

A hybrid decision support system for heart failure diagnosis using neural networks and statistical process control

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ABSTRACT

Timing and precision are two primary keys for myocardial infarction diagnosis. Even minor errors in diagnosis can dramatically increase the treatment process, increase treatment costs, and put the patient in dangerous health states. This paper presents a decision support system (DSS) based on neural networks and statistical process control charts for diagnosing and controlling myocardial infarction (MI) and continuously monitoring the patient's blood pressure. To this aim, the data was collected from 175 medical documents of patients with MI and 92 recorded successful diagnoses of MI type. A group of patients was used to validate the effectiveness of the proposed system. The results prove that the proposed hybrid model can diagnose MI with high accuracy and precision compared to machine learning algorithms. Tighter control limits with a confidence level of L=2 (confidence interval of 95.45%) in the control determination stage and wider control limits with a confidence level of L=3 (confidence interval of 99.73%) in the condition determination stage led to higher overall accuracy. This method can help physicians make better decisions on diagnosing cardiovascular diseases.

1. Introduction

Decision support systems (DSSs) have attracted many researchers in a wide range of applications, such as rental accommodations [1], supply chains [2], transportation [3], and energy [4]. Nowadays, DSS has entered into clinical approaches for supporting medical decisions [5–7] to assist emergency care clinicians [8]. One of the most critical tasks of clinical DSSs is the diagnosis of different diseases [9,10], which the current paper focuses on.

One of the essential and initial tasks of predicting and preventing a possible widespread disease is to provide reliable tools for early and accurate disease diagnosis. Cardiovascular diseases, including MI, are among the world's most frequent causes of death [11]. MI, commonly referred to as heart attack, occurs when part of the heart muscle (myocardium) experiences an irreversible cell death due to the loss of blood flow, low oxygen levels, and severe ischemia. One of the reasons for this condition is high blood pressure, increasing the probability of fat deposits and narrowing the arterial duct by thickening the walls of the arteries and reducing their elasticity. As a result, a blood clot is formed in the artery and blocks the blood path, causing a heart attack. Continuous blood pressure monitoring (CBPM) could be considered a priority in reducing the fatality rate of patients with cardiovascular diseases. It helps to estimate the risk of cardiac death and prevent cardiovascular diseases. However, continuous blood pressure monitoring

is challenging [12]. A better understanding of processes and methods for clinical decision-making enables practitioners and physicians to diagnose disease faster [13]. Early diagnosis is essential for deadly diseases such as heart disease and can drastically prevent patients from dying [14]. Also, an accurate diagnosis depends upon analyzing various variables that differ from one person to another. Therefore, making effective diagnosis decisions requires much time for a clinical study on the influential variables [14,15]. A decision support system (DSS) can help health professionals to make an effective decision about a diagnosis [16–19]. Additionally, clinical methods for diagnosing heart failure are expensive and dependent on high-level expertise [20].

Several studies have been conducted on this topic, including Bhaskar [21], in which a support vector machine and an artificial neural network (ANN) were utilized to diagnose myocardial infarction (MI) using electrocardiography (ECG) signals. Kong et al. [22] presented a decision-making tree to distinguish between cardiac and non-cardiac pain. They categorized patients into zero, low, high, and critically high cardiac risk, improving the efficiency and accuracy of the system's diagnosis. Krisciukaitis et al. [23] presented a computer-based DSS to forecast the clinical condition of patients with MI. They analyzed the three indices of heart rate, ECG, and thoracic impedance signal, to promote the quality of patient monitoring.

Sheibani et al. [24] developed a DSS to improve adherence to the principles in treating cardiovascular-related issues such as atrial

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fibrillation [24]. AHA/ACC (i.e., the most common guideline in clinical practice in Iran) was applied to manage patients with atrial fibrillation. By measuring the proportion of patients with AF treated according to guidelines, the effect of the intervention was assessed. The proposed DSS based on interrupted time series and regression is utilized for a real-life case study including 373 patients in Mashhad, Iran. Findings showed that the proposed DSS could help improve adherence to patient treatment guidelines. In another study, Piazza et al. conducted a case study including 458 patients using a computer-based DSS for high-risk hospitalized patients diagnosed with atrial fibrillation [25]. Lindow et al. [26] developed a graphical DSS for MI patients to detect acute coronary occlusion. They did a case study with a sample of 135 patients to improve the DSS accuracy in terms of MI diagnosis. Safdar et al. present a comprehensive literature review for applying machine learning algorithms for medical DSS to diagnose heart failure issues [27].

There are also ANN-based predictive processes, in which a set of data is fed into the neural network in order to perform interpolation by estimating the system behavior [28,29]. Perceptron networks are among the most useful neural network types, yielding acceptable results in various applications of DSS by minimizing the output mean square error using the backpropagation learning algorithm [30,31]. The proposed model in the current study offers advantages like considering the offline part of the model as a reference for the index values in different disease severity levels. By comparing the actual index values in the online part (a model used to estimate the future values) to the reference values, the difference is calculated as a residual value. It is known that the mean of the indices increases with the level of disease severity. The residual values show this incremental trend, reflecting changes in the process mean by considering the model uncertainty. In addition, in some applications of control charts, the process is described in terms of the relationship between a dependent variable and one or several independent variables (which enable the prediction of the process as well). A combination of control charts with neural networks can be used to account for the linear and non-linear relationships between such variables. The presented model also comes with a decrease in the effect of data dynamics and uncertainty on both prediction and measurement error. It considers the weight element based on temporal data.

The current study uses a DSS as a three-stage model to diagnose MI through a systematic and holistic perspective. After a patient is referred to the emergency center with MI clinical symptoms, the first stage is the preliminary diagnosis using a guiding flowchart. In the second stage, a graphical rule table is used to determine the infarction type. When the cardiac enzymes are confirmed to have been released into circulation, a model is constructed to determine the severity of the heart attack in order to provide the required medical services. The patient's blood pressure from admission to discharge is continuously monitored to prevent a recurrent attack. The proposed hybrid model is a combination of control charts and predictive models as ANN. Control charts, which are used to discern changes in a process, determine whether it is under or out of control by examining its statistical indices [32]. They consist of two phases, Phase I and Phase II. In Phase I, the aim is to estimate the unknown parameters of the process while they are known in Phase II, and the statistical hypothesis of the parameters' equivalency to the values estimated in the first phase is tested so that the procedures are quickly discovered [33]. There is a very close relationship between the control charts and the hypothesis test. Control charts analyze data and help detect the common cause and special cause variation in the statistical control condition of the process [34]. A point drawn within the control limits implies that the under-control hypothesis is confirmed, while a point beyond these limits implies its rejection. It should also be noted that getting close to the upper or lower control limits is regarded as a warning, indicating the need for modification actions [32,34]. Nowadays, control charts are used beyond manufacturing and industrial systems, finding applications in different fields such as biology, engineering, economics, and medicine.

The study published by Morton et al. [35] is a great example of the applications of statistical control charts in medicine and healthcare.

This research addresses the problem of heart diagnosis failure using included factors by providing a hybrid DSS in the following sections. In Section 2, we give a comprehensive description of the problem, the methods, and the case study. Results and findings are presented in Section 3. In Section 4, managerial insights for heart disease diagnosis are discussed. Finally, we conclude in Section 5.

