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PREDICARD: A WEB-BASED DIAGNOSTIC AND EARLY SCREENING TOOL FOR CARDIOVASCULAR DISEASES INTEGRATED WITH ARTIFICIAL INTELLIGENCE (AI) USING MACHINE LEARNING

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ABSTRACT

Cardiovascular diseases (CVDs) remain the leading cause of morbidity and mortality worldwide, including in Indonesia, largely due to diagnostic challenges such as overlapping symptoms, inaccurate interpretation of test results, and delayed detection linked to socioeconomic limitations and invasive diagnostic methods. To address these issues, this study aims to develop PrediCard, a web-based diagnostic and screening tool integrating Artificial Intelligence (AI) through machine learning algorithms. The research employed a narrative review design, gathering data from databases such as PubMed, Google Scholar, and ResearchGate, followed by descriptive and critical appraisal analysis to design a low-fidelity prototype of the website. The conceptual framework utilizes both pre-existing clinical data from official cardiology guidelines and real patient data input. Algorithms such as decision trees, K-nearest neighbors (KNN), and K-means clustering process these data to produce diagnostic predictions and personalized lifestyle recommendations. A strengths, weaknesses, opportunities, threats (SWOT) analysis revealed that this innovation exerts significant potential for enhancing diagnostic accuracy, promoting early detection, and expanding screening accessibility, though challenges remain regarding internet access and the need for clinical validation. The findings demonstrate that integrating AI into digital diagnostic tools like PrediCard can support medical professionals in confirming diagnoses while enabling high-risk individuals to conduct self-screening efficiently. Ultimately, this innovation is expected to reduce CVD morbidity and mortality rates, improve patient outcomes, and advance progress toward Sustainable Development Goals (SDGs) in health. Further clinical trials and government support for internet infrastructure are required for practical implementation.

Keywords: Cardiovascular disease; Artificial intelligence; Machine learning; Diagnostic tool; Early screening

INTRODUCTION

Cardiovascular diseases (CVDs) are a group of disorders that affect the heart and blood vessels, including coronary heart disease, stroke, hypertension, and peripheral artery disease. These conditions may result from structural abnormalities, arterial obstruction, or dysfunction of the cardiovascular system, leading to reduced quality of life, heart failure, myocardial infarction, arrhythmia, stroke, and long-term disability. Due to their broad impact, CVDs have become the leading cause of morbidity and mortality worldwide (Netala et al., 2024). Cardiovascular diseases are among the four major non-communicable diseases responsible for premature death in individuals under the age of 70. Therefore, they are a key focus of the Sustainable Development Goals (SDGs) in the health sector, which aim to reduce premature mortality from non-communicable diseases by one-third by 2030 (World Health Statistic, 2025). In addition to posing significant health challenges, these diseases also impose a substantial economic burden on patients' families and the global healthcare system (Gooding et al., 2020).

The World Health Organization (WHO) reports that cardiovascular diseases are the leading cause of death globally, accounting for approximately 17.9 million deaths each year. Among these, heart attacks and strokes represent the primary causes (World Health Organization, 2025). According to data from the Institute

for Health Metrics and Evaluation (IHME) in 2019, cardiovascular diseases caused 651,481 deaths annually in Indonesia (Roth et al., 2020). Furthermore, based on the Riset Kesehatan Dasar (Riskesdas) report in 2018, 15 out of every 1,000 individuals—or approximately 2,784,064 people—in Indonesia suffer from heart disease (Badan Penelitian dan Pengembangan Kesehatan, Kementerian Kesehatan Republik Indonesia, 2018). These diseases can occur suddenly, as in the case of a heart attack, which can be fatal if not treated promptly (Nafisah et al., 2024). Therefore, early detection and diagnosis are crucial to prevent increased morbidity and mortality (Harmadha et al., 2023). Despite their importance, the diagnostic process for cardiovascular diseases continues to face various challenges.

