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Mortality among older adults Jordanians with coronary heart disease: Intelligent algorithms prediction

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ABSTRACT

Background and aim: Worldwide, coronary heart disease (CHD) is the main cause of death. To prevent heart disease and save lives, this study uses a machine learning algorithm (MLA), a subfield of artificial intelligence, to predict death vs. life outcomes among older persons with CHD.

Methods: Large-scale data was retrieved from the electronic health records of 3,331 elderly patients with congestive heart failure retrospectively. Information was gathered on the population in Jordan who were hospitalized in public health hospitals between 2015 and 2021.

Results: Based on the accuracy level (91.4%) and area under the curve (71.7%) of the eight prediction models created, the Chi-square automatic interaction detector algorithm was chosen to predict death versus life among older adults with CHD. The sequence of death prediction algorithms began with the medical diagnosis, location, age, and pulse pressure.

Conclusion: Attempts should be made to use the expertise of many specialists and clinical screening data gathered from patient databases to speed up the diagnosis process with MLAs, which are thought to be a useful tool for identifying CHD patients who are at high risk of dying.

Keywords: coronary heart diseases, death, artificial intelligence, algorithms, older adults

INTRODUCTION

The term coronary heart disease (CHD) refers to heart conditions when the main blood arteries narrow or clot, causing ischemia of the heart tissue and a loss of blood flow [1]. According to the American Heart Association (AHA), one person develops acute MI every 40 seconds in the United States, thereby increasing the risk of further cardiovascular adverse events and the burden of healthcare expenditures due to the high morbidity rates associated with MI cases [2].

The development of a massive prevalence of CHD is expected due to the following reasons:

(1) the world's population is aging and expanding rapidly,

(2) older adults aged 60 years and more, and

(3) the advancement in the invasive and non-invasive diagnostic tests that help in the initial diagnosis of CHD [3].

CHD cases affect 5% to 7% of the elderly population [4]. In Jordan, heart disease death reached 7,615 cases which demonstrated 22.97% of the total deaths ranking Jordan as 52 in the world in heart disease death cases [5].

Electronic health records (EHRs) provide an opportunity for the healthcare system to collect and store patient's clinical data that gather a range of medical data of individuals over a long period as well as manage the clinical overflow of data [6]. In addition, EHRs provide healthcare professionals access to comprehensive medical, surgical, and physical exam findings, procedural reports, current medications, and clinical notes. So, healthcare professionals are required to deal with large-scale data. Dealing with a huge amount of data has the potential to advance the profession in practice, education, administration, and policy by getting the direction to involve the nurses as a frontline in the revolutionary changes in their healthcare institutions and play a critical role in helping elderly patients to navigate this data and encourage them to change their unhealthy lifestyle and thus improve their health outcomes [7].

Prediction of heart disease mortality using a machine learning algorithm (MLA) as a branch of artificial intelligence (AI) is a crucial step in preventing cardiac diseases and saving lives [8]. Most large-scale data analytical techniques achieve an accuracy of more than 70% in predicting heart diseases, which provides the insight to use these techniques in predicting undiagnosed diseases before they become severe, thereby enhancing the quality of care and reducing the financial burden on patients, families, and healthcare institutions [9].

Large-scale data stored in the EHRs have little effort to take the benefits from analysis to inform the precision of clinical decisions, manage and recover diseases, and conduct proactive management through the prediction of specific health conditions using patterns of hidden data [10]. Thus, the purpose of this study was to predict death versus a life outcome among the older adult population in Jordan who are diagnosed with CHD using an MLA.

METHODS

Study Design

A retrospective design in retrieving data from the EHRs known as electronic health solutions [11] for older adult Jordanian patients with CHD was used. Data were collected for Jordanian elderly patients who were admitted to public health hospitals from 2015 to 2021.

Sample and Variables

For the admitted patients from 2015 to the end of 2021, the health data analytics (HDA) department collected the following information: patient sex, geographic location (governorate), medical diagnosis based on the international classification of disease (ICD-10), and laboratory results, including high-density lipoprotein (HDL), lactate dehydrogenase (LDH), cholesterol level, fasting blood sugar (FBS), and systolic blood pressure (SBP) and diastolic blood pressure (DBP). Excel sheets containing numerous files were downloaded from the HDA. There are no missing values for age, sex, or place of residence. However, there were many missing values for vital signs such as pulse oximetry, heart rate, SBP, and DBP, as well as variables of LDH, HDL, glycated hemoglobin (HbA1c), creatinine, and FBS. Data were merged in a single file using the international business machine statistical package for social science (SPSS) modeler (version 18.0) program [12], and then sorted and cleaned.

