Is Serial ECG Analysis of Value for the Diagnosis of Acute Myocardial Infarction?

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Abstract

Aims: The **purpose** was to evaluate if automated detection of acute myocardial infarction using artificial neural networks was improved when a previous ECG was used as input in addition to the current ECG.

Methods and Results: A total of 4691 ECGs recorded at an emergency department on 902 patients with acute myocardial infarction and 3789 control patients were studied. For each ECG, a previous ECG recorded on the same patient was selected from the clinical ECG database. The material was divided into a training group and a test group. Artificial neural networks were trained to detect acute myocardial infarction based on either the current ECG only or the previous and the current ECGs. The neural network, an experienced cardiologist and an intern classified separately the ECGs of the test group, both with and without access to the previous ECG.

The performance, measured as the area under the ROC curve increased with access to previous ECGs for neural network from 0.85 to 0.88 (p=0.02), for cardiologist from 0.79 to 0.81 (p=0.36), and for intern from 0.71 to 0.78 (p<0.001).

Conclusion: Artificial neural networks detect acute myocardial infarction in the ECG better when a previous ECG is used as input in addition to the current ECG.

This type of networks may be useful as decision support even for experienced physicians.

Key words:

Myocardial Infarction**,** Electrocardiography, Diagnosis; Computer-Assisted, Artificial Neural Networks

Introduction

Early diagnosis of acute coronary syndromes is based on several types of clinical data such as patient history, physical examination, biochemical markers of myocardial injury and the 12-lead electrocardiogram (ECG). It is an intriguing task even to the experienced cardiologist to attain optimal clinical decisions by integrating these data. Artificial neural networks represent a computer-based method to assist the physician in the interpretation of available data. Neural networks achieve their performance during training sessions in which for each example in the training group a number of measurements and the correct classification are fed to the network. The neural networks learn by associating patterns of measurements with the desired classification and not by being fed a set of predefined diagnostic criteria.

Baxt and coworker trained a neural network to identify acute myocardial infarction in patients presenting with chest pain at an emergency department [1]. The networks identified acute myocardial infarction with a high degree of accuracy. They used as inputs to the neural networks data on the patient history, physical examination and ECG. An advantage with the approach to feed the network with all relevant data is the possibility for the network to make very accurate interpretations. On the other hand a disadvantage is the intra- and interobserver variability when variables such as “significant ischaemic ECG changes”, “ST depression”, “shortness of breath”, and “faintness” are used. The difficulties to manually produce objective findings even if strictly defined interpretative criteria are used was clearly illustrated by Scott and colleagues [2]. In another study, the same group showed that a network trained with cases reported by one physician performed well when tested with new cases from the same physician but not so well when tested with new cases reported by another physician [3]. It could be difficult to make a neural network widely used if manual inputs are required. In contrast a completely automated method will perform equally well in different locations. A neural network for automated detection of acute myocardial infarction in the ECG based on neural networks has been presented [4]. The network showed to be superior to both conventional ECG interpretation programs and an experienced cardiologist. The neural network was fed with measurements from a single ECG from each patient. In contrast, the physician at the emergency department who interprets an ECG, recorded on a patient with suspected acute myocardial infarction, often has a previous ECG for comparison. The clinical value of serial ECG analysis is well known. One approach to improve the automated ECG interpretation by neural networks could be to include a serial analysis.

The purpose of the present study was to evaluate if automated detection of acute myocardial infarction using artificial neural networks was improved when a previous ECG was used as input in addition to the current ECG. A secondary purpose was to compare the results for the neural networks to the results of an experienced cardiologist and an intern who classified ECGs recorded on patients at an emergency department both with and without access to previous ECGs.

Methods

Study population

The study was based on ECGs recorded on patients who presented to the emergency department of the University Hospital in Lund, Sweden during the period January 1990 - June 1997. Each of these ECGs was analyzed as follows:

- If 1) the ECG was recorded on a patient who was admitted to the coronary care unit after the ECG recording, and was discharged with the diagnosis "acute myocardial infarction" and 2) an earlier ECG recorded on the same patient was found in the ECG database of the hospital (not necessarily recorded at the emergency department) then this pair of ECGs was defined as an "acute infarction" case.
- If 1) the ECG was recorded on a patient not suffering an "acute myocardial infarction" at that occasion and 2) an earlier ECG recorded on the same patient was found in the ECG database of the hospital (not necessarily recorded at the emergency department) then this pair of ECGs was defined as a "control" case.

