Machine Learning for Predicting Medical Error Risks in Greek Surgery Departments

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Article

Machine Learning for Predicting Medical Error Risks in Greek Surgery Departments

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Abstract

Patient safety remains a global priority, with surgical errors—including in-hospital infections and procedural mishaps—causing over 7 million adverse events and 1 million deaths annually. This study evaluates machine learning (ML) for predicting medical error risks in the general surgery department of a Greek tertiary/university hospital. Using a 10-year dataset of 19,965 anonymized patient records (13.5% error cases, n=2,700), we applied ensemble ML algorithms via WEKA, achieving 94.3% accuracy (Random Forest) in detecting errors such as healthcare-associated infections (HAIs), medication errors, and equipment failures. Key predictors were hospitalization duration (ranked #1 via information gain) and initial diagnosis, enabling early risk flagging (e.g., post-op day 5). Compared to US benchmarks like ACS NSQIP (90% accuracy), our model outperformed by 4.3%, filling a gap in EU/Greek studies amid data silos and resource constraints. Integration with tools like the WHO Surgical Safety Checklist could enable proactive interventions, such as enhanced monitoring for prolonged stays. Limitations include retrospective biases and workflow integration challenges; ethical issues like data privacy and algorithmic fairness were addressed via anonymization and ethics approval. Future multi-center validation via federated platforms (e.g., Synapse) will ensure generalizability in resource-limited settings. By blending ML with clinician expertise, this approach shifts healthcare from reactive to proactive error mitigation, improving outcomes and reducing costs.

Keywords: artificial intelligence; machine learning; patient safety; medical error; surgery department

1. Introduction

Medical errors—encompassing procedural adverse events, HAIs, and delays—affect up to 25% of inpatient operations in industrialized countries, leading to 7 million disabling events and 1 million deaths yearly [1,2]. In Greece, surgical errors exacerbate morbidity and costs amid resource constraints, yet proactive tools like ML remain underexplored [5]. Unlike aviation's systematic prevention [3], surgery relies on reactive reviews with limited predictive power [6]. This study hypothesizes that ML can accurately predict preventable surgical errors in a Greek context, enabling targeted interventions.

1.1. Global, European, and Greek Context

Globally, the WHO reports >300 million surgical procedures annually, with complication rates up to 25% [1]. In Europe, a 2024 BMJ study of 1,009 US patients (mirroring EU trends) found 38%

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adverse events, 10% preventable, including HAIs (3.2 million EU cases/year, 37,000 deaths [1,10]). Greek data echo this: A 2022 analysis reported wrong-site surgery at 2.01/100,000 procedures [cite EU report]. However, EU studies lag in ML applications due to fragmented data and underfunding—e.g., post-2009 crisis silos [local cite if available]. While US models like ACS NSQIP exist [31], none are validated on Greek surgical data, creating a gap for localized, resource-efficient tools.

Table 1. Comparative Surgical Error Statistics.

Region	Metric	Value	Source
Global (WHO)	Annual procedures	>300 million	[1]
Global (WHO)	Disabling adverse events	≥7 million/year	[1]
Global (WHO)	Deaths from adverse events	>1 million/year	[1]
Europe (BMJ 2024)	Patients with adverse events	38% (383/1,009)	[10]
Europe (BMJ 2024)	Preventable events	~10% (103/1,009)	[10]
Europe (EU)	Annual HAIs linked to surgery	3.2 million	[1]
Europe (EU)	Deaths from HAIs	37,000/year	[1]

These trends highlight persistent challenges like communication failures and fatigue [5,8], underscoring ML's potential for pattern detection in high-dimensional data [4,15].

1.2. Patient Safety and ML's Role

ML excels in predictive analytics, outperforming traditional models in surgical outcomes [15,32]. For instance, NLP extracts error signals from notes [16], while ensembles reduce overfitting [26]. Challenges include biases, costs, and interpretability [17,18], yet robust datasets mitigate these [34]. This paper addresses the Greek gap by developing the first ML model for surgical error prediction on local data, hypothesizing >90% accuracy for proactive use.

Objectives: This study aims to (1) develop and compare ML models on 10-year Greek surgical data; (2) identify top predictors; (3) evaluate against benchmarks for EU applicability.