Inclusion and Exclusion Criteria

The necessary attributes were used to retrieve all patient records from hospitals that used Hakeem (EHS) as a component of EHRs. Since they are more likely to acquire IHDs, information regarding older adult patients who are 60 years of age or older is one of the necessary data. Records that contained information about patients who were

(1) less than 60 years old and

(2) admitted to the system for trial purposes were not included.

Data Analysis

Data processing

Using frequency descriptions, a large, selected data pool was examined for noise, inconsistency, and missing values. Noisy and inconsistent data were identified and eliminated from the large dataset; however, missing data for variables like the biochemical results of fasting blood glucose, cholesterol, LDL, HDL, and HbA1c were eliminated to prevent errors in those variables. Many variables, such as age, sex, governorate, and medical diagnosis, were provided completely without any missing values, so all of these variables were retained and used in the analysis process.

Data transformation

Using data visualization, the researchers selected the most pertinent characteristics of CHD. Additionally, the data was manipulated, analyzed, and visualized using the SPSS modeler (version 18.0), which offers the capabilities of data management for descriptive and predictive modeling as well as powerful data presentation for statistical analysis [13]. To determine the primary risk factors for CHD that result in death, descriptive modeling was employed. Conversely, based on the area under the curve (AUC) and overall accuracy, predictive modeling was selected to create the best model.

Table 1. Sample characteristics (N = 17,507)

Item	Number (percentage [%])
Age (M = 70.9 years & SD: 7.37)	
Gender	
Male	1,955 (58.7)
Female	1,376 (41.3)
Medical diagnosis	
AMI	192 (5.8)
Angina pectoris	2,216 (66.5)
CHF	923 (27.7)
Governorate	
Irbid	206 (6.2)
Ajloun	3 (0.1)
Jarash	57 (1.7)
Mafraq	33 (1.0)
Balqa	146 (4.4)
Amman	2,219 (66.6)
Zarqa	422 (12.7)
Ma'daba	74 (2.2)
Karak	102 (3.1)
Tafilah	3 (0.1)
Maan	36 (1.1)
Aqaba	30 (0.9)

Note. AMI: Acute myocardial infarction & M: Mean

Ethical Consideration

The study has been authorized by the University of Jordan School of Nursing's Scientific Research Committees. Additionally, the Ministry of Health's (MOH) ethics committee approved the collection of data under number #MOH/REC/2022/3. By using an ID as each record's unique identifier, patient records were managed anonymously and with secrecy. The retrieved data was kept in a different file that was locked up and kept in a safe place in the researcher's workspace.

RESULTS

The health records of 3,331 older adult patients (≥ 60 years) were extracted. Males were predominant (58.7%) in the sample. The mean age was 70.9 years (standard deviation [SD] = 7.37). Most of the patients were diagnosed with angina pectoris (n = 2,216, 66.5%). The majority were living in the middle of Jordan, which includes the following governorates; Balqa', Amman, Zarqa', and Ma'dba (n = 2,861, 85.9%) (**Table 1**).

The laboratory results, including LDH, HDL, cholesterol, HbA1c, creatinine, and FBS are collected. Vital signs, including pulse oximetry, heart rate, SBP, DBP, pulse pressure (PP), and mean arterial pressure (MAP) were used to stratify the patient results. Unfortunately, not all patient health records had all the workup results in their EHR. **Table 2** displays the clinical and laboratory results' minimum, maximum, mean, and standard deviation.