Several patients contributed more than one pair of ECGs; e.g., a patient presenting to the emergency department on three different occasions could contribute two pairs of ECGs. If acute myocardial infarction was diagnosed only at the last of these three occasions, the pair consisting of the second and last ECGs was part of the acute infarction group while the pair consisting of the first and second ECGs was part of the control group. Only ECGs with severe technical deficiencies and pacemaker ECGs were excluded.

During the study period, the policy of the diagnosis of acute myocardial infarction was as follows [4]. At least two of the following three criteria must be fulfilled; characteristic chest pain lasting >20 minutes, elevated creatine kinase levels and characteristic serial ECG changes. Creatine kinase-B values >0.23 µkat/L together with a typical rise and fall were used as diagnostics for acute myocardial infarction. ECG evidence of acute myocardial infarction included new Q waves in at least two adjacent leads, and/or persistent T-inversions in more than two adjacent leads after a newly developed ST elevation in those leads. A senior cardiologist at the department of cardiology confirmed each discharge diagnosis.

The acute infarction group consisted of 902 pairs of ECGs (546 recorded on males and 356 recorded on females). The mean (±SD) age was 74±11 years. The control group consisted of 3789 pairs of ECGs (1954 recorded on males and 1835 recorded on females). The mean (±SD) age was 70±15 years.

The material was devided into a training group used for the development of the artificial neural networks and a test group used for network evaluation. A total of 1000 cases (200 acute infarction cases and 800 control cases) were randomly selected for the test group and the remaining cases comprised the training group. After exclusion of ECGs with severe technical deficiencies and pacemaker ECGs the test group comprised 988 cases (199 acute infarction cases and 789 control cases) and the training group 3703 cases (703 acute infarction cases and 3000 control cases).

Electrocardiography

The 12-lead ECGs were recorded by the use of computerized electrocardiographs (Siemens-Elema AB, Solna, Sweden). The following 11 measurements, from each of the 12 leads were selected for further analysis: QRS duration, QRS area, Q, R, and S amplitudes, and six ST-T measurements (ST-J amplitude, ST slope, ST amplitude 2/8, ST amplitude 3/8, positive T amplitude and negative T amplitude). The ST amplitude 2/8 and ST amplitude 3/8 were obtained by dividing the interval between ST-J point and the end of the T wave into eight parts of equal duration. The amplitudes at the end of the second and the third intervals were denoted ST amplitude 2/8 and ST amplitude 3/8. In total 132 measurements from each 12-

lead ECG were used. For each measurement of the current ECG a measurement describing the difference between the corresponding measurements of the current and the previous ECGs was also calculated.

Each case consisted of two ECGs, the current and the previous ECG and from these two ECGs two different data sets were generated. The first consisted of the 132 measurements of the current ECGs. The second data set consisted of 264 measurements namely the 132 measurements of the first data set and in addition 132 measurements describing the difference between the current and the previous ECG.

There is a high degree of correlation between the measurements from the 12-lead ECGs. The two data sets comprising 132 and 264 measurements for each case were reduced to smaller sets of more "effective" variables. The reduction was accomplished using principal component analysis [5]. Prior to this analysis the measurements were grouped into the following 6 sets of measurements namely: QRS Area, QRS Duration, QRS Amplitudes, ST Amplitudes, ST Slope and positive/negative T Amplitudes. Each of these sets were then subject to a principal component analysis reduction, e.g. the 12 ST slope variables (one from each lead) were reduced to 2 variables. The first data set was reduced to 16 variables and the second data set to 32 variables used as inputs to the neural networks.

