racic tracings. Atrial reversal flow, however, is most important in assessing LV diastolic pressure. Because pulmonary veins are located far from the transducer in the apical 4-chamber view, PV flow assessment by pulsed Doppler TTE is thought to be limited in some cases. Although a recent report[7] suggested that transthoracic measurements are of sufficient quality in PV flow recordings, operator-, patient-, and equipment-related limitations of the transthoracic approach can make the examination difficult and the results of questionable reliability in some cases.

Intravenous injection of sonicated albumin provides enhancement of the Doppler flow signals in the left heart chamber. It has been reported that this technique can be used in evaluating aortic stenosis by enhancement of Doppler flow signal through the aortic valve. In the present study, in most of the patients, PV flow signal was enhanced after intravenous injection of sonicated albumin. This result suggests that improved visualization of pulmonary venous flow Doppler signal by intravenous injection of sonicated albumin should be useful in the clinical setting.

**In conclusion, color Doppler signal of PV flow was enhanced and the otpimal recordings could be detected in most cases after intravenous injection of sonicated albumin. Improved visualization of PV flow Doppler signal by intravenous injection of sonicated albumin should have important clinical implications for the assessment of LV diastolic function by using Doppler technique.**


**1.** Appleton CP, Hatle LK, Popp RL. Relation of transmitral flow velocity patterns to left ventricular diastolic function: new insights from a combined hemodynamic and Doppler echocardiographic study. *J Am Coll Cardiol* 1988;12:426–440.
**2.** Nishimura RA, Abel MD, Hatle LK, Tajik AJ. Relation of pulmonary vein to mitral flow velocities by transesophageal Doppler echocardiography: effect of different loading conditions. *Circulation* 1990;81:1488–1497.
**3.** Kuecherer HF, Muhiudeen IA, Kusumoto FM, Lee E, Moulinier LE, Cahalan MK, Schiller NB. Estimation of mean left atrial pressure from transesophageal Doppler echocardiography of pulmonary venous flow. *Circulation* 1990;82:1127–1139.
**4.** Feinstein SB, Cheirif J, Ten Cate FJ, Silverman PR, Heidenreich PA, Dick C, Desir RM, Armstrong WF, Quinones MA, Shah PM. Safety and efficacy of a new transpulmonary ultrasound contrast agent: initial multicenter clinical results. *J Am Coll Cardiol* 1990;16:316–324.
**5.** Hozumi T, Yoshikawa J, Masahiro Shakudo, Shinobu Miyake, Yasuhiro Honda, Hiroyuki Ohkura, Yasuko Yamaura, Tsutomu Takagi. Improved visualization of pulmonary venous flow Doppler signal by intravenous injection of sonicated albumin *Circulation* 1994;90(suppl I):I–555.
**6.** Castello R, Pearson AC, Lenzen P, Labovitz AJ. Evaluation of pulmonary venous flow by transesophageal echocardiography in subjects with a normal heart: comparison with transthoracic echocardiography. *J Am Coll Cardiol* 1991;18:65–71.
**7.** Rossvoll O, Hatle LK. Pulmonary venous flow velocities recorded by transthoracic Doppler ultrasound: relation to left ventricular diastolic pressures. *J Am Coll Cardiol* 1993;21:1687–1696.


# Detection of Frequently Overlooked Electrocardiographic Lead Reversals Using Artificial Neural Networks


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In the electrocardiographic recording situation, lead reversals occasionally occur.[1–3] They are often overlooked, both by the electrocardiogram (ECG) readers and by the conventional interpretation programs; this may lead to misdiagnosis and improper treatment.[3,4] Artificial neural networks represent a computer-based method[5,6] that have proved to be of value in pattern recognition tasks, such as ECG analysis.[7–10] They have showed high performance, exceeding that of 2 well-known interpretation programs, detecting right/left arm lead reversals on the 12-lead ECG.[1] Left arm/left foot lead reversal is also clinically important, as some precordial lead reversals do occur quite frequently. The purpose of this study was to detect the left arm/left foot lead reversal and the 5 precordial lead reversals involving 2 adjacent leads with the help of artificial neural networks, and to compare the results with those of a widely used interpretation program concerning the precordial lead reversals.

