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Original Article

Validation of Self-Assessment-Based Chest Pain Algorithm (DETAK) as An Early Identification Tool for Acute Coronary Syndrome

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ABSTRACT

Background: The most common reason for prehospital delay in acute coronary syndrome (ACS) patients is a lack of symptoms awareness. Patient-oriented machine learning algorithms may help the patient recognize ACS symptoms, reducing the prehospital delay that determines the clinical outcome of ACS patients.
Objective: Assessing the accuracy of the self-assessment chest pain algorithm (DETAK) in identifying ACS
Methods: This study was conducted from August 2021 to June 2022 and included seven hospitals: five PCI-capable hospitals and two non-PCI-capable hospitals. All patients with chest pain who visited the hospital and used the DETAK algorithm were included. Patients with unstable angina, as well as those who died or declined to participate in this study, were excluded. The area under the curve receiver operating characteristic (AUROC) was used to verify DETAK's performance in identifying ACS. We compare the DETAK algorithm's diagnosis with the definitive diagnosis based on ECG and/or troponin results.
Result: A total of 539 patients (mean age 58 years) participated, with a higher proportion of male patients (n = 424). An AUC value of 0.854 was obtained. The cut-point accuracy of DETAK in identifying ACS for the entire sample had a sensitivity of 89.5% and a specificity of 81.2%. The algorithm's specificity decreased in certain subgroups, including type 2 diabetes, women, and hypertensive patients. The algorithm reliability test obtained moderate to strong levels of agreement.
Conclusion: As a leap in the digital era, DETAK's self-assessment-based chest pain algorithm offers excellent diagnostic performance to identify ACS symptoms and reduce prehospital delays for patients.

1. Introduction

Acute Coronary Syndrome (ACS) is still a common medical emergency that contributes to high morbidity and mortality in the world.[1] ACS is a clinical spectrum in patients associated with inadequate coronary vascular flow resulting in acute myocardial ischemia. As a clinical entity, ACS is divided into ST elevation MI (STEMI), Non-ST elevation MI (NSTEMI) and unstable angina pectoris (UAP).[2] When clinical conditions are consistent with myocardial ischemia accompanied by evidence of injury to myocardial necrosis in the form of elevated cardiac marker enzymes (troponin) values with at least one value above the upper reference limit of the 99th percentile, the diagnosis of acute myocardial infarction (AMI) can be made.[3,4]

The high morbidity and mortality of ACS is influenced by various factors, one of which is the lack of public awareness of ACS, so they do not recognize the symptoms which ultimately result in delays in treatment. Chest pain is the most common symptom that prompts individuals with ACS to seek emergency help for this potentially life-threatening condition. However, the individual's response to chest pain is very heterogeneous and is influenced by several factors. Failure to notice symptoms and/or act quickly and effectively is the most common cause of prehospital delay.[5–9] This has the potential to further increase the total ischemic time resulting in a poor clinical outcome. Every half hour delay in providing reperfusion with either thrombolysis or angioplasty increased the 1-year mortality rate by 7.5 percent.[10–12]

An effort to improve the quality of health services, including reducing delays in diagnosis, in the current modern era the development of machine learning in the health sector has great potential.[13,14] Based on probability theory, mathematical models and algorithms, several machine learnings in the health sector have been developed to facilitate patient management, especially related to diagnostics and prognostics.[15] Malang ACS Score is a scoring system that is the basis for developing an algorithm based on self-assessment of chest pain patients (DETAK). The algorithm was developed into a decision tree classifier-based machine learning that can increase alertness and make it easier for patients to respond to complaints of chest pain. The use of this algorithm needs to be researched to assess its validity as an early identification tool for ACS.

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The purpose of this study was to determine the sensitivity and specificity of t an algorithm based on self-assessment of chest pain patients (DETAK) as an early identification tool for acute coronary syndromes.

2. Method

This study is a multicenter diagnostic test involving 5 cardiovascular network hospitals in Malang, where 4 of them are PCI capable centers, 1 PCI capable center hospital in Tulungagung and 1 hospital with non-PCI cardiovascular services in South Kalimantan within the period July 2021 to June 2022.