A literature review by Kodeboina et al. (2023) explained that early misdiagnosis of coronary heart disease often occurs because its symptoms overlap with other conditions, such as nonspecific chest pain, gastrointestinal disorders, musculoskeletal pain, and arrhythmia. Misinterpretation of electrocardiograms (ECG) and inappropriate selection of diagnostic tests also contribute to missed diagnoses of coronary heart disease. Wong et al. (2021) in their literature review, reported that the misdiagnosis rate for heart failure across several studies ranged from 16% to 69%, primarily due to nonspecific symptoms or those resembling other cardiovascular conditions. Meanwhile, a meta-analysis by Tarnutzer et al. (2017) found that 9% of cerebrovascular events, including ischemic strokes, were misdiagnosed, leading to higher morbidity and mortality rates. These challenges ultimately reduce diagnostic accuracy, thereby increasing morbidity and mortality. Additionally, clinical factors such as conventional diagnostic methods, which are often invasive, time-consuming, and costly; and individual factors such as geographical constraints, financial limitations, demanding work schedules, and lack of health education; further complicate the process of early detection and diagnosis, worsening patient prognosis (Gooding et al., 2020).

The rapid development of digital technology has been widely integrated into the healthcare sector, including diagnostic support. The utilization of digital technology and artificial intelligence (AI) represents a major breakthrough in developing diagnostic tools that are more portable, affordable, and accurate (Lutviana & Iis Setiawan Mangkunegara, 2024). Through machine learning, which is a field of computer algorithms that enables machines to automatically process data based on prior experience and datasets, AI can analyze medical data accurately and minimize diagnostic errors (Gooding et al., 2020; Taye, 2023). The transition from conventional diagnostic tools to digital and AI-based technologies offers new opportunities to enhance diagnostic accuracy and optimize treatment decisions.

This study aims to conduct review on current literature in order to develop a prototype concept for a web-based digital diagnostic and screening tool called PrediCard to direct current challenges in the diagnosis and screening of CVDs. This website concept utilizes machine learning–based AI to assist medical professionals in confirming previously established diagnoses and improving diagnostic accuracy.Furthermore, as it is designed in the form of a website that can be easily accessed through digital devices such as computers and smartphones, this tool enables individuals at high risk to conduct self-screening to determine their level of risk for specific cardiovascular diseases. The flexibility offered by this platform supports early detection and the prevention of disease progression. This innovation is expected to enhance diagnostic accuracy, improve patient clinical outcomes, and contribute to achieving the Sustainable Development Goals (SDGs) in the health sector, specifically, reducing premature mortality from non-communicable diseases, including cardiovascular diseases, by one-third by the year 2030.

MATERIALS AND METHODS

This study employed a narrative review research design. Literature searches were conducted using several databases, including PubMed, Google Scholar, and ResearchGate. The search process was carried out by entering keywords such as “machine learning-based AI” AND “diagnosis” AND “screening” with the publication year range limited to 2020–2025. The literatures obtained from the data collection step was processed using a descriptive analysis method. This was followed by data analysis using a critical appraisal technique, which consists of the stages of summarizing, synthesizing, comparing, contrasting, and criticizing, to produce a systematic, integrated, and comprehensive review. The analyzed data were then used to develop the concept of the PrediCard website using a low-fidelity prototype design, which is a simple, cost-effective, and fast type of prototype design that does not depict the system in detail, but instead focuses on displaying the interface layout and illustrating the overall conceptual approach.

RESULTS AND DISCUSSION

According to Mishra (2024) artificial intelligence (AI) and machine learning serve as the backbone of modern technological development because they enable machines to perform tasks that typically require

human intelligence and are designed to mimic human cognitive functions. Machine learning is a subset of AI that utilizes algorithms to recognize patterns, make predictions, and reach decisions without explicit instructions. In simple terms, the machine learning method involves a process in which machines find ways to complete a task without being specifically trained to perform such task (Mainali et al., 2021). Consequently, machine learning is capable of making predictions or decisions without being explicitly programmed for a particular dataset.

At present, numerous studies have discussed the potential of AI-based machine learning in the diagnosis of cardiovascular diseases. An experimental study conducted by Koloi et al. (2024) examined the prediction of coronary heart disease (CHD) diagnosis using machine learning with two types of algorithms, such as Random Forest (RF) and Gradient Boosting (GB), and the results demonstrated high levels of accuracy, sensitivity, and specificity. A literature review conducted by Saqib et al. (2024) showed that machine learning models can improve the diagnostic accuracy of heart failure, differentiate between heart failure with preserved ejection fraction (HfpEF) and heart failure with reduced ejection fraction (HfrEF), predict survival rates among HFpEF patients with high accuracy, and determine the prognosis of heart failure patients with a history of diabetes with better performance than traditional prognostic models. These studies indicate that the application of machine learning models in the diagnosis of cardiovascular diseases has highly significant potentials and should be considered for broader implementation in medical practice.