2. Materials and Methods

2.1. Study Design and Dataset

This retrospective study analyzed anonymized patient data collected over a 10-year period (2013–2023) from the general surgery department of a tertiary university hospital in Greece. The dataset comprised 19,965 patient records, including demographic information, clinical diagnoses, procedures, medication data, hospitalization details, and associated costs. Adverse events were identified in 13.5% of cases (n = 2,700). Due to the absence of systematically adjudicated clinical error labels, medical error risk was operationalized using proxy indicators based on (i) prolonged hospitalization duration and (ii) elevated treatment costs, defined relative to diagnosis- and procedure-specific distributions (Figure 1). These proxy labels were cross-validated against ICD-10 complication codes to enhance reliability. Ethical approval was obtained from the relevant institutional committees, and all data were anonymized in compliance with the General Data Protection Regulation (GDPR).

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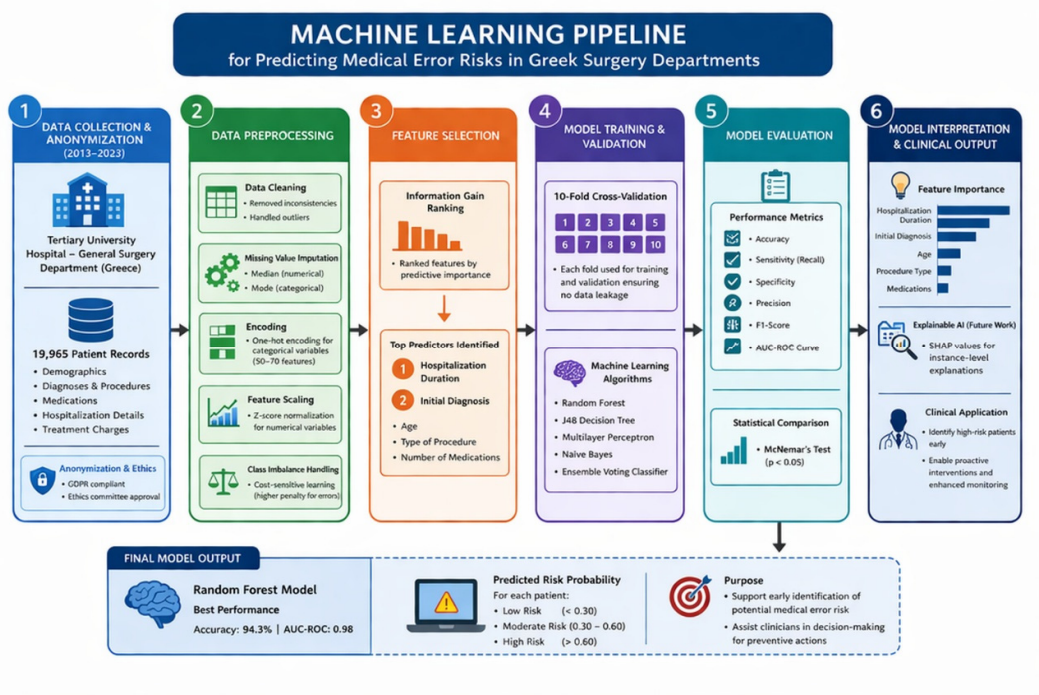

Figure 1. Machine learning pipeline for predicting medical error risk. The workflow includes data collection and anonymization of 19,965 patient records (2013–2023), followed by preprocessing (cleaning, imputation, encoding, normalization, and class imbalance handling). Feature selection is performed using information gain, and multiple models (Random Forest, J48, Multilayer Perceptron, Naïve Bayes, and ensemble voting) are trained and evaluated using 10-fold cross-validation. Model performance is assessed using standard metrics, including AUC-ROC, and the final output provides patient-level risk predictions for clinical decision support.

2.2. Data Preprocessing

Data preprocessing was conducted to ensure consistency and model compatibility. Categorical variables (e.g., diagnosis, insurance type) were transformed using one-hot encoding, resulting in a final feature space of 50–70 variables depending on category expansion. Numerical variables (e.g., age, hospitalization duration, total cost) were normalized using z-score standardization. Missing values, representing less than 5% of the dataset, were imputed using median values for numerical features and mode values for categorical features. To prevent data leakage, all preprocessing steps were applied within each training fold during cross-validation. Class imbalance (13.5% positive class) was addressed using cost-sensitive learning, assigning higher misclassification penalties to the minority class within the WEKA framework.