2. Materials and methods

In order to obtain a systematic and holistic perspective concerning diagnosis, the diagnostic policy of the World Health Organization (WHO) has been used for patients with MI since 1979. Fig. 1 demonstrates the basis of the proposed model in the current study to diagnose, control and determine MI severity. Based on this policy, the emergence of MI clinical symptoms, ECG changes, and laboratory tests are the criteria for assessing infarction patients [36]. Out of these three criteria, at least two are required to diagnose a patient with MI. After the patient is referred to the emergency center, if MI clinical symptoms are observed, the best diagnostic method to help the doctor in this stage is an electrocardiogram. It could demonstrate two types of infarctions, ST-elevation MI (STEMI) and Non-ST-elevation MI (NSTEMI) [37,38]. If the condition is determined to be STEMI, the patient is identified as an MI patient in the preliminary diagnosis since two of the criteria are met, while an NSTEMI patient would be referred to the third stage for the final analysis as the electrocardiogram shows no respective symptoms. In the third stage, after examining for specific enzymes in the blood such as Creatine Phosphokinase (CPK) and Creatine Kinase Myocardial Band (CPK-MB) and the final infarction diagnosis, the condition severity is determined [38]. A principal reason for heart attack is the blockage of the vessels that supply blood to the heart (coronary arteries). Thus, in some cases, methods to unblock the arteries, such as angiography, stenting, open heart surgery, and the patient's expiration, are considered Stages 1, 2, and 3 of the condition.

During all the stages from diagnosis to the determination of MI severity, controlling the blood pressure is vital. According to a report from America's Joint National Committee (JNC) in 2003, blood pressure levels are categorized into normal, prehypertension, Stage 1 hypertension, Stage 2 hypertension, and isolated systolic hypertension [39]. Given the restriction of data resources, isolated systolic hypertension is disregarded, and the other categories are used in this research. The model presented in the third stage to determine the MI severity and monitor the blood pressure consists of two online and offline parts. Exponentially moving average-related approaches are one of the practical approaches in ANNs [40]. In the current study, by examining the system's actual behavior under the online model and its expected behavior under the offline model as a perceptron ANN, the residual values are generated and used as inputs to the exponentially weighted moving average chart (EWMA) statistical quality control chart. Then, a rule table is drawn, and the EWMA chart is used to determine the MI severity and continuously monitor the patient's blood pressure in two stages: assessing the patient's condition and deciding whether it is out of control. In the offline part of the model, inspecting previous literature and using experts' opinions, the MI severity is predicted using indices of age, sex, systolic and diastolic blood pressure, blood sugar, CPK, CPK-MB, the MI type, respiratory rate, background in hypertensive diseases, diabetes, blood lipids, cardiovascular diseases, and substance addiction [40,41]. Systolic and diastolic blood pressure are also predicted in the same fashion, using indices of sex and age, heart rate, and background in diseases such as hypertension, diabetes, blood lipids, cardiovascular diseases, and substance addiction.

A perceptron neural network (PNN) that consists of two layers, a hidden and an output layer, comprised of ten neurons and one neuron, respectively, is considered in the current study. It is trained based on Marquez's training algorithm to determine the MI severity [42].

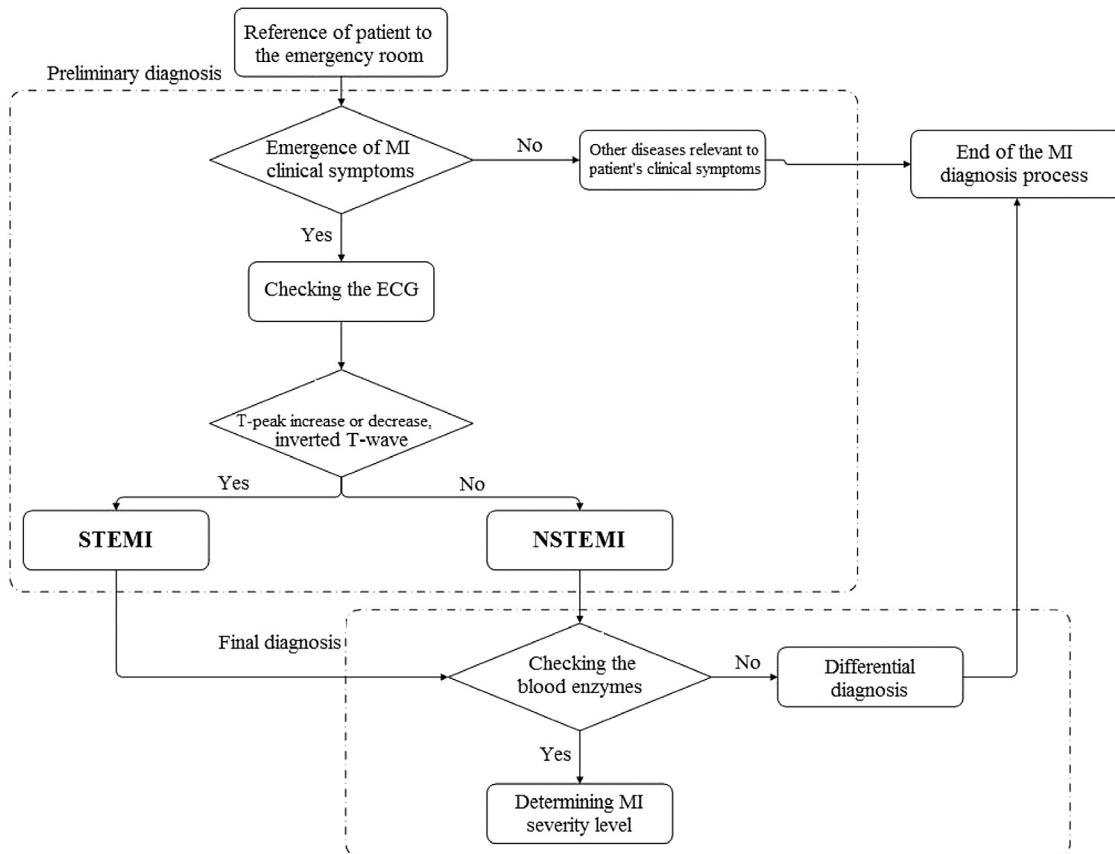


Fig. 1. The basis of the proposed model to diagnose, control and determine MI severity.

The blood pressure prediction network consists of four neurons in the hidden layer, and two in the output, trained by the Neural Net Fitting toolbox available on MATLAB 2016 and based on the Bayesian training algorithm are also taken into account. Among the aggregate data input to the neural network, 60% is allocated to training, 20% to performance, and 20% to test data. After the residual values associated with each severity stage are generated, patients are categorized in different severity levels, and their blood pressures are also classified. The residual values reflect the process behavior. Therefore, after calculating the residual values to determine the MI severity, 80% of the 92 data inputs to the neural network are applied in Phase I to determine the control chart parameters, and the rest are used for validation purposes. In the pressure monitoring case, 175 data inputs are fed to the neural network, of which 60% are utilized in Phase I to determine the control chart parameters, and 40% are used in Phase II to validate the model at different confidence intervals, thanks to Minitab 17. The data corresponding to the normal blood pressure level in Phase I is applied along with the data used for the graphical representation of the model confirmation in Phase II. The process parameters, such as the lower control limits (LCL), the control line (CL), and the upper control limits (UCL), are calculated at every severity level for the EWMA chart from (1), (2), and (3), respectively.

