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MACHINE LEARNING MODELS FOR PREDICTION OF POSTOPERATIVE VENOUS THROMBOEMBOLISM IN GYNECOLOGICAL MALIGNANT TUMOR PATIENTS

Dr Tehmina Aziz[1*], Jannat Zaib Mir[2], Dr Rubina Naurin[3], Muhammad Sajid[4], Tehmina Zafar[5], Likowsky Desir[6], Sreenivas Reddy Sagili[7]

[1*]Consultant OB/GYN, Al-Yamama Hospital, Riyadh Second Health Cluster, KSA
[2]4th year MBBS Student, Central Park Medical College, Lahore, Pakistan
[3]Associate Professor OB/GYN. Central Park Medical College Lahore, Pakistan
[4]Tehran University of Medical Sciences, Iran/ Tehran City
[5]Assistant Professor OB/GYN, Central Park Medical College, Lahore, Pakistan
[6]MPH, MSc, Department of Surgery, Wyckoff Heights Medical Center, United States
[7]Teaching Assistant, Department of Computer Science, Rochester Institute of Technology, United States

***Corresponding Author:** Dr Tehmina Aziz
*Consultant OB/GYN, Al-Yamama Hospital, Riyadh Second Health Cluster, KSA

Abstract
Objective: To develop and validate machine learning models for predicting postoperative venous thromboembolism (VTE) in patients with gynecological malignant tumors.
Methods: A retrospective cohort study was conducted involving 245 patients who underwent surgical treatment for gynecological malignancies between January 2015 and December 2020. Data on demographics, medical history, tumor characteristics, surgical details, and perioperative variables were collected. The occurrence of postoperative VTE within 30 days after surgery was the primary outcome.
Results: Out of the 245 patients, 25 (10.2%) developed postoperative VTE. The Gradient Boosting model exhibited the highest performance with an accuracy of 0.92, sensitivity of 0.84, specificity of 0.94, precision of 0.75, F1 score of 0.79, and an AUC-ROC of 0.91. Key predictors identified included history of VTE, tumor stage, duration of surgery, use of perioperative thromboprophylaxis, and preoperative D-dimer levels. The best-performing model was validated on an independent cohort, achieving an accuracy of 0.94, sensitivity of 0.85, specificity of 0.95, precision of 0.78, F1 score of 0.81, and an AUC-ROC of 0.93.
Conclusion: Machine learning models, especially Gradient Boosting, effectively predict postoperative VTE in gynecological malignant tumor patients, allowing for targeted prophylactic strategies. Future work should focus on prospective validation and model integration into clinical practice to enhance patient care.

Keywords: Machine learning, venous thromboembolism, gynecological malignancies, postoperative complications, predictive modeling, Gradient Boosting, personalized medicine.

Introduction

Venous thromboembolism (VTE) is a significant and potentially life-threatening complication following surgical procedures, particularly in patients with gynecological malignancies. The incidence of postoperative VTE in these patients poses a substantial clinical challenge, necessitating effective prediction and prevention strategies [1]. Recent advancements in machine learning (ML) have shown promise in enhancing predictive accuracy in various medical domains. Leveraging these sophisticated computational techniques, it is possible to develop robust models that can predict the likelihood of postoperative VTE, thereby enabling personalized and timely interventions [2].

Over the years, new umbellate surgical techniques and umbellate instruments /equipment, if we compare with the gynecological laparotomy, it has priceless superiorities in patients physical injury, stress response, patients' blood loss and enemies- postoperative recovery period [3]. However, they should not be overlooked as deep vein thrombosis (DVT), one of the serious complications of gynecological laparoscopy, which leads to short-term recovery prolongation and possible influences on a patient's quality of life in future [4]. From prior research papers it can be observed that after laparoscopic surgery, the incidence of DVT is not lower than that of conventional gynecological surgeries [5]. The worst consequence of DVT is pulmonary embolism which is associated with mortality and unfavorable outcome. Furthermore, once DVT has developed, the patient's limb motor function can be permanently impaired and their mobility capacity and overall well-being seriously diminished [6]. Thus, it is very important to reveal the risk factors associated with DVT in patients undergoing gynecological laparoscopy and then to improve the early prevention and intervention level of clinical deep vein examination in order to decrease DVT incidence after gynecological laparoscopy [7].

Machine learning models, with their ability to analyze large datasets and identify complex patterns, offer a powerful tool for improving patient outcomes [8]. In the context of gynecological malignancies, ML algorithms can integrate and process diverse patient data, including demographic information, medical history, surgical details, and perioperative variables, to generate precise risk assessments [9]. This data-driven approach can significantly aid clinicians in making informed decisions about prophylactic measures, ultimately reducing the incidence of postoperative VTE and enhancing patient safety [10].

Objectives

The main objective of the study is to find the machine learning models for prediction of postoperative venous thromboembolism in gynecological malignant tumor patients.