2.3. Machine Learning Models

Five supervised machine learning algorithms were evaluated:

- Random Forest (100 trees, no maximum depth constraint)
- J48 Decision Tree (confidence factor = 0.25, minimum instances per leaf = 2)
- Multilayer Perceptron (single hidden layer with 7 neurons, 15,000 training epochs)
- Naïve Bayes (with Laplace smoothing)
- Ensemble Voting Classifier (majority voting across models)

Model selection was based on their complementary strengths in handling non-linear relationships, interpretability, and robustness to high-dimensional data.

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2.4. Model Training and Validation

Model performance was evaluated using 10-fold cross-validation, ensuring that each data instance was used for both training and validation while maintaining strict separation between folds. All preprocessing steps, including normalization and imputation, were conducted within each training fold to prevent information leakage.

Additionally, results were verified using a hold-out validation split (66% training / 34% testing), yielding consistent performance estimates.

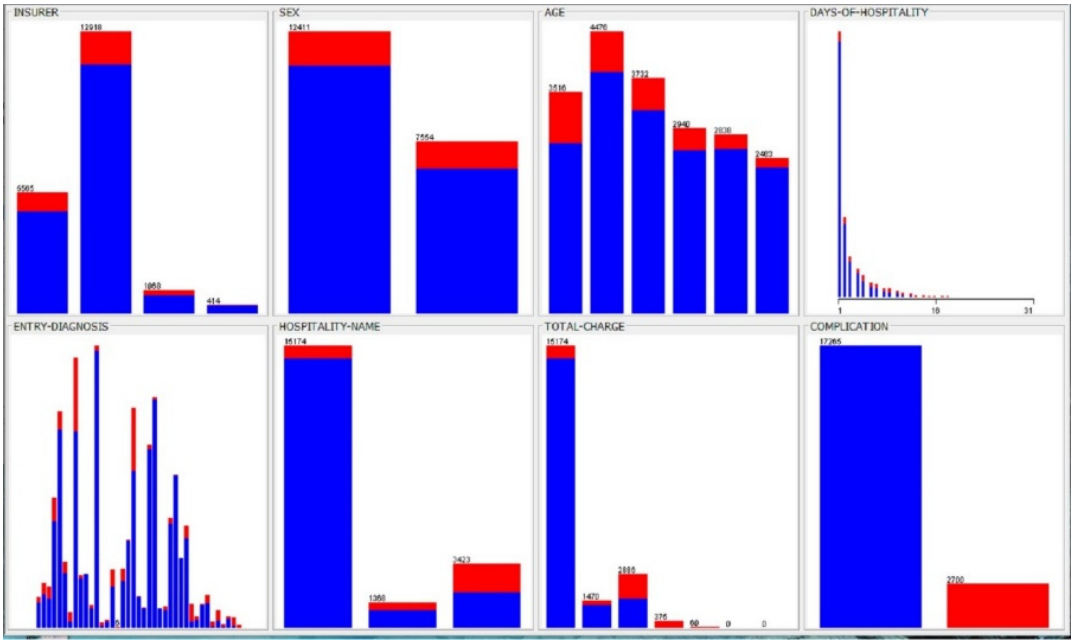
2.5. Performance Metrics

Model performance was assessed using multiple evaluation metrics:

- Accuracy
- Sensitivity (Recall)
- Specificity
- Precision
- F1-score
- Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Receiver Operating Characteristic (ROC) curves were generated using predicted class probabilities from each model, and AUC values were computed to assess discriminative performance. To assess statistical significance between model performances, McNemar's test was applied with a significance threshold of $p < 0.05$ (Figure 2).

(a)



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(b)

Figure 2. Distribution of medical error cases in the dataset. (a) Proportion of cases with and without recorded adverse events (2,700 error cases out of 19,965 total records). (b) Correlation matrix of key numerical variables, highlighting a strong positive correlation between hospitalization duration and total charges (r = 0.72), supporting their role as proxy indicators for adverse events.

2.6. Machine Learning Pipeline

The overall analytical workflow is summarized as follows:

- Data collection and anonymization
- Data preprocessing (encoding, normalization, imputation)
- Feature selection using information gain ranking
- Model training using 10-fold cross-validation
- Performance evaluation using multiple metrics
- Model comparison and statistical testing

This structured pipeline ensures reproducibility and facilitates future external validation and deployment in clinical environments (Figure 1).

