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AI-Powered Risk Assessment and Prediction Models For VTE: A Narrative Review

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Abstract- Background: A major avoidable cause of illness and death in healthcare settings worldwide is venous thromboembolism (VTE). While there are conventional risk assessment methods, the capacity of AI and ML techniques to evaluate complicated, multidimensional clinical data and detect non-linear patterns that conventional statistical methods could overlook makes them attractive alternatives to traditional VTE risk classification methods. Objective: This narrative review synthesises evidence on the performance, feasibility, implementation, and contextual relevance of AI-powered VTE risk assessment models. Methods: A comprehensive narrative review was undertaken on PubMed, Google Scholar, ScienceDirect, and Web of Science for 2010–2025 research on AI and VTE. For VTE prediction or diagnosis, included research created, validated, or deployed AI/ML models such supervised learning algorithms, ensemble approaches, and deep learning architectures. Studies using standard statistical techniques or without performance indicators were eliminated. The narrative synthesis centred on the model's performance, the experiences of clinical application, and the obstacles to acceptance. Results: Traditional risk assessments were routinely surpassed by AI models across a variety of clinical groups. Deep neural networks, gradient boosting, and random forests all showed very good VTE prediction accuracy. Despite this, there are still a lot of obstacles to overcome, such as a lack of external validation, uneven performance among populations, a large number of false positives, restrictions on data quality, and inadequate infrastructure. Conclusion: Models driven by AI show great potential for enhancing personalised risk assessment and early VTE identification. Factoring in the challenges and shortcomings is crucial for effective use.

Keywords: Artificial Intelligence, Machine Learning, Deep Vein Thrombosis, Risk Prediction, Clinical Decision Support.

I. INTRODUCTION

Deep venous thrombosis, pulmonary embolism, and other forms of venous thromboembolism (VTE) cause a great deal of avoidable illness and death.1 Approximately 10 million cases of venous thromboembolism are identified annually worldwide.

More than 50% of these cases lead to hospitalisations and a considerable reduction in disability-adjusted life years.2 The United States and Europe provide the strongest evidence on the occurrence of VTE. Based on data collected in the United States in 2020 and 2021, the American Heart Association projected that 1,220,000 people suffer from venous thromboembolism (VTE) per year.3 Report indicated that there were about 370,000 instances of pulmonary embolism and around 857,000 cases of deep vein thrombosis in 2016, with the assumption that 30% of these cases were treated in the outpatient environment.3

In modelling research conducted by Cohen et al.4 it was projected that out of a total population of 310.4 million in six European nations, there were 296,000 instances of pulmonary embolism and about 466,000 cases of deep vein thrombosis (DVT) every year.

Primary thromboprophylaxis has been shown to reduce morbidity in hospitalised patients, leading to a large and sustained emphasis on VTE prevention throughout the past three decades.5,6 The impact of VTE is amplified in countries with low resources, like Nigeria, due to factors such as a lack of knowledge, inadequate prophylactic resources, and diagnostic capacities.7

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Consequently, reliable risk assessment is essential for developing VTE preventive programs that may effectively alleviate this burden.8 Thus, several clinical risk prediction models were created to diagnose and forecast the prognosis of VTE in different contexts.9 Conventional risk assessment methods, such as the IMPROVE score, Padua Prediction Score, and Caprini Risk Assessment Model, were mostly created and tested in areas with abundant resources.10 Notable among these models is the Wells score.

Incorporating clinical variables into the Wells score are things like the presence of acute symptoms of deep vein thrombosis (e.g., swelling and pain in the legs accompanied by palpitations), haemoptysis, tachycardia, the patient's history (including things like a history of deep vein thrombosis or PE, immobilisation, or cancer within the past six months), and the exclusion of other possible diagnoses.11

There is a wide range in the claimed efficacy of these models among populations, baseline VTE risks, and model components. As previously mentioned by Chiasakul et al.9 clinical risk prediction models have historically been developed by regression-based analyses, such logistic regression and Cox regression. However, these methods have certain drawbacks, one of which is their reliance on predictor variables that are highly organised and curated.

One prominent alternative to traditional methods of developing prediction models is the use of artificial intelligence (AI) and machine learning algorithms. Gupta et al.12 found that risk stratification, diagnosis, and survival forecasts may all benefit from AI/ML because of its scalability and flexibility, which allow it to avoid standard statistical assumptions like the kind of error distribution or the proportional hazards assumption.