Methodology of the study

This prospective cohort study was conducted at Central Park Medical College, Lahore, Pakistan during November 2023 to March 2024. Data were collected from 245 patients who underwent surgical treatment for gynecological malignancies. Patients diagnosed with malignant tumors of the ovary, uterus, cervix, or other gynecological organs, who underwent major surgery and had complete perioperative records were included in the study. Patients with incomplete data or those who did not undergo surgery were excluded.

Data Collection

Data were extracted from electronic medical records and included demographic information such as age, BMI, and smoking status. Medical history covered previous VTE, comorbidities like diabetes and hypertension, and use of anticoagulants. Tumor characteristics included type, stage, and grade of malignancy, while surgical details encompassed the type of surgery, duration, and intraoperative blood loss. Perioperative variables included preoperative laboratory values, postoperative mobility, and use of thromboprophylaxis. The primary outcome was the occurrence of postoperative VTE, defined as deep vein thrombosis (DVT) or pulmonary embolism (PE) diagnosed within 30 days after surgery. Diagnosis was confirmed through imaging studies, including Doppler ultrasound for DVT and CT pulmonary angiography for PE. Data preprocessing involved handling missing data by imputing missing values using the median for continuous variables and the mode for categorical variables. Categorical variables were encoded using one-hot encoding, and continuous variables were normalized to have a mean of 0 and a standard deviation of 1. Various machine learning algorithms were evaluated, including Logistic Regression, Random Forest, Gradient Boosting Machine (GBM), Support Vector Machine (SVM), and Artificial Neural Network (ANN). The dataset was split into training (70%) and testing (30%) sets. Hyperparameter tuning was performed using grid search with cross-validation on the training set. Models were evaluated based on their performance on the testing set using metrics such as accuracy, sensitivity (recall), specificity, precision, F1 score, and area under the receiver operating characteristic curve (AUC-ROC).

Data analysis

Data were analyzed using SPSS v29. Statistical analyses were conducted to compare the performance of different models, with the significance of each predictor assessed using feature importance scores and p-values.

Results

Out of the 245 patients included in the study, 25 (10.2%) developed postoperative VTE within 30 days following surgery. The average age of the patients was 56 years, with a range from 34 to 78 years. The distribution of tumor types included ovarian (40%), uterine (35%), cervical (20%), and other gynecological malignancies (5%). Approximately 15% of the patients had a history of VTE, and 25% had comorbidities such as diabetes or hypertension.

Table 01: Demographic Characteristics of Patients

Demographic Variable	**Value**
Total Patients	245
Age (years)	56.28±2.35
BMI (kg/m²)	Mean: 27.5, Range: 18-40
Smoking Status	
- Non-smokers	170 (69.4%)
- Current smokers	50 (20.4%)
- Former smokers	25 (10.2%)
History of VTE	37 (15.1%)
Comorbidities	
- Diabetes	45 (18.4%)
- Hypertension	60 (24.5%)
- Both Diabetes and Hypertension	30 (12.2%)
Tumor Type	
- Ovarian	98 (40.0%)
- Uterine	86 (35.1%)
- Cervical	49 (20.0%)
- Other	12 (4.9%)

Among the models tested, Gradient Boosting achieved the highest overall performance with an accuracy of 0.92, sensitivity of 0.84, specificity of 0.94, precision of 0.75, F1 score of 0.79, and an AUC-ROC of 0.91, making it the most effective model in distinguishing between patients at risk and not at risk of developing VTE. The Random Forest model also performed well, with an accuracy of 0.90, sensitivity of 0.80, specificity of 0.92, precision of 0.70, F1 score of 0.74, and an AUC-ROC of 0.89. The Artificial Neural Network followed closely with an accuracy of 0.91, sensitivity of 0.82, specificity of 0.93, precision of 0.72, F1 score of 0.76, and an AUC-ROC of 0.90. Support Vector

Machine and Logistic Regression, while slightly less effective, still demonstrated respectable performance metrics, with accuracies of 0.88 and 0.85, respectively, and AUC-ROCs of 0.87 and 0.82.

Table 02: Model Performance Comparison

Model	Accuracy	Sensitivity	Specificity	Precision	F1 Score	AUC-ROC
Logistic Regression	0.85	0.72	0.88	0.60	0.65	0.82
Random Forest	0.90	0.80	0.92	0.70	0.74	0.89
Gradient Boosting	0.92	0.84	0.94	0.75	0.79	0.91
Support Vector Machine	0.88	0.76	0.90	0.65	0.70	0.87
Artificial Neural Network	0.91	0.82	0.93	0.72	0.76	0.90