Artificial Neural Networks

Feed-forward artificial neural networks with a standard multilayer perceptron architecture were used. A general introduction to the subject can be found elsewhere [6]. The neural networks consisted of one input layer, one hidden layer and one output layer. There were 16 (first data set) or 32 (second data set) nodes in the input layer, one for each of the input variables. The hidden layer contained 10 nodes. The output layer consisted of one node that encoded whether the patient suffered from acute myocardial infarction or not. A summed-square error function was used together with a Langevin extension [7] of the back-propagation updating rule. Langevin updating consists of adding a random Gaussian component to the weight updates, which has the effect of speeding up the minimization procedure. In order to avoid over-training a weight elimination regularization term was used [8]. The regularization parameter α was set using a 5-fold cross-validation scheme on the training group, i.e. an average validation error was calculated as the mean of the 5 individual validation errors and the α that corresponded to the smallest average validation error was selected as the optimal α. Finally, a committee of 50 networks was trained on the full training group using the obtained regularization parameter α. The classification performance on the test group was calculated using the average output of the committee. All calculations were done using the JETNET 3.0 package [9].

Physicians Interpretation

Two physicians classified the test ECGs both with and without access to the previous ECGs. One of the physicians was cardiologist and head of the coronary care unit. He had more than 25 years of experience in ECG reading. The other physician was intern with only limited experience in ECG reading (approximately one year). All ECGs in the test group were presented separately to the cardiologist and the intern at two different occasions. At the first occasion only the current ECGs were shown to the physicians, while at the second occasion both the current and the previous ECGs were presented. The ECGs were presented to the physicians in random order. They classified the ECGs (both the single and the pair) into one of the following four classes:

- definite acute myocardial infarction,
- probable acute myocardial infarction,
- probable no acute myocardial infarction, and
- definite no acute myocardial infarction.

Patient data and clinical finding were not available at the classification procedure. The only additional information given to the physicians was at the second occasion was the time difference (in years, months and days) between the current and the previous ECGs.

Statistical Methods

The four-grade scale used by the physicians for classification of the test ECGs made it possible to calculate three sensitivity/specificity pairs for each of the for classifications (two physicians both with and without previous ECG). The three pairs were used to construct an ROC curve and the area under the curve was used as a measure of the performance for the physicians.

The output values for the test ECGs were in the range from 0 to 1. A threshold in this interval was used above which all values were regarded as consistent with acute infarction. For each threshold a sensitivity/specificity pair was calculated. By varying this threshold an ROC curve was obtained and the area under the ROC curve was used as a measure of the neural network performance.

For each of the two physicians and the neural network, two ROC curves were constructed, one based on the current ECG only and one based on both the current and the previous ECG. The difference in performance between the two classifications was measured as the difference in area under the ROC curves. The significance of such an area difference was calculated using Monte Carlo technique as follows.

A new classification list was created by randomly selecting for each of the 988 test cases either the classification made with the current ECG or the classification made with both the current and the previous ECGs. A second list was created from the classification not included in the first one. The two lists were used to construct two ROC curves, and the areas under the curves were calculated, as was the area difference. The procedure was repeated 50000 times. The relative frequency of area differences that had an absolute value greater than the actual difference was taken as the probability of obtaining at least the actual area difference if no true difference existed.

The number of true positive and true negative classifications made by the physicians with the previous ECGs were compared to the corresponding numbers without previous ECGs. The significance of a difference was tested paying attention to the fact that the same ECGs were used, i.e., a McNemar type of statistics was used.

Results

A comparison between the current and the previous ECGs was of value for the neural network diagnosing acute myocardial infarction. The network performance, measured as the area under the ROC curve, was significantly higher when both current and previous ECGs were used as inputs (0.88) compared to when only the current ECG was fed to the network (0.85) ($p=0.02$). The ROC curves are shown in Figure 1a.

The cardiologist did not improve significantly when a previous ECG also was available for analysis (Fig. 1b). The areas under the ROC curves were 0.81 with and 0.79 without previous ECG ($p=0.36$).

The intern improved most when she could compare the current ECG with a previous ECG (Fig. 1c). The area under the ROC curve based on the analysis of current ECG only was 0.71 and the corresponding value for the interpretation based on serial analysis was 0.78 ($p<0.001$). Even though she improved her performance with serial ECG analysis her performance was still worse than those of the cardiologist and the neural network.