The Sample were 539 patients who were divided into 2 groups, namely the group of patients with a diagnosis of ACS and the group of non-ACS patients. The inclusion criteria used were all chest pain patients who came to the hospital, all of whom used the algorithm in the DETAK application. Patients were interviewed after being declared hemodynamically stable. Patients diagnosed with UAP, patients died and refused to be research subjects were excluded from this study. Area under curve receiver operating characteristic (AUROC) was used to assess the performance of DETAK in identifying ACS by comparing the diagnosis of the DETAK algorithm with the definitive diagnostic based on the results of ECG and/or troponin enzymes. Statistical analysis uses the ROC curve to get the AUC value that reflects the sensitivity of the algorithm being tested and at the same time calculates the specificity value.

3. Result

The baseline characteristics of the study population in this study are shown in Table 1.

In this study, the proportion of male patients (n=424) was higher than that of female patients (n=115). The average patient in this study was 58 years old with the proportion of age < 74 years as many as 37 patients. Several risk factors that will be analyzed including type II DM, hypertension, old age (>74 years) and end-stage renal failure (ESRD). However, for the subset of old age and ESRD, it is not possible to analyze the diagnostic accuracy test because of the insufficient sample size. Patients with risk factors for type II DM and hypertension who used the DETAK application for complaints of chest pain were more likely to be diagnosed with ACS.

To test the validity of the DETAK algorithm in identifying ACS patients in the general population, we took data from 539 samples from 7 hospitals. Area under curve receiver operating characteristic (AUROC) was generated to assess the performance of DETAK in identifying ACS. The receiver operating characteristic (ROC) curve is shown in Figure 1. The value of the area under the curve is 0.854. The cut of point for DETAK accuracy in identifying ACS for the general population is indicated by a red circle with a sensitivity of 89.5% and a specificity of 81.2%.

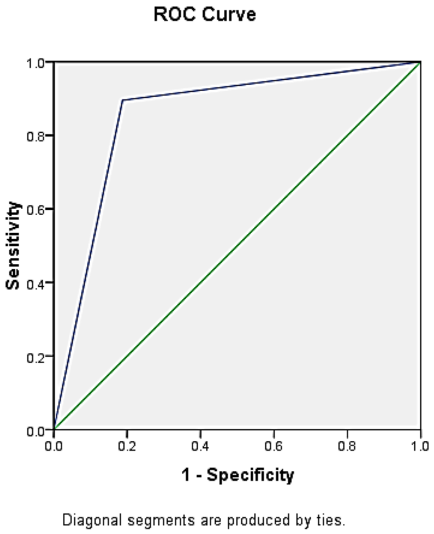

Figure 1. ROC curve of general population (n=539)

To test the validity of the DETAK algorithm in identifying ACS patients in the female population, we took data from 115 samples from 7 hospitals. Area under curve receiver operating characteristic (AUROC) was generated to assess the performance of DETAK in identifying ACS in the female population. The receiver operating characteristic (ROC) curve is shown in Figure 2. The value of the area under the curve is 0.822. The cut of point for the accuracy of DETAK in identifying ACS for the female population is indicated by a red circle with a sensitivity of 87.1% and a specificity of 77.3%.

Table 1. Baseline characteristics

Parameter	DETAK diagnosis		p	Definitive diagnosis		p
	ACS	Non ACS		ACS	Non ACS	
Gender						
Male	290	134	0.411	300	124	0.947
Female (n=115)	74	41	0.411	81	34	0.947
Age (mean 58.04 ± 10.1)						
Age >74 year (n=37)	23	14	0.470	23	14	0.238
Risk factor						
DM type II (n=124)	83	41	0.871	83	41	0.296
Hypertension (n=177)	124	53	0.382	120	57	0.303
ESRD (n=7)	4	3	0.555	6	1	0.379

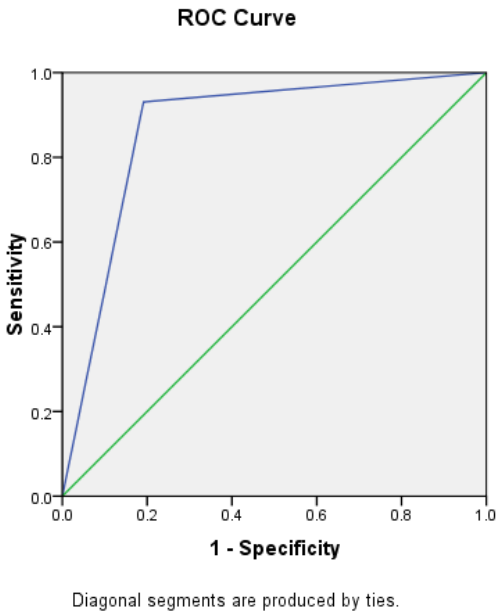

Figure 2. ROC curve in female subset (n=115)