$$LCL = \mu_0 - L \cdot \sigma \sqrt{\frac{\lambda}{n(2-\lambda)}} \quad (1)$$

$$CL = \mu_0 \quad (2)$$

$$UCL = \mu_0 + L \cdot \sigma \sqrt{\frac{\lambda}{n(2-\lambda)}} \quad (3)$$

where σ_0 is the standard deviation, λ is the data weight factor, n is the sample size, and μ_0 is the expectancy of the residual values and

the central line. L is the width of the control limits, used to determine the confidence interval. λ is a chart parameter, with a constant value within $0 < \lambda \leq 1$. In general, its practical value is usually considered $\lambda = 0.2$ under the ideal conditions [43]. In the control chart, if the data lie within the control limits, the patient's blood pressure is undoubtedly under control; otherwise, it is out of control. In Phase I, after the samples corresponding to the control chart are drawn, one or several out-of-control samples are omitted after the reason for this situation is examined, and the control limits are re-calculated using the remaining samples. This omission procedure is continued to the point that all the samples are under control. In this case, Phase I is finished, and the resulting chart is ready to be utilized in Phase II, in which new samples are drawn on it to determine whether the procedures are under or out of control. After the model's parameters are determined, it is assessed using the overall accuracy criterion resulting from the confusion matrix. This criterion is significant in determining a model's overall accuracy, calculated by Eq. (4) [13].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively [13,44].

In order to verify the feasibility and applicability of the proposed DSS, we performed a real-life medical case study in Iran to see how efficiently the proposed DSS can increase the possibility of diagnosing cardiovascular diseases. Through convenience sampling, this cross-sectional research has been conducted on a sample comprising 175 medical documents of patients with MI in a hospital in Zahedan, Iran, between 2014 and 2015 (one year). Among the 175 patients chosen for CBPM, 92 documents with the required supplementary data were chosen to determine the severity of the condition. For data collection, we considered several indicators such as age, gender, infected area by MI, blood pressure, and previous cardiovascular disease records.

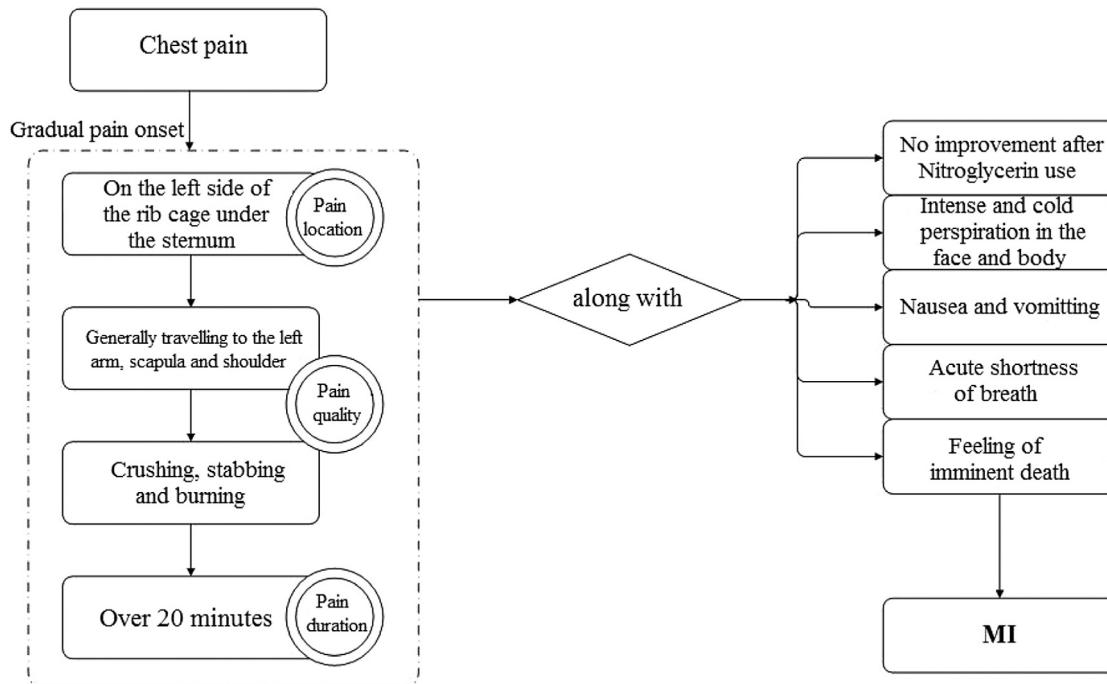


Fig. 2. The guiding flowchart of the emergence of clinical symptoms to diagnose MI.

3. Results and findings

One of the conditions for the input data fed to the control chart is their normality. So, given the inequation $P - V\text{alue}(0.88) > 0.05$ for the data corresponding to the determination of MI severity, and the inequation $P - V\text{alue}(0.13) > 0.05$ for the data corresponding to the diastolic blood pressure, these data are normal and prepared for being inputted into the control chart. However, $P - V\text{alue} < 0.05$ denotes that the data is not normal for systolic blood pressure, and they should first be normalized using Johnson transformation [45] in Minitab before being fed to the control chart.

Based on the proposed model, the diagnosis and control procedures of infarction are performed in the following three steps: the emergence of clinical symptoms based on the guiding flowchart, evaluating the ECG using the graphical rule table, and determining the MI severity level by creating a rule table along with CBPM.

3.1. Stage one: The emergence of clinical symptoms

In this stage, a guiding flowchart is used to investigate the emergence of clinical symptoms as depicted in Fig. 2. Examining the respective medical documents and literature and seeking advice from cardiologists, we can find that among the most widespread MI symptoms is chest pain traveling to the arms, back, neck, and upper part of the abdomen and lasting over 20 min [46]. If this pain accompanies nausea, vomiting, and intense cold sweats, it is identified as one of the MI symptoms [38].

3.2. Stage two: Electrocardiogram

In the second stage, given the ECG leads affected by STEMI, two general types of MI ECG patterns – anterior and inferior ST-segment elevation – were analyzed. In patients with MI clinical symptoms, examining the ECG are necessary to find out possible changes in S, Q, and T waves [38,47]. Some examples of these changes are a negative T wave, ST-segment elevation, and an abnormal Q wave, as seen in leads V1, V2, V3, and V4, and leads DII, DIII, and AVF for Anterior and Inferior Myocardial Infarctions, respectively (see Appendix). In

this research, the graphical rule table has been used as a sample of the patient's ECG to determine the infarction type. The regions involved in both infarction types are shown in red on the graphical rule table depicted in Figs. 8 and 9 (Appendix).

3.3. Stage three: Determining the infarction severity and monitoring the blood pressure

In this part, we consider several indicators as input data for the ANN to determine the infarction severity. According to the records and experts' opinions, we considered age, gender, blood pressure, blood sugar, CPK, CPK-MB, type of MI, breathing rate, past chronic disease, and addiction to narcotics as input for the ANN. For ANN, we use ten neurons in hidden layers and one neuron in the outer layer using the NN toolbox in MATLAB 2016b, where 60% of the data is considered for training, 20% of the data is considered for performance, and the other 20% as test data.

In the next step, we use ANN for systolic and diastolic blood pressure using the NN toolbox in MATLAB 2016b, where age, gender, breathing rate, heart rate, potential records of chronic diseases, blood pressure, diabetes, fat, and addiction are considered as the input data. We considered four neurons in hidden layers and two neurons in outer layers. As in the previous part, 60% of the data is considered for the training, 20% is considered for performance, and the other 20% is test data. The regression results of the ANN in predicting the MI severity and systolic and diastolic blood pressure are demonstrated in Fig. 3.

