AI-Powered Early Detection of Embolism Using Multimodal Clinical Data

AI IN HEALTHCARE

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INTRODUCTION

- Project Focus:
  - AI-driven early detection of Pulmonary Embolism (PE) and Deep Vein Thrombosis (DVT)
- Clinical Significance:
  - Thromboembolic diseases are major contributors to preventable hospital mortality
  - ↠ ~100,000 PE-related deaths annually in the U.S.
- Core Challenge:
  - Predict onset 8–24 hours before clinical symptoms for earlier intervention
- High-Risk Factors:
  - Multimodal clinical data integration
  - Time-critical predictions
  - Requirement for clinician-trustworthy explanations

PROBLEM STATEMENT

- Limitations of Current Tools:
  - Clinical scoring systems (e.g., Wells criteria, PERC) have limited sensitivity
  - ↠ Often activated too late in the disease progression
- Critical Impact:
  - Each hour of delayed treatment for PE/DVT increases mortality risk
- Project Objective:
  - Develop a deep learning model to:
  - Predict embolism 8–24 hours before diagnosis
  - Analyze vital signs, labs, clinical notes, medications
  - Identify hidden patterns beyond clinician perception
  - Provide interpretable explanations to ensure clinical trust

METHODOLOGY OVERVIEW

- 📊 Data Source:
  - MIMIC-IV: De-identified clinical data from 40,000+ patients
- 🔍 Extracted Features:
  - Temporal Vitals: Heart rate, oxygen saturation
  - Lab Values: D-dimer and others
  - Clinical Notes: Indicators like leg swelling
  - Medications & Demographics

CHALLENGES & SOLUTIONS

1. Class Imbalance
   - Challenge: Embolism is a rare event
   - Solution: Balanced sampling + class-weighted loss during training
2. Temporal Drift
   - Challenge: Model performance declined on newer patient data
   - Solution: Identified need for continuous model retraining in deployment
3. High False Positives
   - Challenge: Risk of alert fatigue due to over-triggering
   - Solution: Optimized decision threshold using clinical impact (not just AUC/F1)
4. Interpretability Issues
   - Challenge: Initial explanations were not intuitive to clinicians
   - Solution: Refined to produce context-aware, clinically relevant explanations

RESULTS OVERVIEW

📊 *Performance Metrics:*

- Model AUROC: 0.82
- Sensitivity: 0.77
- Outperformed traditional tools:
  - Wells Criteria: AUROC 0.67
  - PERC Rule: AUROC 0.63

🔍 *Top Predictive Features (SHAP Analysis):*

- D-dimer elevation
- Tachycardia (>100 bpm)
- Leg swelling / chest pain in notes
- Hypoxemia (<94% O_2 saturation)
- Recent surgery or immobilization

🧠 *Key Insight*

- Nursing notes often flagged early signs 12–18 hours before diagnosis
- Highlights value of unstructured text data

👩‍⚕️ *Clinical Feedback*

- Physicians confirmed model surfaced high-risk cases earlier than typical clinical suspicion
- Potential for life-saving early interventions

LESSONS LEARNED & FUTURE DIRECTIONS

🔍 Key Takeaways:

- Model Maintenance is Essential
  - ➳ Continuous updates needed to handle dataset shift
- Sensitivity vs. Specificity Tradeoff
  - ➳ Must balance to prevent alert fatigue
- Cross-Disciplinary Collaboration
  - ➳ Clinical + technical input vital throughout development
- Explainability Drives Adoption
  - ➳ Clinically relevant explanations build trust

🚀 Future Directions:

- Prospective clinical validation
- Enhanced explanation methods aligned with physician reasoning
- Advanced strategies for handling temporal drift

Goal: Enable earlier, life-saving interventions for PE/DVT

CONCLUSION

- Multimodal deep learning can detect early signs of PE/DVT
- ⤜ Up to 24 hours before clinical diagnosis
- Demonstrated strong predictive performance and clinical relevance
- Challenges remain in real-world deployment
- ⤜ But potential life-saving impact makes further research essential

Thank you!