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Development of a machine learning model using 12-lead ECG to improve acute dianosis of pulmonary embolism

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Introduction: Pulmonary embolism (PE) is a life-threatening condition. Given the lack of specificity in symptoms and clinical decision rules, diagnostic uncertainty in PE remains high and in most of the cases requires confirmation by computed tomography pulmonary angiogram (CTPA). This could be critical to decide fibrinolysis indication in hemodynamic unstable patients (pts) with PE suspicion in out-of-hospital setting or if CTPA is not immediately available.

The implementation of artificial intelligence (AI) in medical diagnosis has attracted major attention last years. Electrocardiography (ECG) signals and patterns can be detected by AI networks with precision. The purpose of this study was to develop an AI model for predicting PE using 12-lead ECG.

Methods: We extracted 1014 ECGs of pts admitted to emergency department who underwent CTPA due to PE suspicion: 911 ECGs were used for development of the AI model (derivation cohort) and 103 ECGs were used for testing the PE prediction model (validation cohort). An AI algorithm based on an ensemble neural network was developed using 12-lead ECG signal.

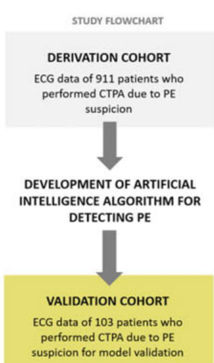
The first endpoint was the diagnosis of PE. To evaluate the performance of the AI model, we compare the performance of AI model against the recommend clinical prediction rules for PE based on clinical probability and D-dimer measurement (Wells and Geneva criteria combined with fixed and age-adjusted D-dimer cut-off, YEARS and PEGeD algorithms).

Results: On validation cohort, AI model achieves greater specificity to detect PE than the commonly used clinical prediction rules ($p<0.001$) -Table 1. The AI model shown a specificity of 100%, which is particularly relevant in the context of fibrinolysis decision. Although the sensitivity of the AI model is lower ($p=0.001$), the biggest gain of this model is to provide security to the physician to stablish a definite diagnosis. Globally, the AI model performed significantly better than all the other models (AUC 0.75, $p<0.001$), which had nearly no discriminative power.

The incidence of typical PE ECG features (S1Q3T3, right bundle branch block and V1-V3 T wave inversion) was similar in pts with and without PE, meaning that AI model provide information beyond these findings and can improve PE prediction.

ECGs were included regardless of cardiac rhythm (including pacing), so these findings can be generalized to all pts. Model performance is similar across gender.

Conclusion: In this study we developed and validated a deep learning-based AI algorithm for PE detection using a 12-lead ECG which demonstrated high performance.



(1A) – Study flowchart

	Wells score + D-Dimer threshold of 500 ng/mL	Geneva score + D-Dimer threshold of 500 ng/mL	Wells score + age-adjusted D-Dimer cut-off	Geneva score + age-adjusted D-Dimer cut-off	YEARS algorithm	PEGeD algorithm	Artificial intelligence model
Sensitivity, % (95% CI)	90 [75-97]	90 [75-97]	90 [75-97]	90 [75-97]	88 [72-96]	87 [72-96]	50.00 [33-67]
Specificity, % (95% CI)	12 [5-23]	12 [5.47-22.82]	18 [10-30]	18 [10-30]	29 [19-42]	31 [20-43]	100 [94-100]
PPV, % (95% CI)	37 [27-48]	37 [27-48]	39 [29-50]	39 [29-50]	42 [31-53]	42 [31-54]	100 [82-100]
NPV, % (95% CI)	67 [35-90]	67 [35-90]	75 [48-93]	75 [48-93]	79 [58-94]	80 [59-93]	77.38 [67 -86]
AUC (95% CI)	0.51 [0.39-0.63]	0.54 [0.43-0.65]	0.51 [0.39-0.63]	0.54 [0.43-0.65]	0.58 [0.47-0.69]	0.59 [0.48-0.70]	0.75 [0.64-0.86]

(1B) – Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and area under the curve (AUC) for different prediction rules