In the next step, healthcare systems often use confidence intervals to monitor and control MI severity and blood pressure. Therefore, to determine whether the patient's condition is out of control and further assess it, the two values of L=2 and L=3 with confidence intervals of 95.45% and 99.73% have been considered in Phase I and Phase II of the control charts, respectively.

3.3.1. Phase I of the control chart

In this stage, regarding the residual values, the mean values and control limits of each MI severity level (1 to 3) are obtained at different confidence intervals to create the rule table, as observed in Fig. 4.

In Fig. 4, the EWMA control chart determines the control limit (red lines) corresponding to each severity level (1 to 3) using the relevant

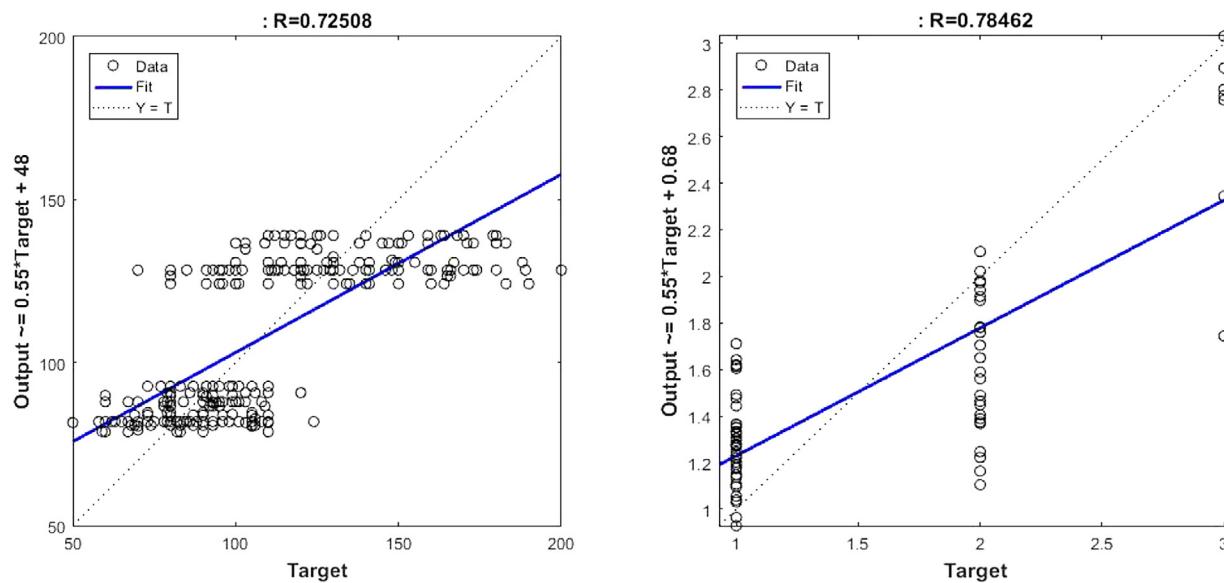


Fig. 3. Regression results of the ANN in predicting the MI severity (78% - left side) and systolic and diastolic blood pressure (73% - right side).

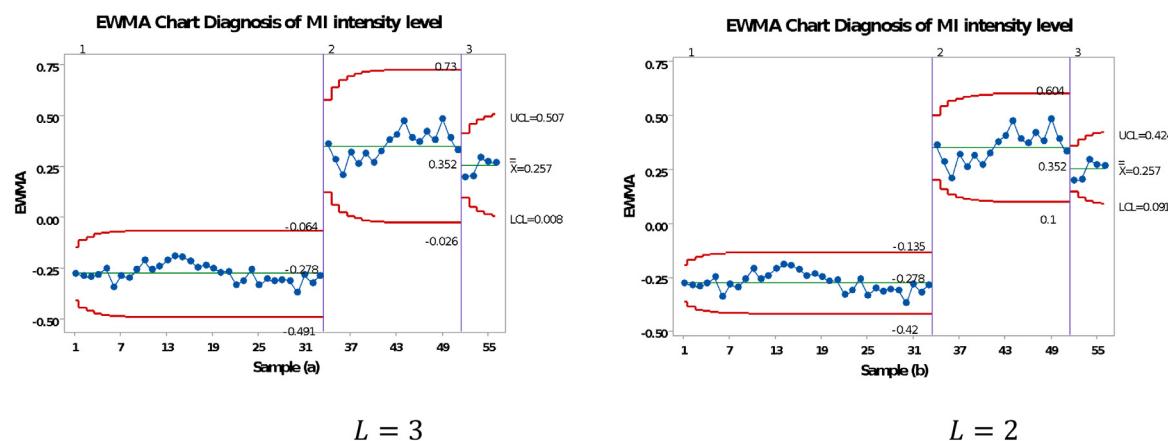


Fig. 4. The EWMA control limits for different confidence intervals and severity levels.

Table 1
The evaluation results of the rule table at different confidence intervals using the control chart.

MI severity levels/ control limits	Level 1		Level 2		Level 3		Total	
	Control limits		Control limits		Control limits		Control limits	
$L=2$	[-0.42, -0.135]		[0.1, 0.6]		[0.091, 0.42]		—	
$L=3$	[-0.49, -0.064]		[-0.026, 0.73]		[0.08, 0.5]		—	
True/false percentage	True	False	True	False	True	False	True	False
$L=2$	71.5%	28.5%	85.7%	14.3%	50%	50%	81.25%	18.75%
$L=3$	71.5%	28.5%	85.7%	14.3%	50%	50%	81.25%	18.75%

data (blue points). The control limits in Fig. 4 are taken as threshold values in Table 1. This table is used as a rule table to determine the MI severity level.

Therefore, the appropriate medical services can be thought to enter the correspondent data and insert them into each range in Table 1. By doing so, they can decide on the MI severity, which is at 81.25% accuracy in this case. Furthermore, the mean values and the control limits for CBPM are shown in Fig. 5 at the confidence levels of $L=3$ and $L=2$, after two steps of data omission for diastolic and one for systolic blood pressure.

According to Fig. 5, the mean of the process is increased when MI severity level increases for systolic blood pressure in samples (a) and

(b), and for diastolic blood pressure in samples (c) and (d) at confidence levels of $L=3$ and $L=2$.

3.3.2. Phase II of the control chart

After monitoring the chart and verifying the model by determining the mean value and control limits at each severity level, the model's overall accuracy is evaluated in the following steps.