PrediCard Website Concept

PrediCard is a machine learning–based digital platform designed to serve as both a diagnostic support tool and an initial screening system for cardiovascular diseases. The website utilizes three cardiovascular disease models such as heart failure, coronary heart disease, and stroke. These three conditions were selected because, according to several studies, they are frequently misdiagnosed and are among the leading causes of death worldwide (British Heart Foundation, 2025; Kodeboina et al., 2023; Tarnutzer et al., 2017; Wong et al., 2021). PrediCard is intended to assist healthcare professionals in confirming established diagnoses, so that its analytical results can be used as a consideration in clinical decision-making to improve diagnostic accuracy and minimize diagnostic errors. In addition, the website can be used as an early screening tool for individuals at high risk by providing disease diagnosis predictions, risk level assessments, and lifestyle modification recommendations based on available data. As a web-based application, PrediCard is designed to be accessible via various devices such as smartphones, computers, or laptops. To ensure operability, the website must be designed with comprehensive data input options and functional features. The conceptual design of the website is outlined as follows.

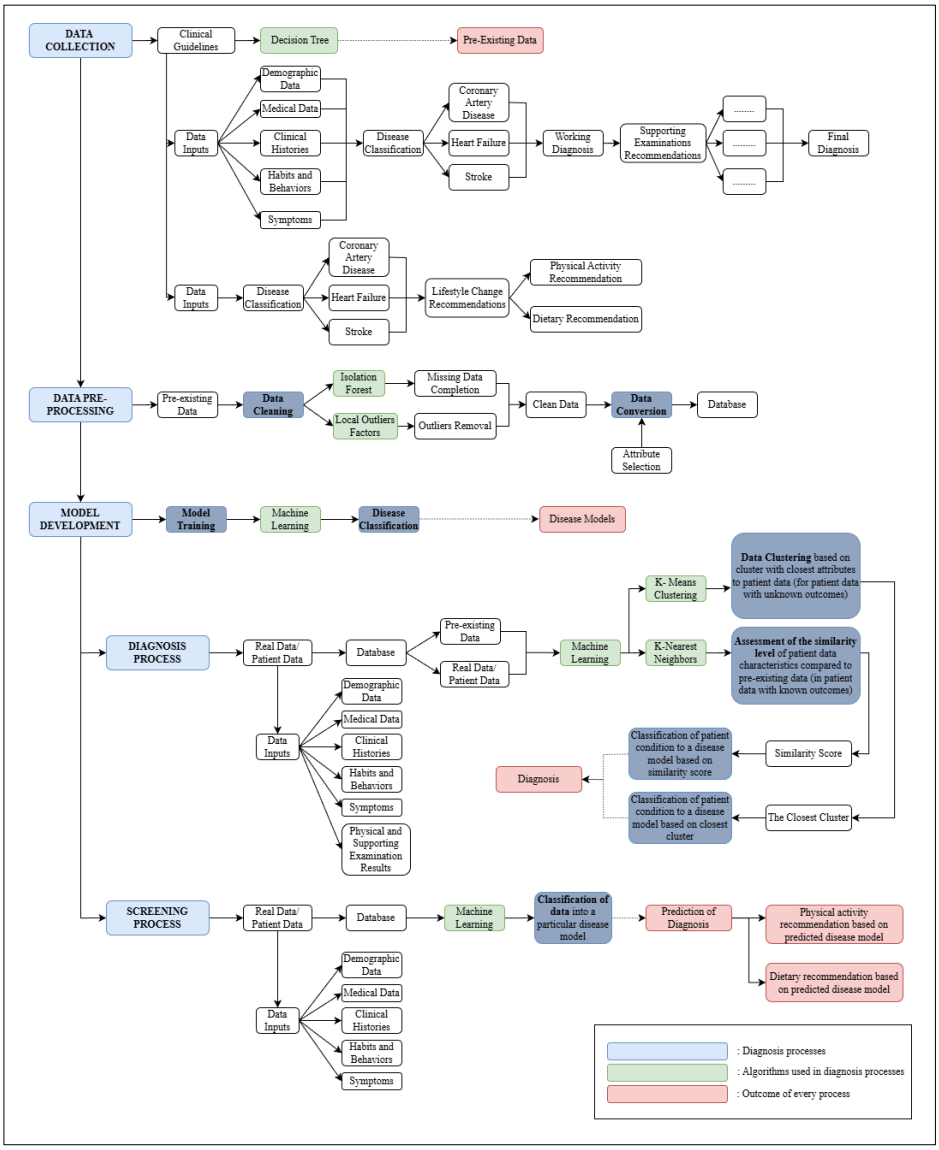
Data Inputs

The data required on this website consist of two types: pre-existing data and real data. Pre-existing data, or data that already exist, refer to a group of clinical data used as the initial dataset to be entered into the database so that the machine learning system can learn algorithms from these data. These data are also used by the machine learning model to develop disease models that serve as diagnostic parameters (Koloi et al., 2024; Njeri, 2022).The pre-existing data on this website are qualitative data obtained from secondary sources in the form of clinical guidelines issued by several national and international cardiology associations, such as the European Society of Cardiology (ESC), the American Heart Association (AHA), and the Perkumpulan Dokter Spesialis Kardiovaskular Indonesia (PERKI). The clinical guidelines include *ESC Guidelines on Cardiovascular Disease Prevention in Clinical Practice*, *ESC Guidelines on Sports Cardiology and Exercise in Patients with Cardiovascular Disease,* and *Panduan Praktik Klinis (PPK) dan Clinical Pathway (CP) Penyakit Jantung dan Pembuluh Darah, dan Panduan Prevensi Penyakit Kardiovaskular Aterosklerosis*.

From these clinical guidelines, the necessary data for the diagnostic process of each disease model were obtained, including patient demographic and medical data, risk factors, symptoms, results of physical examinations, supporting test results, and differential diagnoses established for each disease. In addition, data on exercise recommendations were also collected, including examples of exercises, intensity, and duration recommended for each disease model; as well as data on dietary and nutritional recommendations, such as types of diet, food ingredients, meal plans, macronutrient and micronutrient compositions, and food items recommended for each disease model.