To test the validity of the DETAK algorithm in identifying ACS patients in a population with hypertension, we took data from 177 samples from 7 hospitals. Area under curve receiver operating characteristic (AUROC) was generated to assess the performance of DETAK in identifying ACS in the hypertensive population. The receiver operating characteristic (ROC) curve is shown in Figure 3. The value of the area under the curve is 0.87. The cut of point for the accuracy of DETAK in identifying ACS for the hypertensive population is indicated by a red circle with a sensitivity of 93.1% and a specificity of 80.9%.

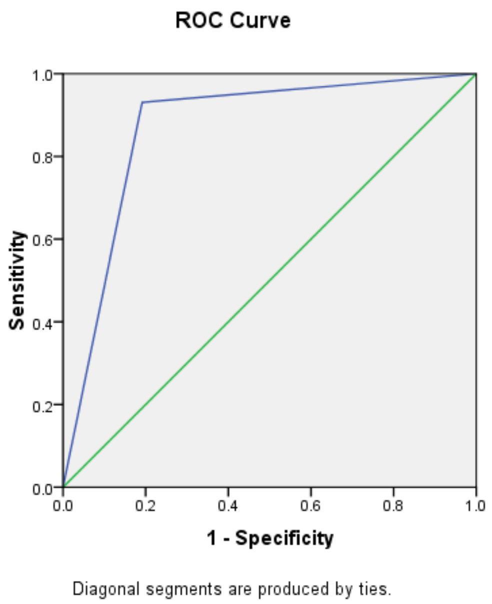

Figure 3. ROC curve in Hypertension subset (n=177)

To test the validity of the DETAK algorithm in identifying ACS patients in a population with type 2 DM, we took 124 samples of data from 7 hospitals. The area under curve receiver operating characteristic (AUROC) was generated to assess the performance of DETAK in identifying ACS in the type 2 DM population. The receiver operating characteristic (ROC) curve is shown in Figure 4. The area under curve value is 0.83. The cut of point for the accuracy of DETAK in identifying ACS for the population with type 2 DM is indicated by a red circle with a sensitivity of 86.7% and a specificity of 79.4%.

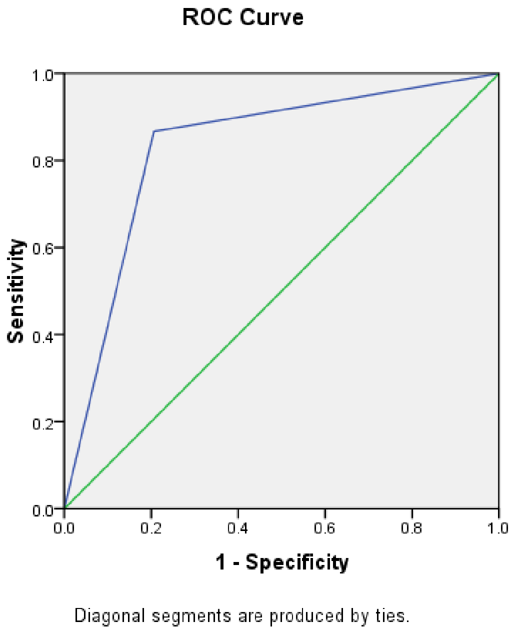

Figure 4. ROC curve in Type 2 DM subset (n=124)