The improvement of the intern was due to her ability to correctly detect more of the acute infarction cases. She classified 113 of the 199 acute infarction cases as "definite" or "probable acute myocardial infarction" with the previous ECGs. The corresponding value for the analysis without the previous ECGs was 100 ($p=0.059$).

In contrast, the cardiologist detected less acute infarction cases with (156) than without (166) the previous ECGs ($p=0.049$). His result in the acute infarction group was counter-balanced by his improved ability to correctly classify control cases as "definite no" or "probable no acute myocardial infarction" with the previous ECGs. He made true negative classifications in 584 control cases with and 499 cases without the previous ECG ($p<0.001$).

Discussion

Main findings

Access to a previous ECG from the same patient was of value for the artificial neural network detecting acute myocardial infarction from the 12-lead ECG. The improvement was measured as a small but significant increase in area under the ROC curves. The cardiologist showed a small and not statistically significant increase in ROC area with access to a previous ECG. Serial ECG analysis improved the performance of the intern to a larger extent. Thus, it is not evident that all ECG readers benefit from serial ECG analysis. For the trained ECG interpreter almost all useful information seems to be obtained from a single ECG recording at the acute event, whereas a substantial gain from serial ECG analysis appears to be limited to inexperienced ECG readers. It should be stressed that the conclusion only may be valid for the diagnosis of acute myocardial infarction in the ECG and it is still conceivable that access to a previous ECG may improve other types of ECG-diagnoses such as arrhythmias, identification of unstable coronary syndromes etc.

Clinical implications

The results of this study corroborate earlier reports from our group that neural networks are able to diagnose myocardial infarction in the 12-lead ECG at least as well as an experienced physician [4, 10] and moreover, the superiority of neural network to an inexperienced physician was clearly demonstrated. The high accuracy of the networks compared to the cardiologist and the intern indicate that this type of networks can be useful as decision support. Experienced physicians can use a decision support as a second opinion and the more inexperienced physicians can be presented with valuable advice and come to more accurate interpretations. Lindahl and co-workers showed that an experienced physician made more consistent classifications with the advice of a neural network in a study of myocardial perfusion images [11].

Access to a previous ECG appears to improve the performance of an inexperienced physician and physicians working at the emergency department are often young and without long experience in ECG reading. The setting up of ECG database in hospitals is an important means to get an easy access to old ECGs for comparison.

Future work

The type of neural networks of the present study could be incorporated into computer-based ECG interpretation programs and could detect acute myocardial infarction in the 12-lead ECG by use of input variables from the measurement programs. Thus, no data would need to be fed manually to the network.

The neural networks could also analyze other clinical variables and one should probably aim at sets of data with minimal variability of preclassification. Connection of neural networks to computerized patient records could offer a user-friendly system for diagnostic support.

Serial ECG analysis

Limitations

The value of identifying acute myocardial infarction in the emergency room varies. Identification of myocardial infarction with ST-elevation is extremely important as it might lead to urgent reperfusion therapy. Infarcts with other more unspecific ECG patterns may also be valuable to detect, as the occurrence of myocardial infarction in general is a negative prognostic factor in patients with acute coronary syndromes. However, physicians in the emergency room are perhaps more inclined to find clues that help to decide on the proper handling of patient e.g. intensity of monitoring and the choice of treatment than to promptly determine whether a patient has a myocardial infarction or not if the ECG is inconclusive.

Further studies are needed to establish the role of neural networks in the former type of decision-making.

Conclusions

Artificial neural networks trained to detect acute myocardial infarction in the 12-lead ECG perform better if a previous ECG is used as input in addition to the current ECG. This type of networks may be useful as decision support even for experienced physicians.