Real data refer to data inputted by users or actual patient data. These include demographic data, medical data, clinical history, patient risk factors, results of physical examinations, and supporting test results (Koloi et al., 2024). This real data are analyzed by the algorithm and compared with the pre-existing data so

that the machine learning system can classify a patient's condition into a specific disease category based on the comparison results (Qasimi, 2024).



Algorithm Design of PrediCard Website

The workflow of the machine learning algorithm on this website begins with the data acquisition stage (**Figure 1**). The initial or pre-existing data are obtained from clinical guidelines. These data contain various types of information about the general characteristics of patients for each disease to be used as a model. The data are processed using the decision tree algorithm, which has a tree-like structure and is used to classify data by dividing them into several subsets based on feature values. According to Mishra (2024), this algorithm is highly suitable for medical diagnostic systems because it can classify patients into disease groups based on their symptoms.

After obtaining the pre-existing data, the process continues to the pre-processing stage. In this stage, the data undergo several preparation steps, including data cleaning and data transformation. Data cleaning is performed to fill in any missing information from data entry and to filter or remove outlier data, which are abnormal or deviant data points (Njeri, 2022). The process of filling in missing data is carried out using the Isolation Forest algorithm, while removing outlier data is done using the Local Outlier Factors algorithm. The outcome of the data cleaning process is clean data (Koloi et al., 2024). The pre-processing stage then continues with data transformation, in which the clean data are converted from one format into another that can be understood by the program (Qasimi, 2024). This transformation process employs the attribute selection

method, which facilitates classification, clustering, and regression algorithms, making it highly suitable for this dataset (Njeri, 2022). After transformation, the data are input into the database.

The next stage is model development, where the pre-existing data stored in the database are used to build disease models. This stage begins with model training, during which the machine learning system uses the pre-existing data to train its ability to process information. The system then classifies diseases based on the available data, resulting in three disease models that serve as parameters in the diagnostic process: coronary heart disease, heart failure, and stroke (Koloi et al., 2024).

The process continues with the diagnosis and screening stag, which require patient data (real data) to be entered into the database. The patient data needed for the diagnosis feature include demographic data, medical data, clinical history, lifestyle history, symptoms, physical examination results, and supporting examination results. For the screening feature, the required input data are similar to those for the diagnosis feature, but they do not include physical and supporting examination results.