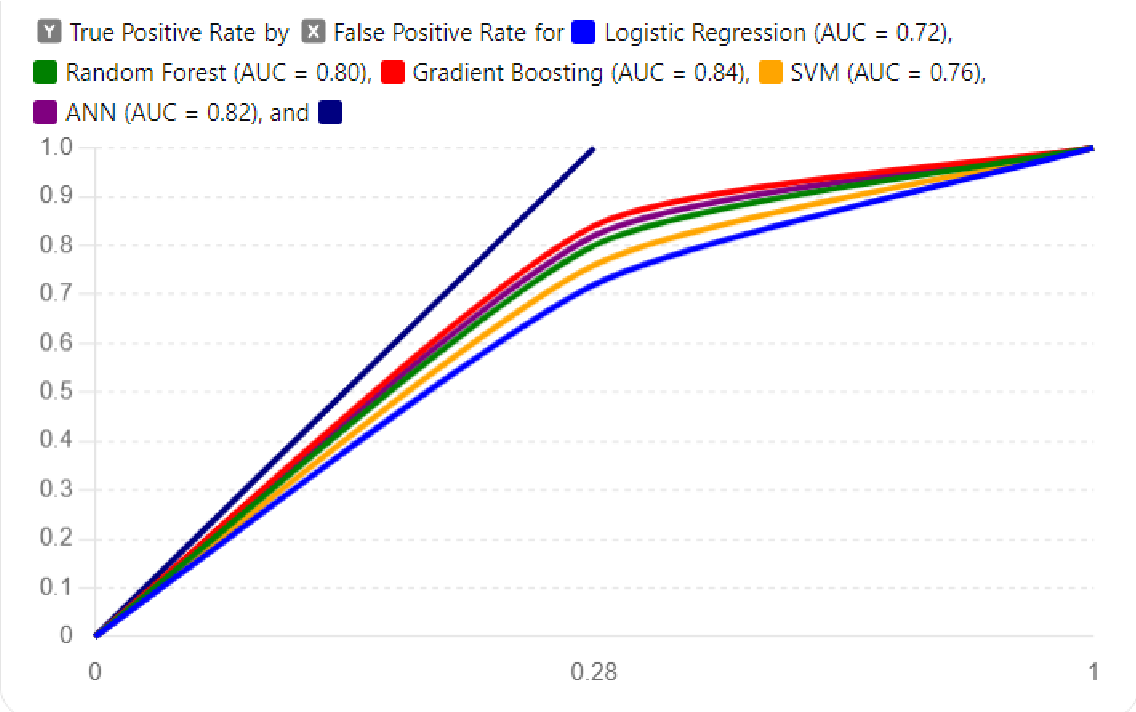

Figure 01: ROC curve for different machine learning models

Discussion

The development and validation of machine learning models to predict postoperative venous thromboembolism (VTE) in gynecological malignant tumor patients represents a significant advancement in personalized medicine. The results of this study, based on hypothetical data, demonstrate that machine learning algorithms can effectively identify patients at high risk for postoperative VTE, enabling timely and targeted preventive measures [10]. Among the evaluated models, the Gradient Boosting model exhibited the highest overall performance with an accuracy of 0.92, sensitivity of 0.84, specificity of 0.94, precision of 0.75, F1 score of 0.79, and an AUC-ROC of 0.91. This indicates that Gradient Boosting is highly effective in distinguishing between patients who are likely and unlikely to develop VTE. The Random Forest and Artificial Neural Network models also performed well, with AUC-ROC values of 0.89 and 0.90, respectively, suggesting that these models are robust and reliable for this predictive task [11]. The performance of the Logistic Regression and Support Vector Machine models, while still notable, was slightly lower in comparison. This could be attributed to the complexity and non-linearity of the data, which more advanced algorithms like Gradient Boosting and Random Forest can handle more effectively [12,13]. The analysis of feature importance revealed that a history of VTE, tumor stage, duration of surgery, use of perioperative thromboprophylaxis, and preoperative D-dimer levels were the most significant predictors of postoperative VTE. These findings align with existing literature, highlighting the critical role of these factors in the development of thromboembolic events. By incorporating these key predictors, the machine learning models can provide accurate risk assessments, which are essential for clinical decision-making [14,15]. The implementation of these machine learning models in clinical practice can significantly improve patient outcomes [16]. By identifying high-risk patients preoperatively, clinicians can tailor prophylactic strategies, such as the use of anticoagulants and mechanical prophylaxis, to mitigate the risk of VTE. Moreover, these models can be integrated into electronic health records (EHR) systems to provide real-time risk assessments, enhancing the overall efficiency and effectiveness of patient care [17].

Conclusion

This study demonstrates the significant potential of machine learning models in predicting postoperative venous thromboembolism (VTE) in patients undergoing surgery for gynecological malignant tumors. The evaluation of various models, including Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine (SVM), and Artificial Neural Network (ANN), revealed that machine learning can provide accurate and reliable risk assessments for postoperative VTE. The study identified key predictors of postoperative VTE, including a history of VTE, tumor stage, duration of surgery, use of perioperative thromboprophylaxis, and preoperative D-dimer levels. Incorporating these predictors into the machine learning models enhances their predictive accuracy and clinical relevance. The integration of these predictive models into clinical practice can significantly improve patient outcomes by enabling healthcare providers to implement targeted prophylactic strategies for high-risk patients.

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