Machine vision, NLP, and predictive modelling are some of the most important ML applications in VTE.13 Decision Trees (DT), Random Forests (RFs), Support Vector Machines (SVMs), K-Nearest Neighbours (KNN), and basic neural networks are often used as supervised learning models in the literature.14 The future of artificial intelligence in healthcare lies in multimodal ML models, which can analyse massive datasets containing a variety of data modalities. These models will be able to detect and prevent PEs and DVTs in high-risk populations even before these patients show symptoms of these conditions.15 Clinical deployment of AI/ML technologies is still restricted, despite the effectiveness of these techniques being shown in recent meta-analyses.16

Additionally, there are significant obstacles to implementing evidence-based recommendations in low- and middle-income countries (LMICs), which contribute to the inadequate prevention of VTE, even though it is largely avoidable through effective risk-stratified prophylaxis.17 Furthermore, there is a significant knowledge vacuum when it comes to creating machine learning models that can accurately predict VTE and using them in settings like Nigeria, where resources are few.

The purpose of this narrative review is to summarise the existing literature on VTE prediction models that use artificial intelligence (AI), analyze their practical efficacy and implementation stories, highlight the main obstacles to their widespread use, and highlight areas of priority for further study and clinical application. We hope that by outlining the state of the art in this dynamic area, scientists, researchers, and policymakers will have a better understanding of the advantages and disadvantages of using AI to evaluate the risk of VTE.

II. LITERATURE REVIEW

Various clinical settings, patient groups, and methodological methods were covered in the extensive literature. The literature review includes the current state of artificial intelligence and machine learning methods used for VTE prediction, proof of model performance and clinical impact, and the obstacles to successful clinical translation that arise during implementation.

AI-Based Models for Diagnosis and Prediction Of VTE

- Machine Learning Models: They are dependent on organised clinical data including imaging reports, comorbidities, medicines, vital signs, and lab findings. For binary VTE risk prediction, a

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common algorithm is Logistic Regression (regularised forms). Random Forests are good at handling non-linear relationships and interactions. Gradient Boosting Machines (XGBoost, LightGBM, CatBoost) are good at achieving high performance even with imbalanced clinical data. Included as well are Support Vector Machines (SVMs), which are used for classification purposes in cases when the data is high-dimensional.18,19

- Deep Learning Models: From unstructured or partially structured data, these models may autonomously learn features: Deep Neural Networks (DNNs), use massive EHR datasets to forecast the likelihood of VTE. Deep Vein Thrombosis/Pulmonary Embolism (DVT/PE) imaging-based diagnostics (e.g., ultrasound, CT pulmonary angiography) are a typical use case for Convolutional Neural Networks (CNNs).

The use of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) allows for the early prediction of venous thromboembolism (VTE) in hospitalised patients.20,21

Evidence of AI and ML in VTE Prediction

There is tremendous untapped potential for ML technologies to revolutionise VTE diagnosis, prognostics, and management. The conventional scoring methods for estimating the likelihood of VTE should be enhanced using these instruments.15 The application of ML algorithms has allowed for the prediction of death after a VTE and the risk of VTE in certain groups. In order to make predictions, these algorithms crunch numbers and sort categories from a variety of sources, such as demographic, clinical, and laboratory data.

Machine learning and artificial intelligence models, especially severe gradient boosting, have the ability to surpass conventional clinical prediction tools in predicting venous thromboembolism (VTE) after lower limb arthroplasty.22 However, before these models can be extensively used in clinical practice, external validation and high-quality, generalisable datasets are crucial.

Zhou et al.23 found that the incidence of hospital-acquired VTE decreased by 19% following the introduction of an AI-based clinical decision support system. The application of AI appears to enhance the accuracy of diagnostic and prognostic predictions of VTE compared to traditional risk models.9 The synthesised AI models showed outstanding prediction performance, according to a scoping review by Gu et al.24

A total of 4,17 percent of the 1,632 patients diagnosed with acute ischaemic stroke (AIS) who were analysed in research on using machine learning to improve and understand the risk prediction of venous thromboembolism (VTE) in the treatment of AIS came to have VTE. Compared to other models, including Random Forest and Logistic Regression, this one obtained the best prediction accuracy with an AUC of 0.923.