**TABLE I** Reasons for Exclusion of ECGs (n = 11,423)

| Reason for Exclusion | | No. of ECGs Excluded |
|---|---|---|
| Lead reversals | | 208 |
| Left arm/left foot | 12 | |
| $V_1/V_2$ | 3 | |
| $V_2/V_3$ | 16 | |
| $V_3/V_4$ | 6 | |
| $V_4/V_5$ | 11 | |
| $V_5/V_6$ | 68 | |
| Right/left arm | 47 | |
| Right arm/right foot | 31 | |
| Other lead reversals | 14 | |
| Pacemaker ECG | | 197 |
| Technically deficient ECG | | 118 |
| Total | | 523 |


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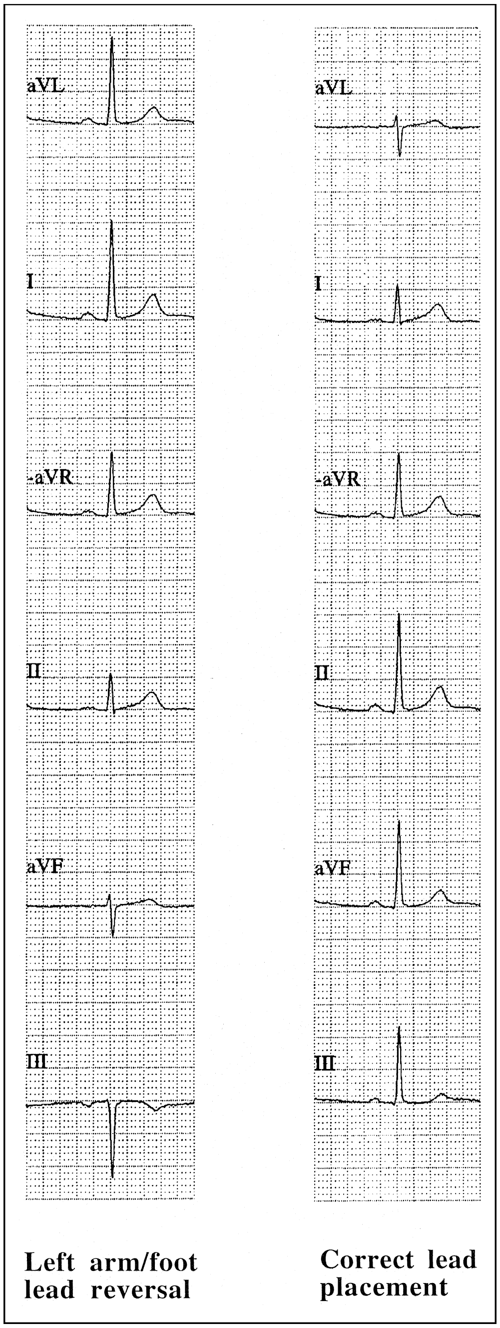


FIGURE 1. ECG with left arm/left foot lead reversal *(left)* and the correctly recorded ECG on the same subject *(right)*. This lead reversal can be simulated by relabeling of correctly recorded leads.

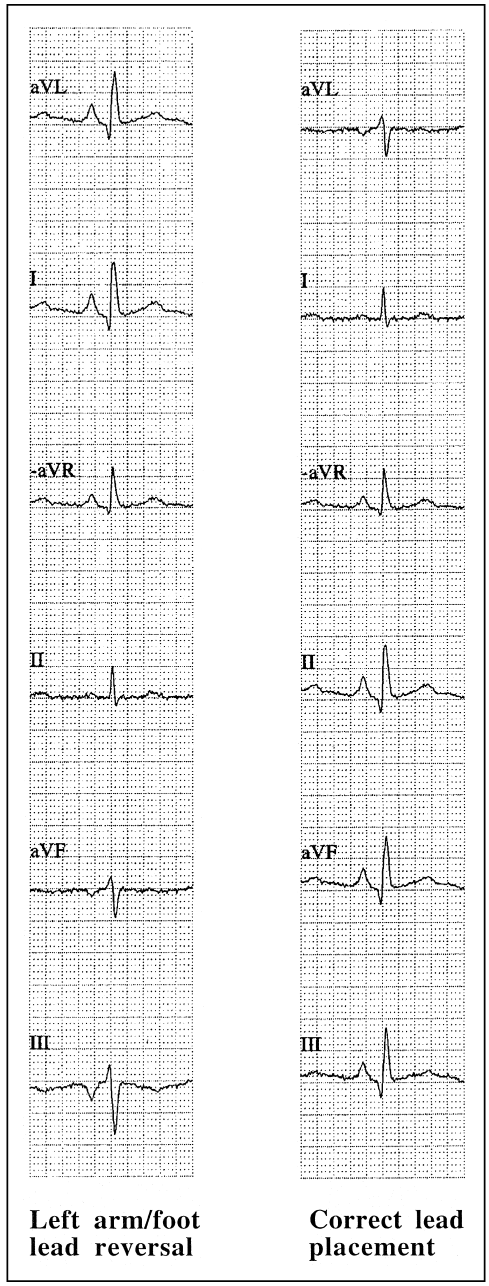


FIGURE 2. The interpretation program reported ectopical atrial rythm in this ECG with left arm/left foot lead reversal *(left)*. Also note that no Q waves are present in the inferior leads. The ECG with correct lead placement *(right)* shows sinus rhythm and a healed inferior myocardial infarction.