Acknowledgments

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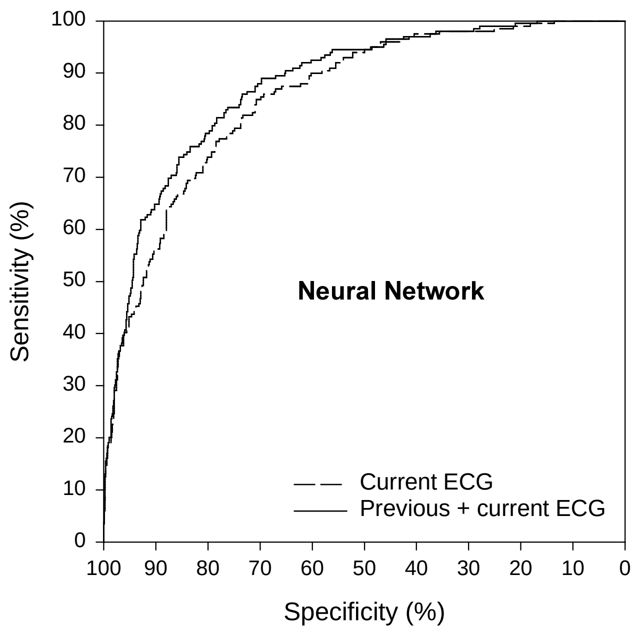
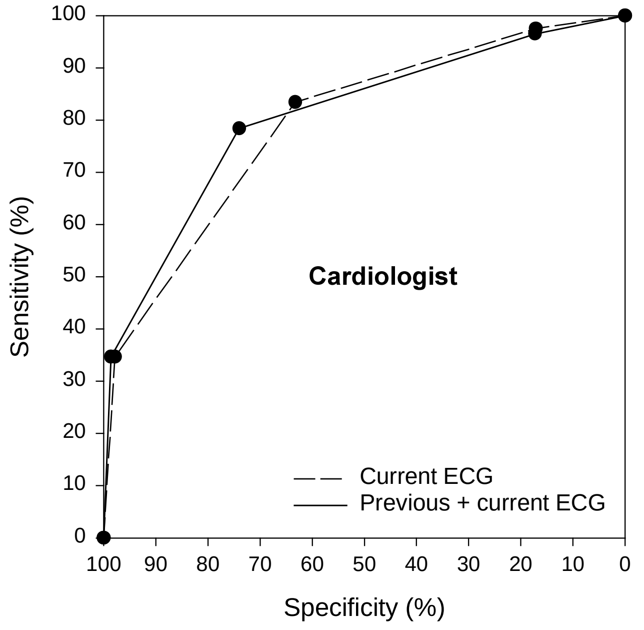
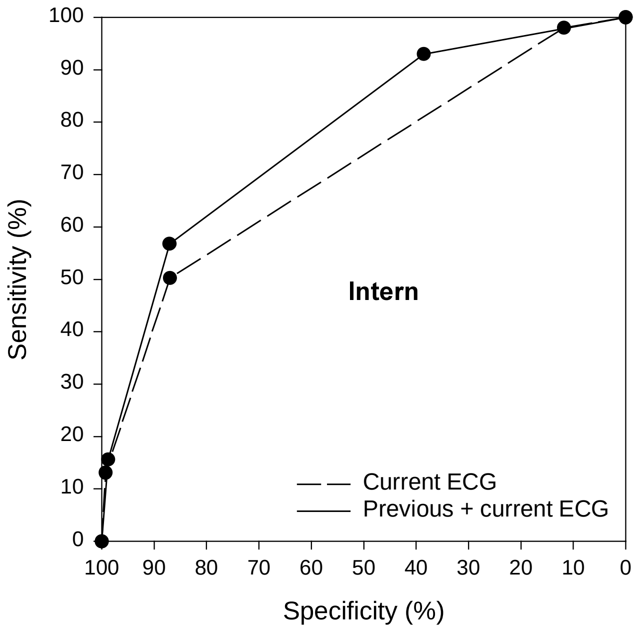
Figure Legend

Figure 1: The ROC curves for the (a) artificial neural network, (b) the cardiologist and (c) the intern. For each plot two curves are shown, one for the classification based on the current ECG only (broken line) and one for the classification based on both current and previous ECGs (solid line).


Neural Network
Current ECG
Previous + current ECG
Sensitivity (%)
Specificity (%)


Cardiologist
Current ECG
Previous + current ECG
Sensitivity (%)
Specificity (%)


Intern
Current ECG
Previous + current ECG
Sensitivity (%)
Specificity (%)