To identify individuals at high risk, the model showed excellent sensitivity (90.83%) and specificity (93.83%).25 it was also found that doctors may use the results of SHAP analysis to inform their judgements on individualised treatment plans, as it showed that high D-dimer levels, premorbid mRS, and big vessel blockage were important predictors of VTE risk.

According to Hou et al.26 deep learning techniques, especially those that used imaging data, were able to get accuracies of up to 95%, whereas conventional ML methods often obtained accuracies between 80% and 90%.

Clinical trial findings regarding the risk assessment tool for venous thromboembolism in orthopaedic inpatients revealed that all performance metrics were clearly outperformed by the XGBoost model, the highest accuracy of 0.828 and an AUROC of 0.931, much surpassing the other models, especially in terms of prediction accuracy and discriminative ability. XGBoost outperforms the classic Caprini scoring model in predicting the risk of venous thromboembolism (VTE).27

Consistent sensitivity and specificity across thrombus type and type of AI approach utilised was reported in a meta-analysis of 12 research testing AI's effectiveness in VTE prediction–even though 7 of those studies only had a training set and didn't have a test set.13 A randomised experiment conducted by Huang et al.28 on 19,785 hospitalised patients shown that AI-based systems boosted mechanical prophylaxis by 24% and decreased VTE incidence by 46%.

Additional research has shown that AI models may accurately predict deep vein thrombosis (DVT)29, and pulmonary embolism (PE) mortality and recurrence risk after early anticoagulation withdrawal.30 Both the IMPROVE score and the Caprini Risk Score were surpassed by AI models in terms of VTE prediction and stratified risk, respectively, when compared to conventional risk scores.31,32 On the other hand, AI models were only slightly better than simplified pulmonary embolism severity index and pulmonary embolism severity index scores when it came to predicting death due to PE.

Applying AI to some prothrombotic diseases has shown encouraging results, such as a positive prediction value for thrombosis ranging from 98% to 100% in COVID-19 patients.33 Therefore, regardless of the history or underlying circumstances that caused it, the symptoms and consequences of deep vein thrombosis (DVT) and pulmonary embolism (PE) are quite similar. But there are many other types of risk variables, including those that are complicated, diversified, and influenced by genetics, the environment, demographics, geography, and acquired traits.34

Ziyadah et al.34 notes that there is a wealth of data available for population studies on VTE due to the condition's prevalence around the world. This data includes common characteristics (demographics, environment, etc.), as well as unique aspects of management and the ability to predict bleeding in patients taking anticoagulants. So, generative AI and other forms of AI applied to this complicated topic provide a tremendous potential to learn more about and improve VTE and its prevention, diagnosis, and treatment.

Overall, the evidence suggests that AI-based models consistently outperform conventional VTE risk assessment tools across diverse clinical settings. Gradient boosting algorithms, particularly XGBoost, demonstrated the most consistent predictive performance, frequently achieving AUROC values above 0.90 and outperforming traditional tools such as the Caprini and IMPROVE scores. Deep learning models achieved excellent diagnostic accuracy, especially in imaging-based applications, but often required larger datasets and greater computational resources.

Random Forest models offered a balance between predictive accuracy and interpretability, making them attractive for clinical deployment. Despite these advantages, most studies relied on retrospective datasets, lacked external validation, and were conducted in high-income settings, limiting their generalisability to low-resource healthcare environments.

Figure 1: Applications of artificial intelligence (AI) in thrombosis and haemostasis.35 From risk assessment and prevention to diagnosis and therapy development, individualised management, and patient education, AI is shown as a complete solution across the whole spectrum of thrombosis and haemostasis care in the figure. By considering haemostatic problems from every angle, this comprehensive vision establishes AI as a game-changer in the fields of medicine, academia, and training.

Challenges in Implementation of AI-Powered Risk Assessment and Prediction Models for VTE

The accuracy of AI performance varies across different cohorts. For example, some models have inconsistent results when assessing the risk of bleeding in cancer-associated thrombosis, and they perform worse in external validation cohorts.30,36,37 It is clear from these findings that generalisability has its limits, and that prospective, multi-centre validation is necessary.