3.3.2.1. Stage one: Realizing whether the patient's condition is out of control. After stabilizing the blood pressure to normal levels and securing a steady state for the patients, the trend of their blood pressure changes is examined. At first, according to Fig. 6-sample(a) at $L=3$

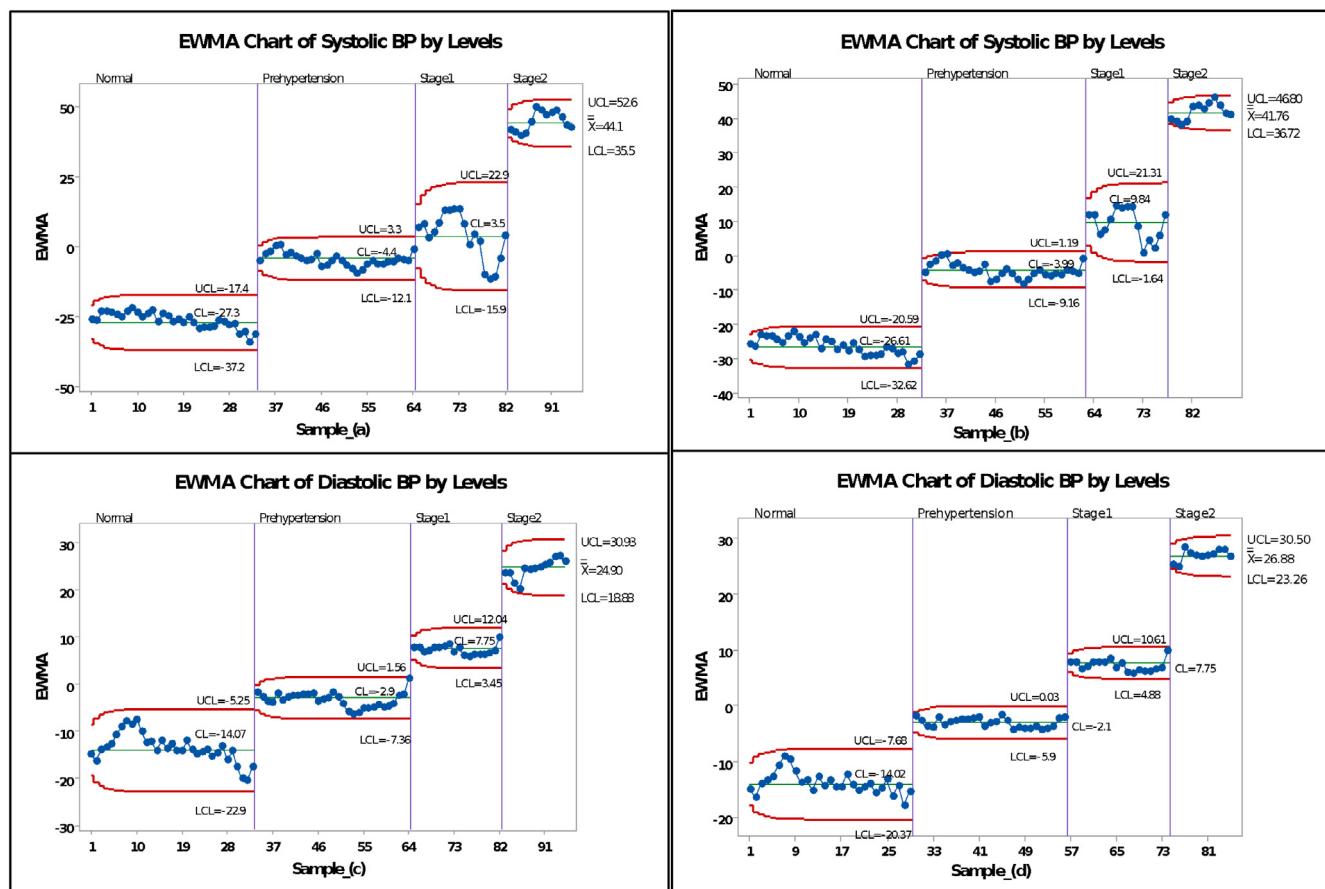


Fig. 5. The EWMA chart control limits for different confidence intervals and severity levels for systolic and diastolic blood pressure.

Table 2
The model evaluation results in the control determination stage at different confidence intervals.

Overall accuracy of the control chart	Normal		Prehypertension		Stage1		Stage2		Total		
	True	False	True	False	True	False	True	False	True	False	
L=3	Systolic	100%	0%	80%	20%	100%	0%	100%	0%	95%	5%
L=2	Systolic	100%	0%	80%	20%	100%	0%	100%	0%	95%	5%
L=3	Diastolic	100%	0%	90%	10%	100%	0%	100%	0%	97.5%	2.5%
L=2	Diastolic	100%	0%	95%	5%	100%	0%	100%	0%	98.75%	1.25%

and Fig. 6-sample(b) at L=2 for systolic blood pressure, considering the normal blood pressure trend and stabilizing the condition resulting from Phase I up to the 33rd sample, the trend of changes in the patient's blood pressure is recorded from the 34th sample on. Likewise, for diastolic blood pressure at L=3 in Fig. 6-sample(c) and at L=2 in Fig. 6-sample(d), this trend is recorded from the 32nd sample. For instance, the entire set of data corresponding to different patients is assumed to be the chart input for a selected patient, presuming that the data has been continuously (and even momentarily if required) measured over one day on different occasions. According to Fig. 6-sample(a), the patient's blood pressure is recorded from the 34th sample for systolic blood pressure at L=3. Consequently, the selected patient's blood pressure condition is under control up to the 53rd sample and out of control from that point forward. The 58th sample warns that the patient's blood pressure is out of control. Through samples 54 to 58, the blood pressure is out of control, but the chart shows otherwise. The points approach the upper control limits until finally exceeding them. At this point, the lack of appropriate medical services could cause the patient's blood pressure to rise to higher levels.

In this stage, the results corresponding to the model's overall accuracy at each severity level have been shown in Table 2 for both systolic and diastolic blood pressure.

In the same way, the model acts the same in order to realize whether the patient's condition is out of control in Fig. 6-sample(b) at L=2. As Figures 6-sample(c) and 6-sample(d) and Table 1 demonstrate, by considering a confidence level of L=2 in Fig. 6-sample(d), higher accuracy is observed since false diagnosis points (green points) are fewer. The essential health services are given to decrease the patient's blood pressure as the points approach the control limits, and the disease development to higher severity levels is prevented, avoiding any physical and mental damage to the patient.

3.3.2.2. Stage two: Determining the patient's condition. The control charts show the blood pressure level and the course of the disease development. They also continuously monitor whether the situation is out of control, thus helping more to determine the patient's condition. In this stage, the process parameters measured at Stage 1 hypertension and Stage 2 hypertension levels (Phase I of the control chart) are added to the control chart. For example, for the supposed patient mentioned before, after the normal blood pressure is stabilized up to the 33rd sample, the blood pressure is recorded from the 34th sample. According to Fig. 7-sample(a) for systolic blood pressure at L=3, the blood pressure is under control up to the 53rd sample. From samples 54 to 58, where the first warning is given, the points approach the upper control limits corresponding to normal blood pressure and the lower