Table 2. Work-up results and vital signs of the patients

Work-up results	N	Minimum	Maximum	M [SD]
LDH	84	124.00	816.0	232 (104.00)
HDL	69	11.30	103.4	27.3 (14.40)
Cholesterol	107	46.40	324.0	127 (57.60)
HbA1c	311	2.15	13.4	3.92 (2.29)
Creatinine	349	.02	122.0	3.01 (12.10)
FBS	417	18.00	742.7	141 (101.70)
Pulse oximetry	708	55.00	100.0	93.7 (8.55)
Heart rate	2,401	16.00	192.0	78.2 (15.10)
SBP	3,331	60.00	250.0	151.4 (24.70)
DBP	3,331	30.00	165.0	81.8 (15.40)
Pulse pressure	3,331	17.00	138.0	69.7 (20.10)
MAP	3,331	39.90	183.1	104.7 (16.40)

Note. M: Mean

Table 3. Seven models built for the study data

Model	Overall accuracy (%)	AUC
C5	91.441	0.500
CHAID	91.441	0.717
C&R tree	91.441	0.500
Logistic regression	91.441	0.710
Bayesian network	91.441	0.748
Neural network	91.441	0.664
Discriminant	61.562	0.643

Selecting a Predictive Model

The Chi-square automatic interaction detector (CHAID) model is the most accurate out of seven models to predict death versus life among older adults with CHD, with an overall accuracy of 91.4% and an AUC of 72% (**Table 3**).

The CHAID model uses Chi-square tests to analyze correlations between categorical variables and the desired outcome to identify significant predictors for mortality among older Jordanians with CHD. Typical predictors include laboratory markers like BMI or cholesterol levels, clinical diseases like diabetes, hypertension, and smoking status, and demographic characteristics like age and sex [14]. By constructing decision trees based on statistically significant divisions in the data, the model divides the population into risk categories. For instance, CHAID may show that older persons who have excessive cholesterol and uncontrolled hypertension are at greater risk of dying. In this context, CHAID can be used practically to prioritize treatment by stratifying patients based on risk, guiding targeted therapies, and enhance clinical decision-making by displaying the interplay between various predictors and mortality outcomes [15].

The SPSS modeler was used to generate the 11 nodes model. **Figure 1** illustrates that a randomly selected sample (from the 3,331 clean data) that represents roughly 70% of the data is included in the study's graph, which is generated by the interactive CHAID tree's initial node. To ascertain whether the model produces trustworthy results, about 30% of the data used during model training is utilized. The root node of the decision tree in **Figure 1** shows the medical diagnosis as the most important predictor in an outcome field. The first and second nodes demonstrated that the mortality rate among patients with congestive heart failure is higher, at 14%, than that of patients with acute coronary syndrome, at 6.4% (Chi-square = 50.03, p < .001).

The CHAID has combined certain governments as the next predictor in the model because it has determined that the merging of such categories is statistically significant and provides a meaningful and substantial split for this variable. The governorate merger by CHAID ended with 2 groups, namely node 3 three, and node 4. The governorates of Mafraq, Zarqa, and Karak were added to the governorate of Irbid under node 4 with a death status of 14.1%, while Irbid, Ajloun, Jerash Balq'a, Amman, Tafilah, Ma'an were added to Aqaba, under node 3 with a death status of 4.9% (Chi-square = 33.11, p < .001).

The model's next split was for age. Node 3 was divided into 3 nodes (≤ 70, 71-80, > 80 years). Those who are older than 80 years have the highest death status 11.6 % as shown in node 9 (Chi-square = 29.5, p < .001).

The congestive heart failure (CHF) node was split into two nodes, namely node 5 and node 6 for the age predictor. Individuals who were above 70 years had death rates of 17.2%, while those who were 70 years or less had a death rate of 9.7% (Chi-square = 10.3, p = .012). Then, the model's next split was based on the PP. Node 10 showed that those with PP ≤ 87 had a death rate of 14.4%, while those with PP > 87 had a death rate of 26.2% (Chi-square = 9.66, p = .017).

DISCUSSION

Several significant factors emerged to predict the mortality of CHD cases among older adults using the CHAID model. The CHAID model is an MLA that branches from AI applications [16]. In the current study, we were able to build a model from the tremendous amount of data stored in the EHRs, which could be used to improve patient outcomes. Furthermore, the analysis based on the CHAID model matches the nature of the given data and the type of variables used in this study.

Retrospective data from the Jordanian health information system were used to develop a model for predicting death vs life status in older persons with CHD. Numerous risk-predicting equations have been constructed using the regression model as a foundation. To identify the cardiovascular disease risk variables described in earlier investigations, we applied automated machine learning in this study [17]. Data-driven modeling that makes use of MLAs can improve risk prediction. In order to visualize the most significant risk factors and account for the interaction between predictors, the CHAID model was employed in this investigation. A small set of attributes and techniques are still sufficient to do this [18].