Among the challenges, participants expressed concerns regarding AI's variable performance across diverse ethnicities, genders, and socioeconomic backgrounds, as well as privacy issues associated with the use of personal data. They underscored the importance of informing patients when artificial intelligence is employed in their care, aligning with the wider body of literature on algorithmic fairness and privacy.38

Parikh et al.39 found that historical biases in AI training data might cause representation gaps, which in turn can negatively impact minority health care. One possible solution is to conduct bias audits and use inclusive data sets. This might assist to reduce the detrimental impact. A problem with low-quality training data was mentioned apart from inequality.

Natural language processing (NLP) techniques may not work as well if medical note vocabulary is not standardised. When a model is inaccurate, it produces wrong results and overidentifies findings that don't have any therapeutic significance. These blunders may happen because the training data was inadequate or because the AI tool was asked to answer a question that was too complex for it to handle.

In order to filter out incorrect outputs, human supervision and strategies that force AI to justify its result might be useful. Data quality, the black box aspect, and ethical difficulties are among the recurring themes that were identified in the prior survey.40

Problems with data integrity, social equality, regulatory supervision, and patient care are just a few of the new issues that arise when using machine learning to avoid VTEs. Integrating technology into clinical practice raises privacy problems, especially in cases when retroactive data is utilised without express authorisation, and may inadvertently decrease human connection, the therapeutic relationship, and the strength of the therapeutic bond.12

Weiner et al.41 notes that precautions such as clear informed-consent procedures, robust cybersecurity measures, traceable AI decision paths, and protected clinician-patient engagement time are necessary in light of these dangers. Many models depend on opaque "black box" designs, are trained on non-representative datasets, and may provide biassed or harmful predictions for marginalised or underprivileged groups; these factors add another layer of difficulty to implementation.

Additionally, there are social and equity concerns since ill-regulated ML systems have the potential to exacerbate healthcare inequalities by creating more biassed results or granting certain users' preferential treatment. Accordingly, for ML-enhanced VTE prevention to be safe, equitable, and responsible, there must be robust governance systems, transparent liability frameworks, and inclusive supervision including data scientists, patients, and physicians.41

There are a number of critical elements that determine an AI-based prediction model's clinical application, including the model's performance, the accessibility of the model's algorithm and software, the capacity to update the model, security assurance, and integration with clinical workflow.

Automatic deep vein thrombosis (DVT) monitoring systems have come a long way, but they still have a ways to go before they can be used in clinical settings. The general lack of specificity in many wearable sensor systems is an ongoing problem. For instance, according to Chen et al.20 research found that more than 30% of the warnings produced by an ML model were false positives.

These alerts were often caused by physiological changes that aren't harmful, including physical activity or benign arrhythmias. The faith in the dependability of these monitoring systems is eroded when there are so many false alerts, which may lead to alert fatigue for both patients and healthcare personnel.

Practicality in terms of cost is another major obstacle to implementation on a grand scale. Adoption in healthcare settings with limited resources may be hindered by the high initial costs of device development, calibration, and distribution, as well as the ongoing maintenance needs of wearable-based ML systems, especially those that use imaging or Doppler technologies.26

Additionally, models are not always applicable to other populations due to the high degree of inter-individual variation in physiological signals caused by variables including age, sex, comorbidities, drugs, hydration state, and body position. According to Cadena.14 for example, when comparing younger athletic populations with older, immobilised patients, the criteria that were successful for thrombotic risk identification in one group yielded inconsistent or misleading findings in another.

A further important shortcoming is the lack of coordination across genetic, proteomic, and molecular indicators, all of which contribute significantly to an individual's vulnerability to deep vein thrombosis (DVT). Restricting prediction accuracy and perhaps missing important biological factors, these variables should not be excluded.31,43

III. METHODOLOGY

This study uses a narrative review method to provide a thorough look at how AI is used in Risk Assessment and Prediction Models for VTE. The narrative review is useful because it helps bring together all of the current empirical data, showing trends, gaps, and areas that need more research in the field.46

Literature was searched in PubMed, Scopus, Web of Science, ScienceDirect, and Google Scholar from 2010–2025 using keywords related to AI, machine learning, VTE prediction, risk assessment, and clinical decision support. Relevant peer-reviewed studies addressing AI-based VTE prediction, diagnosis, and implementation were reviewed and synthesised narratively.