Within the database, patient data are aggregated and compared with the pre-existing data based on their characteristics. If the patient data include labeled data or data with known outcomes, the aggregation and characteristic assessment are performed using the K-Nearest Neighbors (KNN) algorithm. This algorithm evaluates the similarity between the patient's characteristics and the pre-existing data and generates a similarity score. The machine learning system then uses this score to classify the patient data into the disease model with the closest similarity, thereby producing a diagnostic result (Mishra, 2024).

If the patient data are unlabeled or have unknown outcomes (for example, when a patient presents with unclear or uncommon symptoms but other characteristics still correspond to one of the three disease models), the data aggregation process is performed using the K-Means Clustering algorithm. This algorithm groups patient data into a cluster with attributes most similar to the pre-existing data, producing the nearest cluster as the result. Classification of the patient data into a specific disease model is then based on the cluster with characteristics most closely resembling the disease model, thereby generating a diagnostic result (Mishra, 2024).

The screening stage follows a process similar to that of the diagnosis stage but differs in the input data used, as it does not involve physical or supporting examination results. The machine learning system classifies patient data into predicted disease models using the same algorithmic workflow as in the diagnosis stage, resulting in an analysis output in the form of a predicted diagnosis. The predicted disease results are then used to generate lifestyle modification recommendations, such as physical exercise suggestions and dietary recommendations tailored to the predicted disease.

Mechanism of Diagnosis and Screening using PrediCard Website

Diagnosis Menu

In medical settings, the PrediCard website is designed as a diagnostic support tool for healthcare professionals, such as physicians, to help confirm a diagnosis that has already been established. This website is intended for use after the physician has completed the diagnostic process, which includes anamnesis, physical examination, supporting examinations, and determination of the final diagnosis. To operate this website as a diagnostic aid, users can select the "Diagnosis" menu on the main page (**Figure 2**, a)). They will then be directed to a patient data input page, where they are required to fill in information such as patient identity, demographic data, and medical data (**Figure 2**, b)). Next, users will be directed to the anamnesis page, which contains questions regarding the patient's symptoms, including the type of symptoms experienced, symptom onset, duration, time of occurrence, as well as aggravating and relieving factors (**Figure 2**, c)). These data can be obtained from previous anamnesis records.

After completing all the required data, users are directed to the "Start Data Analysis" menu to generate a preliminary diagnosis based on three available disease models: coronary heart disease, stroke, and heart failure. If there is a tendency toward one of these three disease models, a preliminary or working diagnosis will be displayed (**Figure 2**, d)). Based on the obtained working diagnosis, the website can provide recommendations for additional examinations that healthcare professionals may perform to support the final diagnosis (**Figure 2**, e)). Users are then prompted to input the results of the recommended examinations and proceed again to the "Start Data Analysis" menu to obtain the final diagnosis. On the following page, the website presents the final diagnosis based on the supporting examination results that have been entered (**Figure 2**, f)). The diagnostic result includes the specific type and classification of cardiovascular disease, along with the percentage likelihood of each possible condition. Thus, these results can serve as supporting information to confirm the final diagnosis previously established by the physician and as a reference for making the final diagnostic decision.



Figure 2 Diagnosis menu. a) Homepage display; b) Input of the patient's informations; c) Input of the patient's symptoms; d) Working diagnosis and supporting examination recommendations; e) Input of the supporting examination result; f) Final diagnosis.

Screening Menu

The screening menu is intended for the general public who wish to detect the early risk of cardiovascular disease. The target users are individuals with cardiovascular risk factors, such as middle age, hypertension, diabetes, dyslipidemia, obesity, a family history of cardiovascular disease, and other related risk factors. To operate the website, users can select the "Screening" menu on the main page (**Figure 2**, a)). Similar to the diagnosis menu, users will be directed to a data input page and are required to enter basic information consisting of personal identity, demographic data, medical data, and experienced symptoms along with their characteristics (**Figure 3**, a) and b)). The difference is that in the screening menu, users are not required to input data from physical examinations or supporting laboratory tests, as this menu is designed to be used by the general public without medical supervision.