The current study concluded that medical diagnosis is the most important predictor of death versus life status among older adults. It was shown that individuals with CHF had higher mortality rates compared with acute coronary syndrome cases. This finding is consistent with the study in [19] who found that mortality rates were high among patients with IHD.

The residency place (governorate) is the second predictor for mortality among older adults. We found that patients who lived in Mafraq, Zarqa, 'Ma'daba, and Karak had the highest mortality rate among Jordan's 12 governorates, with a death rate of 14.1%. In Jordan, circulatory system disorders account for 42.36% of all deaths among all age groups, according to 2017 MOH statistics. Furthermore, the mortality rate was found to be the highest in the Zarqa governorate (15.7%) [20]. This result was consistent with a study conducted by Bhatnagar [21] who found that in a highly developed society, there was a great influence of the natural environment such as pollution, socioeconomic status, and social network. These findings were

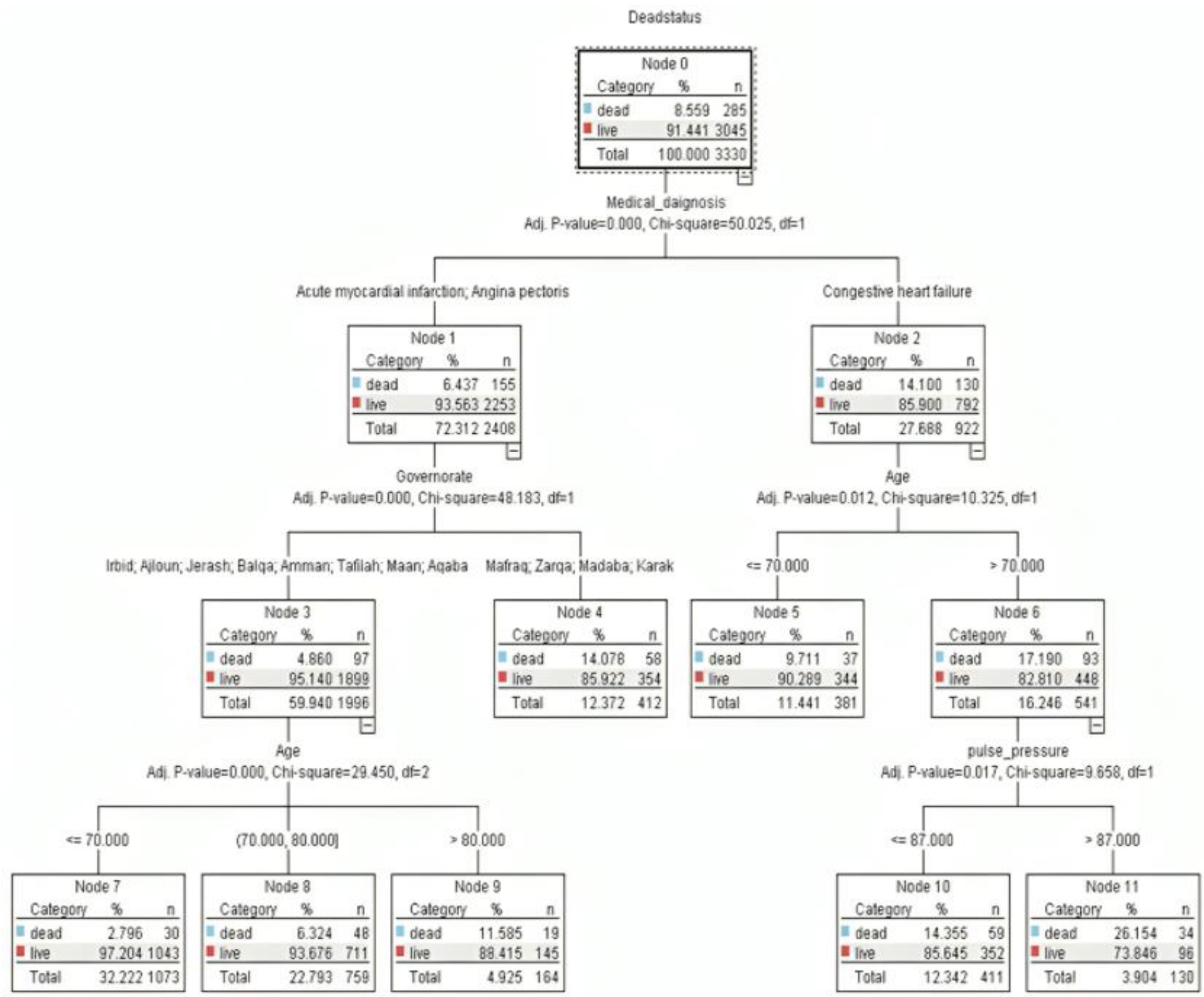

Figure 1. Predictive model of death versus a life outcome for older adults (60 years and above) (Source: Authors' own elaboration)

consistent with the study in [22] that aimed to create and validate a multivariate prediction model for estimating the risk of CHD in middle-aged and elderly individuals who found that a combination of predictors like age, HbA1c, ankle-brachial index, flow-mediated vasodilatation as risk factors in a prediction model for CHD.

The third attributable risk factor of death among older adults was age. Older adults with CHF aged above 70 years had a mortality rate of 17.2% compared with a mortality rate of 9.7% among patients ≥ 70 years. This result is consistent with many studies that found the effect of age on the development of CHDs [23, 24]. The aging process is associated with a decline in all physiological functions leading to an increased risk of developing health complications and other related diseases. Besides, aging has a remarkable effect on the heart and vascular system leading to heart diseases including atherosclerosis, hypertension, myocardial ischemia, and stroke [25].

The fourth attributed factor of mortality among patients older than 70 years was PP. It was found that PP more than 87 mmHg was a significant predictor of death with a ratio of 26.2%. This finding was highly consistent with studies that showed the main role of wide PP as an independent risk factor for high mortality rates among patients with cardiovascular diseases [26, 27]. Our finding can be explained by the fact that the elderly population had an increase in the artery's stiffness that is associated with an increase in wave reflection amplitude [28]. Furthermore, after the age of 70 years, diastolic blood pressure decreases, while systolic pressure increases which creates a wide PP that is related to peripheral vascular resistance which is known as an age-related phenomenon among this age group population [29].

