Analysis:**This force plot visualizes the impact of various features on the model's prediction for a specific patient (instance #988). The plot shows how each feature contributes to pushing the model's output from the base value (average prediction) to the final prediction for this individual case. This detailed breakdown helps interpret how different patient characteristics and clinical factors influence the model's decision for this particular case.

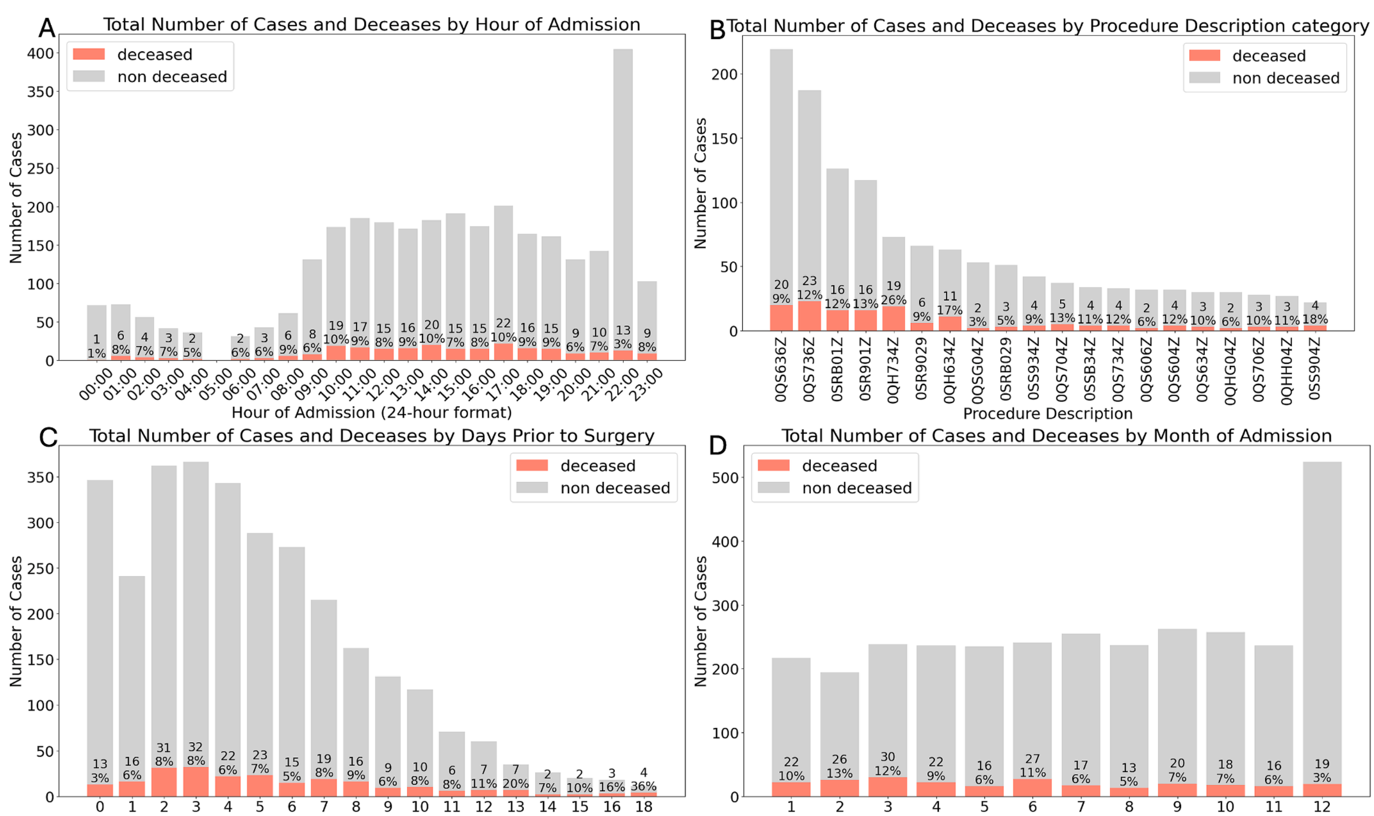


Fig. 8. Figure 8. Comprehensive analysis of mortality rates across factors in surgical cases. **A** distribution of decease and total cases by pre-operative days. **B** different surgical procedures. **C** pre-operative days. **D** month of admission. Red bars represent deceased patients, grey portions show survivors, and labels indicate death counts and percentages. These visualizations provide insights into how factors such as procedure type, and admission timing and period correlate with mortality rates.

The significance of the PROCEDURE DESCRIPTION (according to ICD10), DRG code, BASE PROCEDURE ORDER DESCRIPTION in predicting mortality risk suggests that certain diagnostic categories may be associated with higher risk. For example, the procedure OQH734Z as a mortality rate of 26 %.

The use of SHAP values in our analysis provides valuable insights into the model's decision-making process. This approach allows for a more transparent and interpretable machine learning model [23], which is crucial for building trust and facilitating adoption in clinical settings.

Like previous studies [4], we found that the machine learning algorithms performed exceptionally well in predicting adverse outcomes. This consistency across different medical domains suggests that algorithm may be particularly well-suited to handling the complex, multifaceted nature of medical data.

Also, Angraal et al. [4] noted that health status variables, particularly those derived from the Kansas City Cardiomyopathy Questionnaire, were among the strongest predictors of outcomes in heart failure patients. Similarly, our study identified several patient-reported and clinical variables as key predictors of post-orthopedic surgery mortality. This highlights the value of incorporating a broad range of data types, including patient-reported outcomes, in predictive modeling.

The development of our personalized risk prediction tool represents a significant step towards translating our research findings into practical clinical applications. This approach aligns with the growing trend towards personalized medicine [24,25], enabling tailored interventions based on individual patient profiles.

6. Conclusion

Our study demonstrates the efficacy of machine learning, specifically the LightGBM model, in predicting one-year mortality following orthopedic hospitalization. The development of our personalized risk prediction tool showcases the potential for translating complex models into practical clinical applications.

However, it is crucial to emphasize that while our model demonstrates high predictive accuracy, it should be viewed as a tool to augment, rather than replace, clinical judgment [26]. The complex interplay of factors contributing to mortality within one year of orthopedic surgery necessitates a nuanced approach to patient care that combines predictive analytics with experienced clinical decision-making.

CRediT authorship contribution statement

Filipe Ricardo Carvalho: Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Paulo Jorge Gavaia:** Writing – review & editing, Funding acquisition, Formal analysis. **António Brito Camacho:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijmedinf.2024.105657.

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