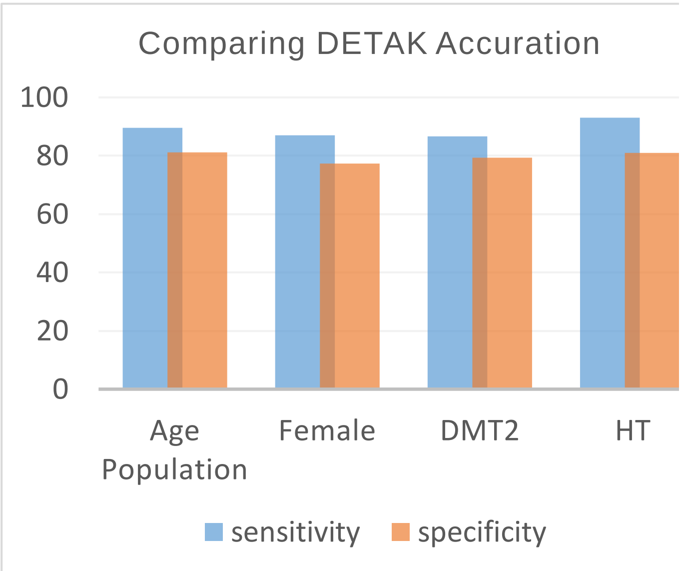

Figure 5. Comparison of diagnostic performance among sub-population sample

Figure 5 shows a decrease in the specificity of the algorithm in specific populations, namely type 2 diabetes mellitus, women and in the hypertensive population. The female population had the lowest specificity rate of 77.3%. The sensitivity results are relatively the same in all sample sub-populations, the numbers obtained are as good as the sensitivity in the entire sample population.

The algorithm in the DETAK application consists of sequential questions arranged using the decision tree classifiers method (table 2). The answers to each question in the sub-population determine the recommendations for health facilities by this algorithm. We tried to analyze the understanding of the questions in the algorithm among the DM and non-DM, HT and non-HT populations, as well as in the female population.

Table 2. Questions in DETAK algorhytm

	Questions
Q1	Does chest pain interfere with daily activities? *(yes/ no)*
Q2	Where is the location of chest pain ? (*left middle/ right)*
Q3	What is the precipitating factor of chest pain? *(activities/ emotional/ fever/ cough or other respiratory symptoms)*
Q4	Have you ever felt a similar chest pain before? *(ya/ tidak)*
Q5	What is the degree of activities precipitating the chest pain ? *(Heavy/moderate/daily activity/rest)*
Q6	Compared to the previous chest pain, how is the current chest pain? *(heavier/more frequent/longer/lighter activity triggered/same as before)*

Table 3. Reliability sub population question and answer

	Reliability					
	Q1	Q2	Q3	Q4	Q5	Q6
DM and non-DM	0,831	0,569	0,651	0,533	0,792	0,634
HT and non-HT	0,851	0,787	0,638	0,837	0,839	0,683
Male and female	0,880	0,642	0,625	0,914	0,773	0,643

Table 3 shows that Q2 and Q4 in the patient population with type II DM have a weak level of agreement because they are in the range 0.40-0.59. Meanwhile, the other questions have a fairly good reliability value with a moderate to strong level of agreement range. For the population of patients with comorbid hypertension, the reliability test performance showed good results with a moderate to strong level of agreement, as well as in the female population.

4. Discussion

Machine learning methods help analyze the data effectively for further processing. The use of machine learning as a clinical application has great potential in the transformation of traditional healthcare. Three main aspects of health services, namely prognosis, diagnosis, and treatment, are greatly helped by the presence of machine learning.[16] But behind this potential there are major challenges, namely the security of patient data and the accuracy of the algorithm used.[17–19]

Otherwise in the field of heart failure (HF), as it is known that heart failure has a broad clinical spectrum, the development of machine learning is still being carried out. The application of diagnostic tools in heart failure is carried out through several approaches, including clinical, supporting examinations (EchoGo Core, Ultromics), therapy and monitoring of complications. One of the application validation tests in the field of heart failure was carried out in 2020 in Korea, namely the Artificial Intelligence-Clinical Decision Support System (AI-CDSS) which was used to assess the number of matches between diagnoses using applications and diagnoses by HF consultants. The study was conducted in an outpatient setting and gave a sensitivity rate of 98%, and a specificity of 76%.[20–22]

In the coronary field, an algorithmic model has been developed to diagnose patients with CAD. A study in Belgium developed machine learning based on memetic pattern-based algorithms (MPA), hereinafter referred to as Basel-MPA and Optimized Basel MPA. This algorithm has a better performance than the Framingham Risk Score (FRS) model.[23]