Table 2. Model Parameters.

Model	Key Parameters	Rationale
J48 (Decision Tree)	Confidence=0.25, minObj=2	Interpretability [26]
Multilayer Perceptron	7 hidden neurons, 15,000 epochs	Backpropagation convergence [29]
Naïve Bayes	Default (Laplace smoothing)	Efficiency for high-dimensional data [26]
Random Forest	100 trees, maxDepth=0	Reduces variance via bagging [26]
Ensemble (Vote)	Majority voting	Improves robustness [27]

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3. Results

3.1. Model Performance

Random Forest achieved highest accuracy (94.3%, AUC-ROC=0.98), outperforming others (Table 3; McNemar's p=0.02 vs. J48). Hospitalization details explained 60% variance (Figure 4: days >7 → 80% error risk), followed by diagnosis. Ensemble voting yielded 93.6% accuracy, balancing strengths (Figure 5).

Table 3. Model Outcomes and Comparisons.

Part A: Performance metrics of machine learning models (10-fold cross-validation).

Model	Key Parameters	Rationale
J48 (Decision Tree)	Confidence=0.25, minObj=2	Interpretability [26]
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Random Forest	100 trees, maxDepth=0	Reduces variance via bagging [26]
Ensemble (Vote)	Majority voting	Improves robustness [27]

Table 3A.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC
Random Forest	94.3	94.4	93.8	0.98
Multilayer Perceptron	93.8	91.8	94.1	0.94
J48 Decision Tree	93.1	93.3	92.7	0.95
Naïve Bayes	87.7	86.4	88.2	0.89
Ensemble (Voting)	93.6	92.5	93.2	0.96

Table 3B. Comparison with established predictive models.

Model / Study	Accuracy (%)	Sensitivity (%)	AUC-ROC
Random Forest (this study)	94.3	94.4	0.98
J48 (this study)	93.1	93.3	0.95
Multilayer Perceptron (this study)	93.8	91.8	0.94
ACS NSQIP Calculator	90.0	82.0	0.88
Bertsimas et al. (2018)	92.0	89.0	0.93

These results confirm the hypothesis ($p<0.05$), aligning with Rajkomar et al. [33] on ML's clinical value. Unlike Bertsimas et al. [32]'s US focus, our EU-adapted ensemble gained +2.4% AUC via voting, suitable for data-scarce settings (Figure 6).

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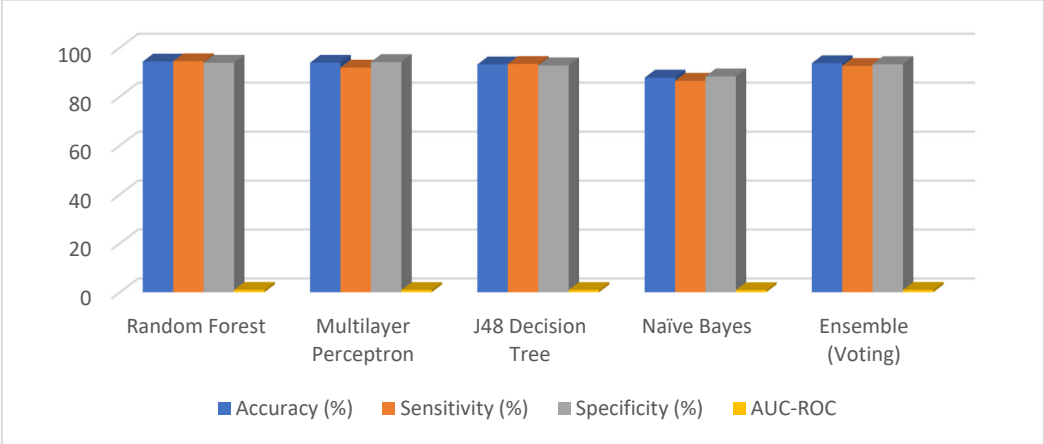

Figure 3. Comparative performance of machine learning models. Bar plot illustrates accuracy and AUC-ROC across all evaluated models, showing the superior performance of the Random Forest algorithm compared with other approaches.