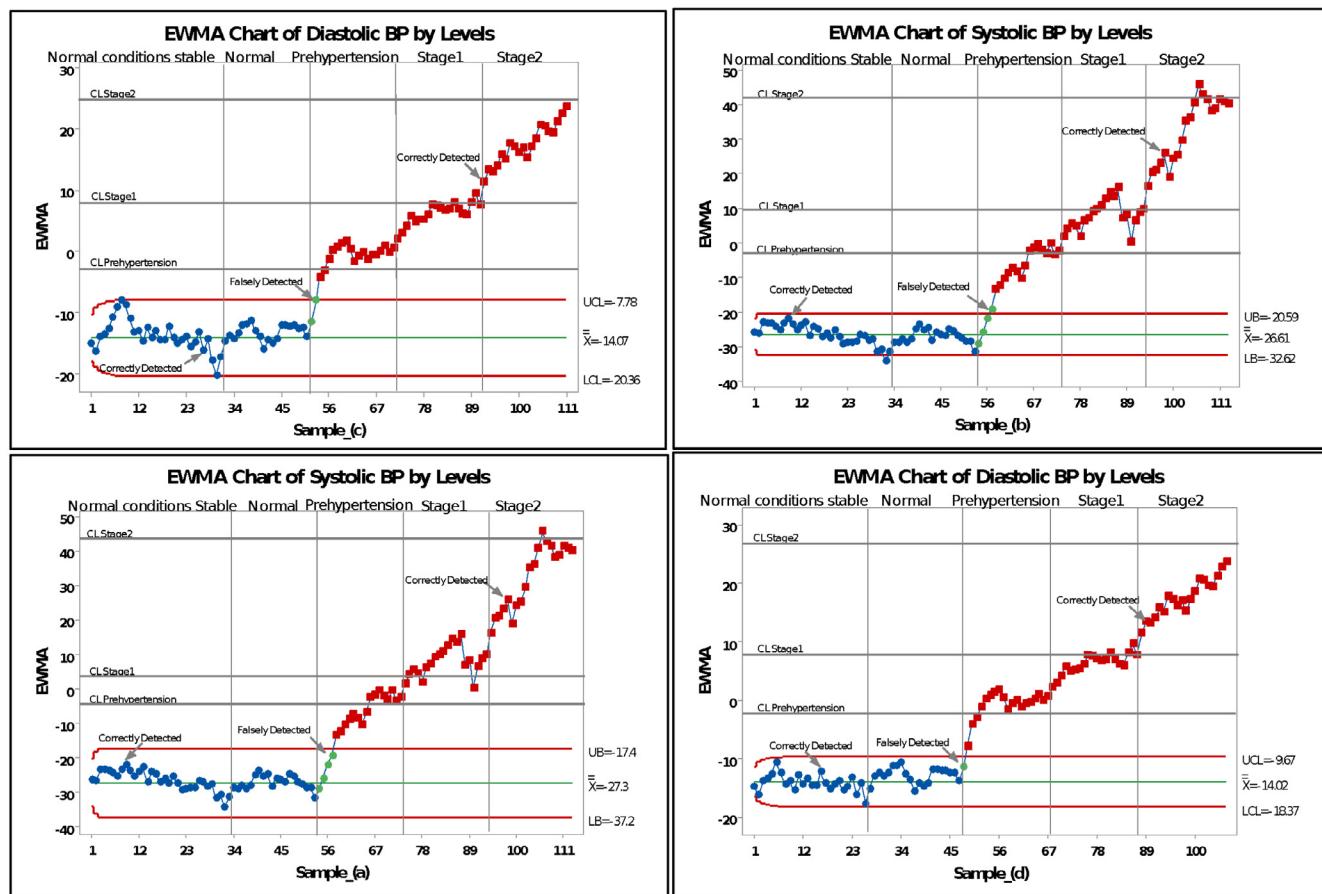
 $L = 3$ $L = 2$

Fig. 6. The procedure of preventing and examining the out-of-control points for systolic and diastolic blood pressure at different confidence intervals.

Table 3
The model evaluation results in the diagnosis and control stage at different confidence intervals.

Overall accuracy of the control chart		Normal		Prehypertension		Stage1		Stage2		Total	
		True	False	True	False	True	False	True	False	True	False
L=3	Systolic	100%	0%	80%	20%	100%	0%	55%	45%	83.75%	16.25%
L=2	Systolic	100%	0%	60%	40%	100%	0%	55%	45%	78.75%	21.25%
L=3	Diastolic	100%	0%	90%	10%	95%	5%	40%	60%	81.25%	18.75%
L=2	Diastolic	100%	0%	100%	0%	10%	90%	10%	90%	70%	30%

limits corresponding to prehypertension and Stage 1 hypertension. The points indicated in red are assumed as out-of-control points at the prehypertension stage since the EWMA chart shows them within the normal range. Then, from samples 58 to 74, the points are within the normal prehypertension range, although they are out-of-control and approaching the central prehypertension line. From the 74th sample, the points approach the upper limits of prehypertension and the central line of stage 1, which is taken as a warning. From samples 75 to 93, even though the points are beyond the normal and prehypertension limits, they are considered under control due to proximity to the central line of Stage 1. From samples 94 to 102, the points become close to the upper control limits of stage 1. The blood pressure corresponding to these points indicates stage 2 hypertension, but the EWMA chart still shows them in stage 1. Hence, they are shown in red as out-of-control points in Stage 2 hypertension. From samples 103 to 113, the points are located around the central line of Stage 2, being under control in this stage, despite being out of control in normal, prehypertension, and Stage 1.

The model's overall accuracy in this stage is separately given for each severity level of systolic and diastolic blood pressure in Table 3.

Considering the out-of-control points shown in red and Table 3, the detection accuracy in Fig. 7-sample(b) at $L=2$ is less than Fig. 7-sample(a) at $L=3$ for systolic blood pressure. This inference also holds for diastolic blood pressure, as observed in Figures 7-sample(c) and 7-sample(d). Also, by checking the proximity of each point to the central line and control limits, the hypertension stage can be determined. Since one of the common problems of hypertension patients is choosing the right medicine, controlling the course of blood pressure changes at certain time intervals and prescribing various medicine could help to decide on the appropriate drug suiting the patient's physical condition.

4. Discussion

According to Table 1, using $L=3$ at 95.45% confidence interval is not different from $L=3$ at 99.73% confidence interval in determining the MI severity. This could be due to the restricted number of data resources or the significant difference between Stages 1 and 2. Besides, the guiding flowchart and the graphical rule table would help dubious doctors and nurses select the appropriate medical action. The research results for the blood pressure monitoring presented in Table 2