Moving beyond the traditional prediction technique, MLA as a crucial part of AI provides promising effects on disease prediction including CHD. For instance, the study in [30] explores the use of machine-learning methods for developing risk prediction models in clinical cardiology research. The review uses data from an institution's EHR and 13 laboratory markers to predict mortality after acute myocardial infarction diagnosis. They reported that in the age of precision medicine, MLAs are increasingly used for risk assessment, enabling more accurate prediction of outcomes. These methods address multiple predictors, non-linear relationships, and interactions in large datasets. However, model validation and comparing multiple approaches are crucial for effective risk modeling.

Implications

The prediction model for IHD is integrated into EHR systems for real-time risk stratification and decision support, analyzing patient data to generate risk scores for adverse outcomes, and enabling timely interventions [31, 32]. The system should offer user-friendly visual outputs, including decision trees or color-coded risk categories, right within the EHR interface to guarantee seamless workflow integration. To make sure the tool enhances rather than replaces current procedures, clinicians and support personnel should be trained on how to use the model's insights to guide care plans. The model's relevance, accuracy, and efficacy in enhancing patient outcomes in the management of ischemic heart disease will be ensured by frequent validation and updates with local and recent data.

Limitations

We found that not all the targeted variables had complete documentation in the EHR. Thus, the primary factor that affected the final clean sample size was the proportion of missing data for crucial factors in our study. The patient's smoking status, substance misuse history, body mass index, and socioeconomic position are a few examples of factors with a high rate of inadequate recording. These factors were thus not included in our AI model.

CONCLUSION

This is the first study of its sort to be conducted in Jordan and the region using an AI technology that facilitates predictive modeling. A hopeful outcome of the potential of MLAs and other AI techniques to predict death among cardiovascular illness using accessible attributable data from patients' health records. These data may aid medical professionals and other healthcare providers in interpreting and analyzing the most efficient algorithms within a specific data set. In addition, the implementation of AI approaches has the potential to improve the accuracy of CVD risk factor prediction and, as a result, develop heart disease prevention efforts.

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Ethical statement: The authors stated that the study was approved by the Ethics Committee of the MOH, Jordan with approval number #MOH/REC/2022/3. Written informed consents were obtained from the participants.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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