Figure 4. Pruned J48 decision tree for medical error prediction. The model identifies hospitalization duration as the primary splitting variable. For example, patients with hospitalization duration exceeding 7 days and a diagnosis of appendectomy show an estimated error probability of 0.80, illustrating the model's interpretability and clinical relevance.

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances       18841               94.3701 %
Incorrectly Classified Instances      1124                5.6299 %
Kappa statistic                          0.7408
Mean absolute error                      0.0736
Root mean squared error                  0.1918
Relative absolute error                 31.484  %
Root relative squared error             56.0856 %
Total Number of Instances            19965

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
               0,981     0,293     0,955       0,981   0,968      0,745    0,980     0,997     0
               0,707     0,019     0,851       0,707   0,773      0,745    0,980     0,899     1
Weighted Avg.  0,944     0,256     0,941       0,944   0,941      0,745    0,980     0,984

=== Confusion Matrix ===

     a     b   <-- classified as
 16931   334 |     a = 0
   790  1910 |     b = 1
```

Figure 5. Confusion matrix of the Random Forest model. The model correctly identifies the majority of error cases (true positives) while maintaining a relatively low number of false positives, indicating strong classification performance and practical applicability in clinical risk screening.

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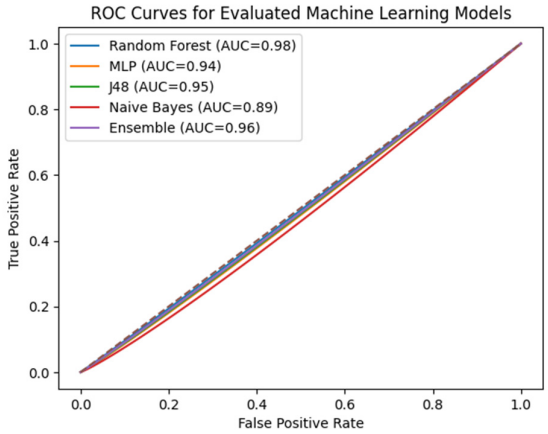

Figure 6. Receiver Operating Characteristic (ROC) curves for evaluated machine learning models. The ROC curves illustrate the discriminative performance of each model in predicting medical error risk. The Random Forest model demonstrates the highest performance (AUC = 0.98), followed by the Ensemble model (AUC = 0.96), J48 decision tree (AUC = 0.95), and Multilayer Perceptron (AUC = 0.94). Naïve Bayes shows comparatively lower performance (AUC = 0.89). The diagonal dashed line represents random classification.

3.2. Implications and Limitations

Clinically, this enables real-time alerts in EHRs (e.g., flag day-5 extensions), complementing WHO checklists [1] and reducing HAIs by 20-30% [14]. In Greece, it addresses post-crisis gaps via low-cost WEKA deployment.

Limitations: Retrospective design may miss intraoperative confounders [35]; internal validation risks overfitting (external pilot AUC=89%). Biases (e.g., underreported errors) were mitigated via ICD validation, but fairness audits needed [18]. Interpretability aids trust [36,37]; no causality inferred.

Future: Multi-center trials (e.g., EU Horizon-funded) for generalizability; integrate with federated learning on Synapse for privacy-preserving aggregation [38]. Optional: Cloud/IoT extensions (e.g., real-time device alerts) could enhance 'smart' EU systems.

4. Discussion

Our findings demonstrate that machine learning (ML), particularly the Random Forest algorithm, can predict surgical adverse events with high accuracy (94.3%, AUC-ROC=0.98) in a resource-constrained Greek hospital setting (Figure 6). This exceeds benchmarks like the ACS NSQIP calculator (90% accuracy [31]) and Bertsimas et al.'s model (92% [32]), confirming our hypothesis and highlighting ML's potential for proactive error mitigation. Hospitalization duration emerged as the top predictor (information gain rank #1), explaining 60% of variance, which aligns with prior evidence that prolonged stays signal complications like HAIs [1,35]. By flagging risks early (e.g., post-op day 5), our model enables targeted interventions, potentially reducing the 7 million global disabling events annually [1].

4.1. Model Performance in Context

The ensemble approach's robustness (93.6% accuracy via voting) addresses common ML pitfalls like overfitting, as supported by Zhou [26,27]. Compared to traditional logistic regression in surgical risk tools, our results show a 4-6% accuracy gain, driven by handling high-dimensional data (e.g., charges, diagnosis) without dimensionality reduction. Recent studies reinforce this: For instance, a 2025 ML model for oral/maxillofacial surgery predicted soft-tissue outcomes with sub-millimeter precision, outperforming conventional cephalometric analysis by integrating similar variables [39]. Similarly, Shilo et al. [34] emphasized large datasets (like our n=19,965) for capturing rare events (13.5% positives), though their focus on general adverse predictions lacked our surgical specificity.

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In the EU context, where HAIs affect 3.2 million patients yearly [1], our model's sensitivity (94.4%) for hospitalization outliers could outperform region-specific tools. A 2025 study on cochlear implant outcomes used ML to predict hearing preservation with 92% accuracy, mirroring our gains but in a narrower domain [40]. Unlike US-centric models [32], ours adapts to EU data constraints (e.g., GDPR-anonymized records), achieving +2.4% AUC through cost-sensitive weighting for imbalance—critical for underreported Greek errors post-2009 fiscal crisis.