After completing all data inputs, users are directed to the "Start Data Analysis" menu, where the system will generate an analysis result in the form of disease prediction and risk level (**Figure 3**, b)). If the user's risk of a particular disease is very high, the website provides a warning feature that advises the user to immediately seek medical assistance and intervention. In addition, the website includes a feature recommending nearby healthcare facilities, integrated with GPS applications such as Google Maps, allowing users to locate and access recommended health services (**Figure 3**, c)).

Furthermore, the website provides lifestyle modification recommendations, including physical exercise and dietary recommendations tailored to the predicted disease and risk level (**Figure 3**, d)). The physical exercise recommendations include information on the type and examples of exercises, as well as the recommended intensity and duration based on the predicted disease (**Figure 3**, e)). The dietary recommendations include types of diets, food ingredients, meal menus, macronutrient and micronutrient composition, and specific food items recommended according to the predicted disease (**Figure 3**, f)). Finally, the website offers a feature that allows users to monitor their health progress through the "Health Progress" menu, which displays a progress curve showing the user's health status relative to disease risk (**Figure 3**, g)). This enables users to maintain lifestyle changes more consistently.

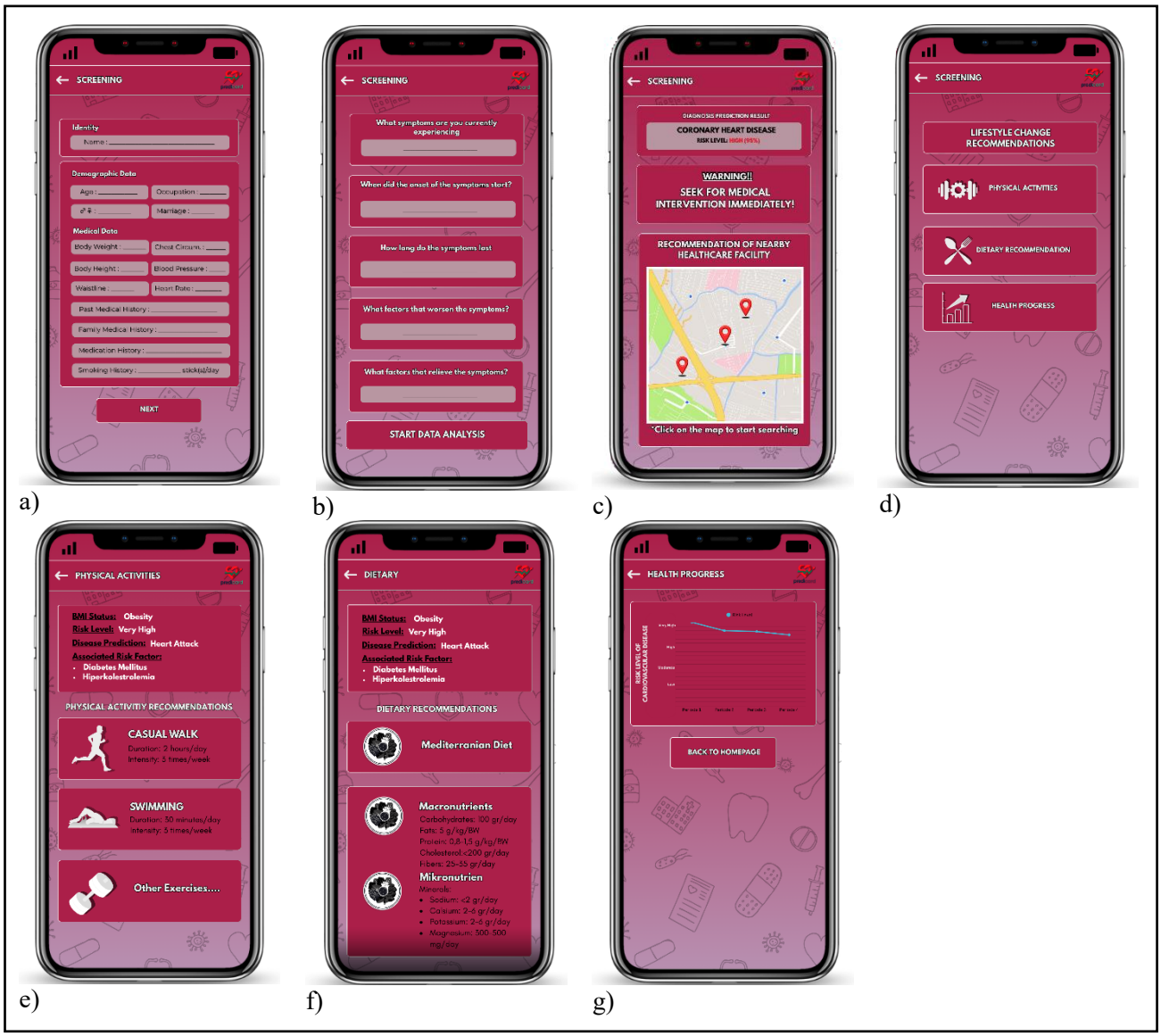


Figure 3 Screening menu. a) Input of the patient's informations; b) Input of the patient's symptoms; c) Diagnosis prediction; d) Lifestyle change recommendations; e) Physical activity recommendations; f) Dietary recommendations; g) Health progress chart.

Future Prospects of the PrediCard Website in Medical Diagnosis

The website serves as a digital diagnostic tool that utilizes artificial intelligence based on machine learning, trained to accurately process patient data according to pre-existing data and disease classification models. Consequently, this tool can help reduce the risk of diagnostic errors and improve the accuracy of diagnostic results. In addition, the machine learning technology implemented on the website uses specialized algorithms capable of processing complex patient data and classifying it into the disease model with the closest

characteristics. This makes it suitable for assisting physicians in handling complicated cases, such as those involving patients with unclear symptoms or symptoms that overlap with other cardiovascular diseases.

PrediCard is also capable of providing reliable and relevant diagnostic results because it uses reference data derived from credible cardiology society clinical guidelines, which can be updated periodically. Moreover, this device is accessible and cost-effective since it can be operated directly through a web browser on hardware such as a smartphone. This facilitates screening for individuals with limited access to healthcare facilities or financial constraints. PrediCard can also deliver real-time diagnostic predictions without lengthy processing time, thereby