In this study, the DETAK algorithm was tested for its performance in directing patients with chest pain related to the possibility of ACS. This algorithm is the first to be patient-oriented, assessing the probability of ACS at the prehospital level. So it is very important to ensure this algorithm can predict ACS accurately and efficiently. In all samples, this algorithm provides a fairly good diagnostic performance, namely sensitivity of 89.5% and specificity of 81.2%. With the high rolling-in capability, it is hoped that patients with ACS can be directed appropriately to the nearest PCI center quickly. However, according to the theory which states that there are several subsets of the ACS patient population with atypical chest pain, including female patients or with comorbid type II DM, this study found a decrease in specificity in this population.

In the study by Goldberg et al, the problem of prehospital delay was found in many countries. The broad clinical spectrum, especially the symptoms of ACS, is responded to heterogeneously by patients.[24,25] The delay in realizing the symptoms of ACS greatly affects the speed of subsequent treatment. On average, the handling of SKA cannot reach the door to device target according to the guidelines. Late treatment will give a poor clinical outcome.[5,24] Various efforts have been made to increase public understanding and awareness of the symptoms of ACS.[26] In contrast to campaigns and public outreach about ACS, the algorithm in the DETAK application seeks to reach closer to the community because it can be downloaded on a smartphone and used whenever a patient feels chest pain.

By utilizing the symptom report feature in the application, patients will be immediately directed to answer several questions so that in the end they will receive advice to visit the most relevant health facility according to the possible diagnosis related to the chest pain they feel. Along with continuing education and mass socialization about ACS, the presence of DETAK is expected to strengthen public awareness and increase response time if you feel chest pain.

Seeing that the diagnostic accuracy value of the algorithm in the DETAK application is quite good, this application has the potential to be developed further. Integration of the application with the health care system from primary health facilities to a tiered referral system will make it easier for application users to get fast treatment. This can be achieved by inputting more complete user data, including population identification numbers, previous medical history and medications being consumed. Furthermore, if this can be realized, it is very possible to add features in terms of prevention, monitoring of taking medication and side effects of treatment which are expected to increase adherence to application users. Finally, a periodic maintenance system is needed on the application by minimizing bug errors and strengthening security to ensure the privacy of application user data so that it is not misused.

The limitation of this study is that the DETAK algorithm has been downloaded by more than 3000 smartphone users, with 643 patients reporting chest pain symptoms during the period 2021-2022. This number is still relatively small compared to the proportion of the total number of chest pain patients who come to the ED. The results of the study will be more optimal if the DETAK application has been downloaded by more smartphone users in Indonesia, so that automatically the number of patients reporting symptoms will also be higher. Thus the socialization of the use of the DETAK application is still a fundamental factor that needs to be carried out in the future.

The addition number of study samples by interviewing patients who were admitted to the hospital because of chest pain also created a potential bias due to memory recall when the patient had a heart attack some time before. This depends on the patient's ability to remember the perceived pain and the details of the description of the chest pain he is experiencing.

5. Conclusion

The self-assessment-based chest pain algorithm in the DETAK application has good sensitivity in rolling-in and good specificity in rule-out of ACS patients. There was decreased specificity in patients with comorbid type II DM and female patients, the rule-out ability of ACS decreased in the 2 subsets.

6. Declaration

6.1 Ethics Approval and Consent to participate
The subjects in this study are humans, so ethical rules must be followed. This research has passed the ethical due diligence, approved based on the Certificate of Ethical Eligibility No. 400/162/K.3/302/2021 issued by the Health Research Ethics Committee at Dr. Saiful Anwar Malang.

6.2. Consent for publication
Not applicable.

6.3 Availibility of data and materials
Data used in our study were presented in the main text.

6.4 Competing interests
Not applicable.

6.5 Funding Source
Not applicable.

6.6 Authors contributions
Idea/concept: KAN. Design: KAN, MSR. Control/supervision: AFR, SA, AR, TA, AWA, LH. Data collection/processing: KAN. Analysis/interpretation: KAN. Literature review: KAN, MSR. Writing the article: KAN. Critical review: AFR, SA, AR, TA, AWA, LH. All authors have critically reviewed and approved the final draft and are possible for the content and similarity index of the manuscript.

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