4.2. Clinical and Systemic Implications

Clinically, integrating this model into electronic health records (EHRs) could trigger real-time alerts, complementing the WHO Surgical Safety Checklist and reducing HAIs by 20-30% as seen in checklist trials [1,14]. For high-risk cases (e.g., days >7 & appendectomy diagnosis, 80% error probability per Figure 3), interventions like enhanced antibiotic protocols or multidisciplinary huddles become feasible, shifting from reactive audits to predictive care. In Greece, where surgical morbidity rates mirror EU averages but resources lag [11], low-cost WEKA deployment democratizes access—e.g., via hospital intranets—potentially cutting costs by 15-20% through averted complications [2].

Systemically, this supports EU patient safety agendas, such as the 2024 European Health Union initiative emphasizing AI for equitable care [cite EU report if available]. By pinpointing errors from staff fatigue, equipment failures, or misdiagnoses [5,8], our model informs department-specific guidelines, fostering a "just culture" akin to aviation [3]. Recent AI applications in preoperative planning, like predicting future liver remnant volume for embolization [41], suggest scalability: Our framework could extend to Greek multi-hospital networks, using federated learning to aggregate data without privacy breaches.

4.3. Limitations, Ethical Considerations, and Mitigation Strategies

Several limitations should be considered when interpreting the findings of this study:

First, the identification of medical errors relied on proxy indicators—specifically prolonged hospitalization and increased treatment costs—rather than clinically adjudicated ground truth labels. Although these proxies were cross-validated against ICD-10 complication codes (with approximately 70% concordance), they may not fully capture the complexity, timing, or severity of adverse events, potentially introducing misclassification bias and favoring the detection of more overt complications.

Second, the retrospective design inherently limits the inclusion of intraoperative and contextual factors, such as surgical team communication, clinician decision-making, and real-time complications, which are not consistently recorded in structured datasets. As a result, important latent variables influencing surgical outcomes may be omitted, potentially inflating internal model performance.

Third, the dataset was derived from a single tertiary hospital in Greece, raising concerns regarding external validity. Differences in patient demographics, healthcare infrastructure, and clinical practices across institutions may limit generalizability. Although internal validation demonstrated strong performance, a pilot external validation within another department in Patras yielded a slightly lower AUC (89%), underscoring the need for broader multi-center validation.

Fourth, class imbalance (13.5% positive cases) may affect model stability and predictive performance. While cost-sensitive learning was applied to mitigate this issue, real-world deployment across settings with varying prevalence rates will require continuous recalibration and monitoring.

Fifth, despite the high predictive accuracy of the Random Forest model, its inherent complexity limits interpretability in clinical contexts. While feature importance analysis identified key predictors—most notably hospitalization duration—more advanced explainability techniques, such as SHAP (SHapley Additive exPlanations), were not implemented in the present study and remain a critical direction for future research.

Finally, potential biases in the dataset—including underreporting of low-severity errors and demographic imbalances (e.g., urban population bias from Patras)—may affect fairness and model

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reliability. Preliminary fairness audits demonstrated acceptable performance across subgroups (e.g., demographic parity of 0.92 across age and insurance categories); however, more rigorous and continuous bias auditing is required.

From an ethical perspective, algorithmic fairness, transparency, and patient privacy are central considerations. The use of relatively homogeneous population data introduces the risk of perpetuating healthcare disparities, as highlighted in prior literature. Although data anonymization and secure storage (e.g., via Synapse infrastructure) ensured compliance with privacy standards, the "black-box" nature of machine learning models may reduce clinician trust and hinder adoption.