offering an efficient and practical preliminary screening tool. Beside, since the advancement of modern technology has led to a shift from traditional diagnostic and screening devices toward more portable and efficient digital-based systems. This trend presents an opportunity for PrediCard, as it provides the capability to assist in diagnosing and conducting early screening for cardiovascular diseases through a website that can be accessed digitally via smartphones, laptops, or computers.

Even though PrediCard serves a lot of potencies for future use in medical settings, the use of such technology that utilizes artificial intelligence based on machine learning, which possesses the ability to process data more accurately than humans, raises concerns that it could threaten or replace the role of physicians as the authorized professionals responsible for establishing diagnoses. Furthermore, since this innovation is web-based, the tool requires an internet connection to operate, which restricts its use in remote areas with limited internet access. However, to address those weaknesses and threats in its implementation, this website is fundamentally intended only as a diagnostic support tool designed to confirm diagnoses that have already been made by physicians. In other words, the website can only be used after the physician has completed the entire diagnostic process, including anamnesis, physical examination, and supporting tests. Therefore, physicians' diagnostic expertise remains essential and irreplaceable. Additionally, collaboration with local government is required to broaden access of internet in rural areas in order to implement this innovation, thus promoting inclusivity to individuals with restricted access to adequate healthcare facility, and maximizing the use of the innovation.

CONCLUSION

Cardiovascular disease is one of the leading causes of morbidity and mortality worldwide, including in Indonesia, with a significant number of deaths each year. Diagnostic errors and delays remain major challenges due to overlapping symptoms with other diseases, inaccurate interpretation of examination results, and limitations of conventional diagnostic methods, which tend to be invasive, costly, and time-consuming. To address these challenges, digital diagnostic technology based on artificial intelligence (AI) and machine learning has emerged as an innovative solution to improve diagnostic accuracy while providing early screening for individuals at high risk. The PrediCard website concept was developed by utilizing AI technology to assist healthcare professionals in confirming diagnoses accurately and to enable practical self-screening through digital devices. This website is expected to reduce morbidity and mortality caused by delayed diagnoses, support early detection efforts, improve patient clinical outcomes, and contribute to achieving the health-related Sustainable Development Goals (SDGs).

CONFLICT OF INTEREST (if any)

The authors declare that there is no conflict of interest in this article.

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No acknowledgments are necessary for this article.

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