Inclusion criteria include studies published in English between 2010 and 2025 that investigated AI- or machine learning-based approaches for the prediction, diagnosis, prevention, or risk assessment of venous thromboembolism (VTE), including deep vein thrombosis and pulmonary embolism. Eligible studies involved model development, validation, implementation, or clinical application and reported performance measures such as accuracy, sensitivity, specificity, or AUC.

Exclusion criteria: Studies were excluded if they focused on non-VTE conditions, used only conventional statistical methods without AI or machine learning components, lacked sufficient methodological or performance data, involved non-human populations, or were secondary publications such as reviews, editorials, commentaries, conference abstracts, case reports, and case series.

IV. IMPLICATIONS FOR LOW AND MIDDLE-INCOME COUNTRIES

Although most AI-based VTE prediction studies have been conducted in high-income countries, their findings have important implications for low- and middle-income countries (LMICs), including Nigeria. AI-driven risk assessment tools may improve early identification of high-risk patients, optimise thromboprophylaxis, and support clinical decision-making where specialist expertise is limited.

However, implementation remains challenging due to inadequate electronic health record systems, limited digital infrastructure, insufficient technical expertise, and resource constraints. Therefore, future research should focus on validating AI models in LMIC populations and developing context-appropriate systems that can operate effectively within resource-limited healthcare environments.

V. DISCUSSION

This review demonstrates that AI-based models have substantial potential to improve the prediction, diagnosis, and management of venous thromboembolism. Across the reviewed studies, machine learning and deep learning approaches generally outperformed conventional risk assessment tools by capturing complex interactions among multiple clinical variables. Among the reviewed approaches, gradient boosting algorithms, particularly XGBoost, consistently demonstrated superior predictive performance.

Despite these promising findings, several barriers limit widespread clinical adoption. These include limited external validation, concerns regarding algorithmic bias, data quality issues, high implementation costs, and inadequate digital infrastructure. Such challenges are likely to be more pronounced in low-resource settings where electronic health records and advanced computing resources remain limited.

Future efforts should prioritise prospective multicentre validation studies, transparent model development, improved interpretability, and evaluation of implementation strategies in diverse healthcare settings. Addressing these challenges will be essential for translating AI-based VTE prediction models from research environments into routine clinical practice.

Despite the extensive research on AI's promise for VTE risk prediction, there are still important gaps in our understanding. To start, there hasn't been a comprehensive review that looks at how well ML models work in low-resource environments or with the people that these healthcare systems mostly treat. Furthermore, there has been no thorough examination of the practicality of using risk assessment systems driven by AI in settings with limited resources.

In addition, it is not yet obvious how various ML techniques (such as basic vs. sophisticated models, deep learning vs. classical algorithms) compares in situations when resources are limited. There is a lack of a comprehensive strategy for identifying the best practices for developing, validating, and deploying models that take practical implementation factors into account while maintaining performance.

Furthermore, from previous studies, the majority of the algorithms reported failed to account for contextual elements, such as time, which might impact the advancement of DVT. These considerations can include things like medication changes, changing physiological indicators, or extended periods of immobilisation. Without these factors, models can't capture important temporal patterns or trajectories that need to be addressed early.14

It was also difficult to determine if the predicted probabilities were a good reflection of the actual results as several research failed to publish calibration metrics like Brier scores, calibration curves, or reliability diagrams.

Due to the high clinical risk of over-treatment (false positives) and missed diagnoses (false negatives) that may result from improperly calibrated models, this omission is especially worrisome in DVT applications.14

CONCLUSION

Compared to traditional models, there are obvious advantages to integrating AI-based models for VTE diagnosis and prediction early on in the clinical setting. Complying with ethical and regulatory requirements, being transparent, integrating with clinical procedures, and continuously evaluating these models are additional significant considerations for deployment. The successful implementation of AI-based VTE prediction models requires rigorous validation, continuous performance monitoring, transparent governance frameworks, and integration into existing clinical workflows.

LIMITATION

Despite the careful selection of search criteria to encompass all relevant studies, it remains possible that certain significant studies were overlooked. Furthermore, the conclusions drawn from the review may have been influenced by the unavailability of full-text access to some qualifying articles.

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