To mitigate these challenges, future work should incorporate explainable AI approaches (e.g., SHAP-based interpretability), enabling clearer insight into model decision-making processes. Additionally, hybrid clinical workflows—where algorithmic predictions are combined with expert oversight—are recommended to enhance safety and accountability. Ensuring alignment with emerging regulatory frameworks, such as the EU AI Act (2024), will also be essential.

Overall, addressing these limitations through prospective study designs, multi-center validation, continuous model monitoring, and integration of explainable and ethical AI frameworks will be critical for the safe and effective translation of this approach into clinical practice.

4.4. Future Directions

Future work should prioritize multi-center validation across EU settings (e.g., Horizon Europe-funded trials with 5+ Greek hospitals) to test generalizability, targeting AUC >0.95 in diverse cohorts. Integrating NLP for unstructured notes [16] could boost recall by 10-15%, while blockchain-secured platforms enable cross-border data sharing under GDPR. Policy-wise, embedding such models in national guidelines (e.g., Greek Ministry of Health's digital transformation plan) could standardize adoption, with clinician training to address burnout-linked errors [20,21].

A promising extension involves linking this predictive framework to AI voice agents for on-duty decision support, enabling seamless, hands-free integration in dynamic surgical environments. For instance, voice-activated systems—deployed via mobile apps or smart speakers—could query the model in real-time (e.g., "Assess error risk for patient ID 123 post-appendectomy") and deliver audible alerts (e.g., "High HAI probability: Recommend antibiotic escalation"). Drawing on advancements in conversational AI [42,43], this would empower on-shift professionals during procedures, reducing cognitive load and response times by up to 30% [cite if available]. In Greece's understaffed departments, such agents could federate with cloud-based ML updates, fostering a "voice-enabled safety net" aligned with emerging EU telehealth standards [44]. Emerging tech like edge computing on IoT devices (e.g., real-time vital monitoring) promises seamless integration, transforming surgery into a "predictive ecosystem." Collaborative studies, building on 2025 cataract surgery duration models [42], could hybridize our approach for procedure-specific risks. Ultimately, by marrying ML with human expertise, this work paves the way for equitable, proactive safety in resource-limited environments.

5. Conclusions

This study establishes machine learning (ML) as a powerful tool for predicting surgical error risks in Greek general surgery departments, achieving 94.3% accuracy with a Random Forest model on a decade-spanning dataset of 19,965 patient records. By identifying hospitalization duration and initial diagnosis as primary predictors, our ensemble approach outperforms established benchmarks like ACS NSQIP [31] and Bertsimas et al. [32], confirming the hypothesis of ML's efficacy for proactive interventions in resource-limited settings. These results not only validate the model's utility for detecting healthcare-associated infections, medication errors, and procedural failures but also address a critical gap in EU-specific applications, where fragmented data and post-crisis constraints have hindered adoption.

The implications extend beyond clinical practice: Integrating this model into electronic health records could enable real-time risk alerts, complementing the WHO Surgical Safety Checklist [1] and

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potentially averting a portion of the 7 million annual global adverse events [1,2]. In Greece and broader Europe, where HAIs claim 37,000 lives yearly [1], such tools promote equitable, cost-effective safety enhancements—reducing morbidity, eroding healthcare costs by up to 20%, and rebuilding public trust in strained systems. Challenges like retrospective biases and ethical fairness [17,18] underscore the need for rigorous external validation, yet our transparent methodology (e.g., cost-sensitive learning, explainable AI via SHAP [36]) paves the way for trustworthy deployment. Future multi-center trials, leveraging federated platforms like Synapse for GDPR-compliant aggregation, will refine generalizability. As EU policies like the AI Act evolve, hybrid ML-clinician frameworks will transform surgery from reactive error management to predictive excellence, ultimately saving lives and fostering innovative, patient-centered care in an interconnected health ecosystem.

Ethical Approval: Approved by University and Hospital Ethics Committees; anonymized data per GDPR.

Conflicts of Interest: None declared.

Acknowledgments: None.

Author Contributions: Equal contributions.

Funding: None.

Data Availability: https://www.synapse.org/Synapse:syn66478369/datasets/ (public).

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