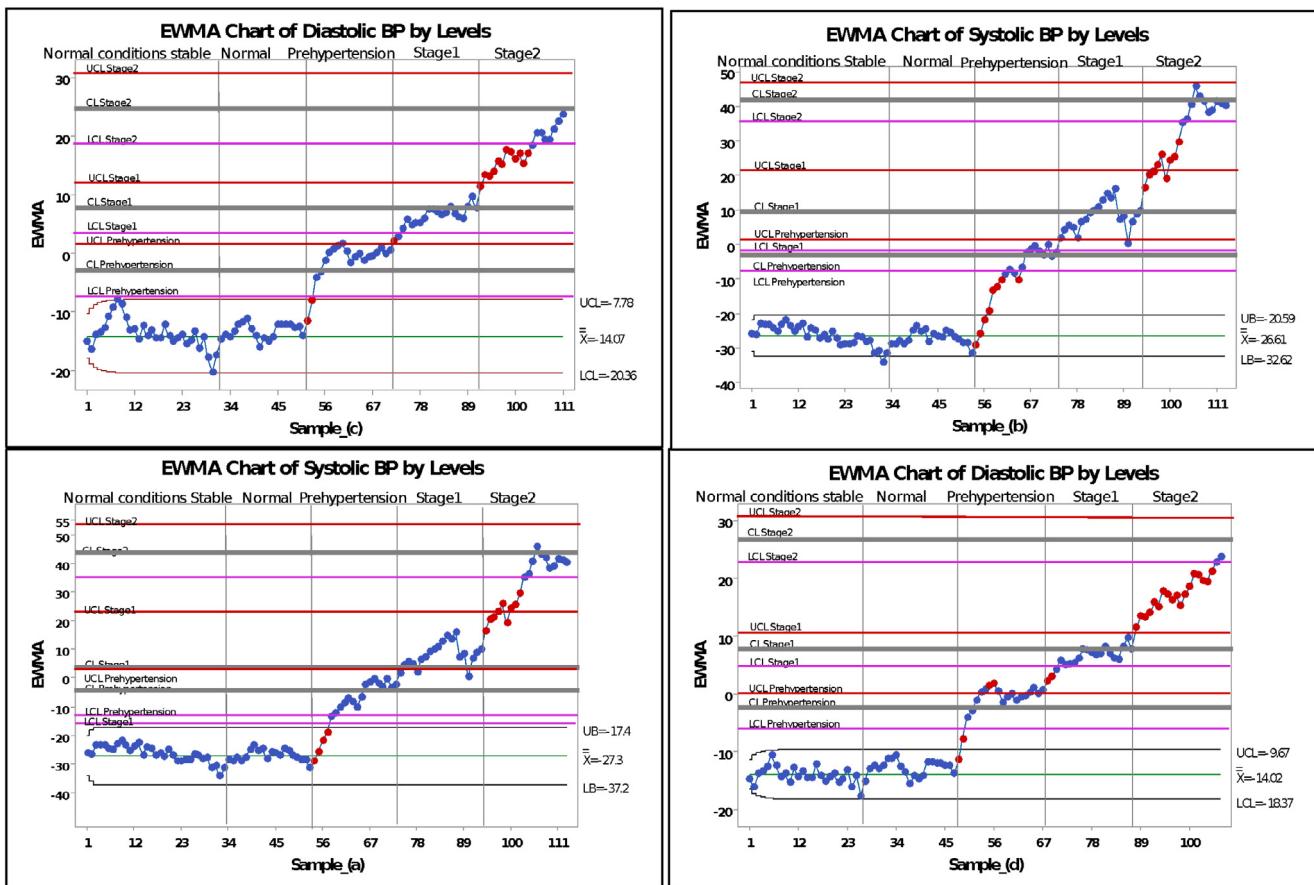
 $L = 3$ $L = 2$

Fig. 7. The determination and control of systolic and diastolic blood pressure at different confidence intervals.

demonstrate the highest and lowest overall accuracy of the proposed model to be 98.75% for diastolic blood pressure and 95% for systolic blood pressure, respectively. Given the overall accuracy in the control determination stage, it makes no difference for the systolic blood pressure whether we use $L=2$ (confidence interval of 95.45%) or $L=3$ (confidence interval of 99.73%). However, for diastolic blood pressure, $L=2$ (confidence interval of 95.45%) yields more precise results than $L=3$ (confidence interval of 99.73%) since the overall accuracy is higher at the prehypertension level.

Consequently, we can conclude that given the sensitivity of the control determination stage, the highest overall accuracy (98.75%) corresponds to diastolic blood pressure and $L=2$ (confidence interval of 95.45%). It could thus be inferred that the tighter the control limits ($L=2$), the higher the overall accuracy. In the statistical control domain, the aim of the control determination stage is to show the out-of-control condition ($1-\beta$) whenever the process is out of control. Nevertheless, if the EWMA shows the condition to be under control while it is actually out of control, a type two error (β) has occurred [48]. In statistical quality control, if this error comes at a high price, the control limits should be set tighter to reduce the error [33]. In this research, by considering the high price of the occurrence of type two error (risking the patient's health) using $L=2$ and the confidence interval of 95.45%, the control limits could be tightened, a decision that is consistent with the research results in Table 2. According to Table 3, the highest overall accuracy (83.75%) of the proposed hybrid model is obtained in the condition determination stage for systolic blood pressure with $L=3$, and the lowest is obtained as 70% for diastolic blood pressure with $L=2$ (30% error). Comparing the overall accuracy for systolic blood pressure

in Stages 1 and 2, it is observed that the confidence interval makes no difference at high severity levels. In lower levels such as prehypertension, higher confidence intervals (99.73% at $L=3$); i.e., wider control limits seem more appropriate. The situation is reversed for diastolic blood pressure. Although no considerable difference is seen in the overall model accuracy at hypertension levels, accurate diagnosis is more difficult in Stages 1 and 2, requiring the limits to be set wider. Given the model's overall accuracy in systolic or diastolic blood pressure, the highest accuracy corresponds to $L=3$ (confidence interval of 99.73%). Hence, it can be interpreted that the model accuracy is increased with the width of the control limits ($L=3$) in the condition determination stage. In the statistical control domain, reducing false alarms or type one error (α) is vital since it also decreases the healthcare expenses and the mental load on the patient. If false alarms impose high expenses on the system, the control limits are set wider to compensate [12]. So, using $L=3$ and a confidence interval of 99.73%, the control limits can be widened, a decision in line with the research results in Table 3.

4.1. Comparison of the proposed method with machine learning (ML) algorithms

In this section, four of the best machine learning algorithms for heart disease diagnosis [49] – Functional Tree, J48, Support Vector Machine (using pairwise classification), and Bayes Net – are applied to the same task and on the same data (92 samples). Fourteen features were initially selected, and finally, seven features were picked using the correlation attribute evaluator algorithm. Five folds cross-validation

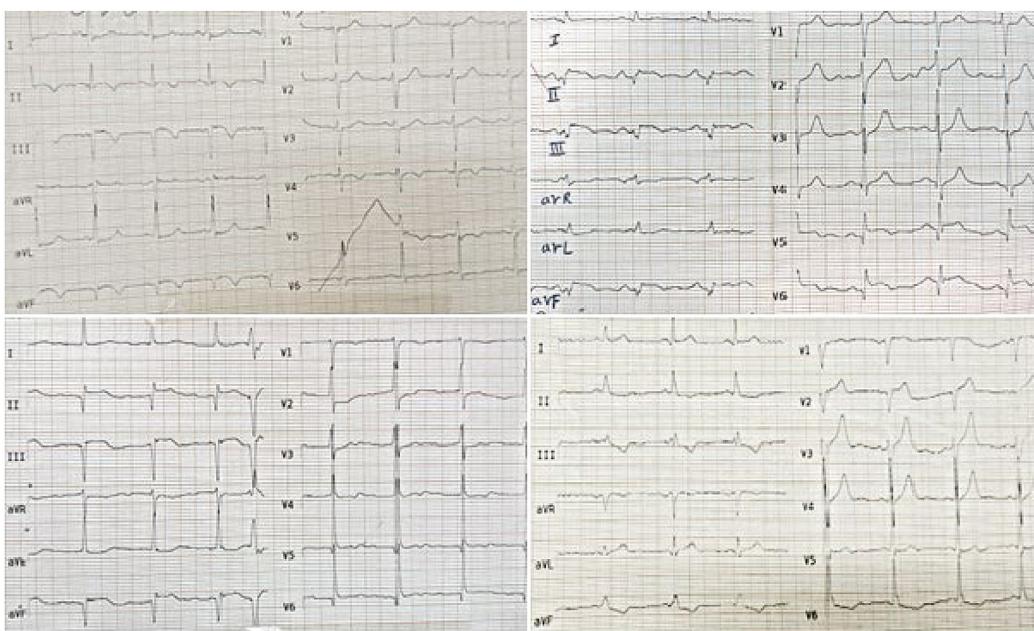


Fig. 8. Inferior Myocardial Infarction.

Table 4
The accuracy of the proposed method vs machine learning algorithms.

Method	Precision
Support Vector Machine (SVM)	69.3%
Functional Tree (FT)	56.1%
Bayes Net	58.3%
J48	62.5%
The proposed method	81.25%

has been used to obtain the accuracy of the ML models. WEKA data mining tool is used for computations. The obtained results are then compared with those obtained through the proposed hybrid method. Table 4 demonstrates the summary of the results and comparisons. As seen in this table, the results show far lower classification accuracy levels for the diagnosis of myocardial infarction given by the applied ML techniques, probably due to the lack of enough data to train the ML models. On the other hand, the results for the proposed method have higher accuracy. In fact, the proposed method plays the same role as the training phase in machine learning algorithms, where DSSs are designed with experts' knowledge while training machines need many observed samples.

5. Conclusion

In this research, a neural network model has been used to generate residual values and assess them via statistical process control charts for the diagnosis of myocardial infarction. Given that the residual values demonstrate the trend of the data, examining these values could determine the infarction severity and monitor the patient's blood pressure. Furthermore, findings demonstrated that using a guiding flowchart and a graphical rule table following the WHO diagnostic policy provides a systematic and holistic view of the infarction diagnosis. The highest overall accuracy of 81.25% (similar value obtained in Section 3.3.1) was achieved at two confidence levels of L=2 and L=3 to create the rule table. In CBPM, the highest and lowest overall accuracies were

obtained as 98.75% and 95% in the control determination stage and 83.75% and 70% in the condition determination stage, respectively. Also, tighter control limits at the confidence interval of L=2 in the control determination stage and wider control limits at the confidence level of L=3 in the condition determination stage result in higher accuracy and fewer errors. Therefore, considering the research results, the proposed model can be used as a DSS for MI diagnosis and CBPM. In addition to controlling and diagnosing MI, in order to track the patient's blood pressure, this system can help physicians and nurses take appropriate therapeutic measures, choose a drug that best suits the patient's physical condition, prevent medical mistakes, improve the treatment process, increase the quality and decrease the related costs of the advanced medical care. Moreover, this hybrid model could develop decision support systems and expand the application of control charts in myocardial infarction diagnosis. For future research, in the offline part of the model, other predictive methods such as linear and non-linear regression and other metaheuristic algorithms such as genetic algorithms [50] could be used to generate the residual values. Fuzzy control charts can also be utilized in this regard [51]. Another research topic could be applying the presented model to monitoring the vital signs and treatment of other diseases, e.g., controlling the blood sugar in people with diabetes.

To find more applications in the field of cardiac-related diseases diagnosis more effectively and comprehensively, bibliometric analysis approaches such as co-word analysis [52–54] can be employed in the literature. In addition, a large data set is involved in some complex medical diagnosis cases, which should be analyzed quickly. As an efficient approach for analyzing massive data sets, big data analytics can be employed to process and analyze diverse health data types [55]. Therefore, we recommend developing and adapting the introduced methodology of the current paper to the big data environment.

This paper was conducted before the COVID-19 pandemic that affected human life from different aspects of health [56–58]. Researchers showed that the probability of an increase in blood pressure among hospitalized patients with COVID-19 is high [59]. Therefore, designing a more comprehensive DSS for heart failure diagnosis could be adapted to the pandemic situation to expand this research.

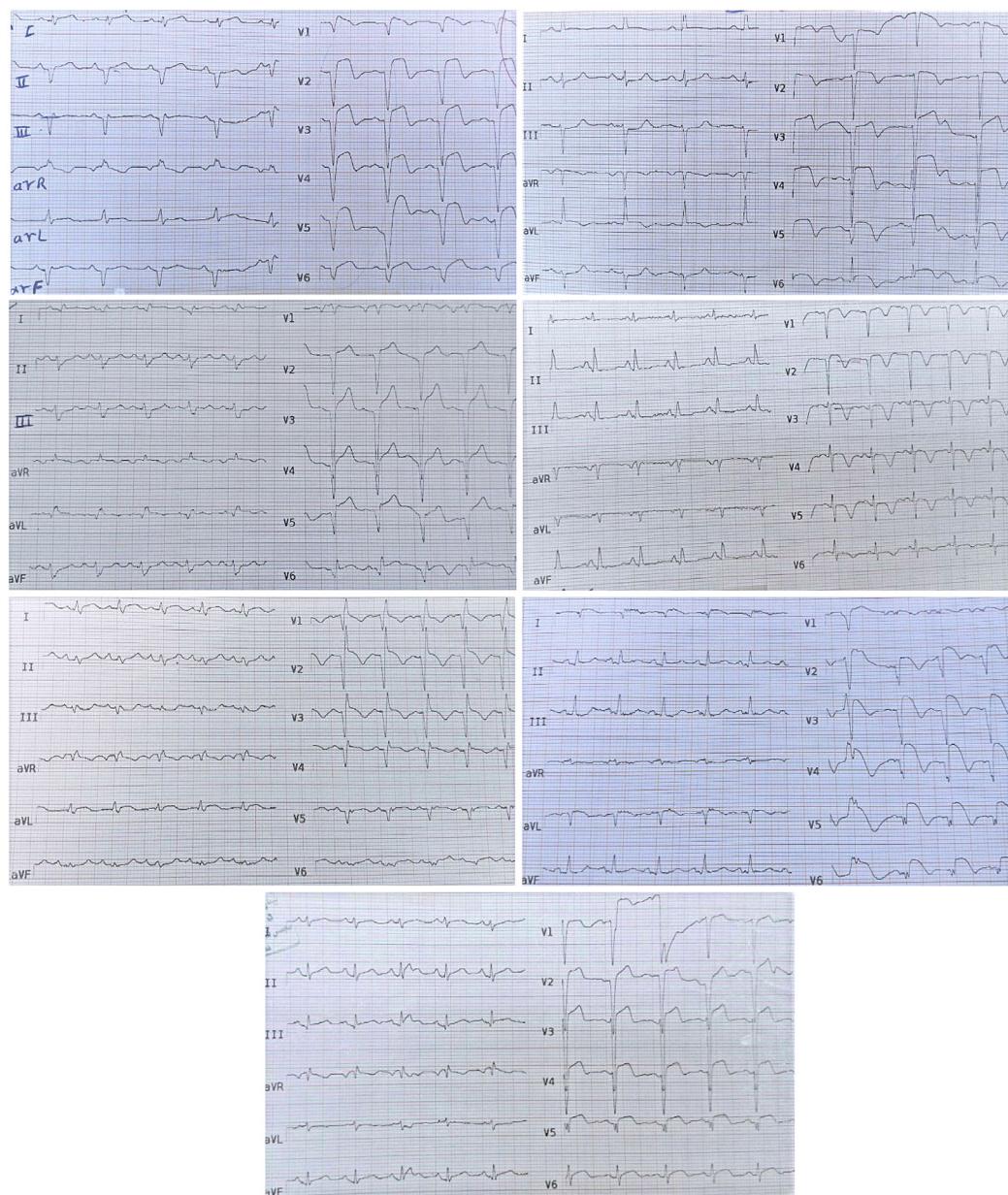


Fig. 9. Anterior Myocardial Infarction.

CRediT authorship contribution statement

Sheida Jabbedari Khiabani: Developed the conceptual model, Wrote the first draft. **Atefeh Batani:** Collaborated with the first author to develop the model. **Ehsan Khanmohammadi:** Revised the paper, Rewrote some sections, Enhanced the quality of the proposed approach.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Inferior and anterior myocardial infarction

See Figs. 8 and 9.

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