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A total of 11,432 ECGs, recorded for patients in the emergency department at the University Hospital in Lund, Sweden, from 1992 to 1993, were studied. The 12-lead ECGs were recorded using computerized electrocardiographs (Siemens-Elema AB, Solna, Sweden). Averaged heart cycles were calculated and transferred to a computer for further analysis. P, QRS, and ST-T measurements used in the criteria and as inputs to the artificial neural networks were obtained from the measurement program of the computerized ECG recorders.

Since artificial neural networks learn by training on a database of examples, it was crucial that no ECG with a lead reversal be presented to the network as an example of an ECG with correct lead placement. Therefore, great care was taken to exclude any ECGs from the database that showed signs of lead reversals or that were technically deficient. Pacemaker ECGs were also excluded. The exclusion process comprised visual inspection by 2 experienced ECG readers and computer-based methods using artificial neural networks.[1] ECGs with suspected lead reversals were verified in most cases by visual com-

**TABLE II** Sensitivities and Specificities of Artificial Neural Networks and Conventional Criteria

| Lead Reversal | Artificial Neural Networks Sensitivity (%) | Artificial Neural Networks Specificity (%) | Conventional Criteria Sensitivity (%) | Conventional Criteria Specificity (%) |
|---|---|---|---|---|
| Left arm/left foot | 57.6 | 99.97 | — | — |
| $V_1/V_2$ | 80.6 | 99.94 | 4.0 | 99.95 |
| $V_2/V_3$ | 44.5 | 99.87 | 9.3 | 100 |
| $V_3/V_4$ | 77.5 | 99.95 | 10.0 | 100 |
| $V_4/V_5$ | 83.0 | 99.95 | 4.7 | 100 |
| $V_5/V_6$ | 73.2 | 99.88 | 0.1 | 100 |

**TABLE III** Measurements Used in Neural Networks Trained to Detect Lead Reversals

| Lead Reversal | Measurements |
|---|---|
| Left arm/left foot | Q, R, and S amplitudes in I, II, III, aVL, and aVF *T sum in I, II, III, aVL, and aVF QRS† axis |
| $V_1/V_2$ | Q, R, S, and T amplitudes in $V_1$–$V_4$ |
| $V_2/V_3$ | R, S, and T amplitudes in $V_1$–$V_4$ QRS area in $V_1$–$V_4$ |
| $V_3/V_4$ | R, S, and T amplitudes in $V_2$–$V_5$ QRS area in $V_2$–$V_5$ |
| $V_4/V_5$ | R, S, and T amplitudes in $V_3$–$V_6$ QRS area in $V_3$–$V_6$ |
| $V_5/V_6$ | Q, R, S, and T amplitudes in $V_3$–$V_6$ |

* T sum = maximal positive T amplitude − |maximal negative T amplitude|.
† QRS axis was presented as $\sin(\text{axis} \cdot \pi/180)$ and $\cos(\text{axis} \cdot \pi/180)$.

parison of the suspected ECG with an earlier or later recording from the same patient. A total of 523 ECGs were excluded, leaving 10,906 ECGs in the database (Table I).

The 10,906 correctly recorded ECGs were used for computational generation of 6 subsets of ECGs, each with 1 type of lead reversal. The left arm/left foot lead reversal was generated by means of changing places of leads I and II, inverting lead III, and changing places of aVL and aVF (Figure 1). The 5 precordial lead reversals were generated by interchanging adjacent leads. This process yielded exactly the same ECGs that would have been recorded had the leads been interchanged on the patient. Thus, the final material consisted of 76,342 ECGs, divided into 7 groups.

A multilayer perceptron artificial neural network architecture[11] was used. A more general description of neural networks can be found elsewhere.[5] One neural network was used for each lead reversal. The neural networks consisted of 1 input layer, 1 hidden layer, and 1 output layer. The latter consisted of 1 unit and encoded whether the ECG was recorded with correct lead placement. The hidden layer of the neural networks contained 7 (left arm/left foot lead reversal) and 4 (precordial lead reversal) neurons, respectively. Different combinations of P, QRS, and ST-T measurements were used as inputs to the neural networks. The number of neurons in the input layer was equivalent to the number of input variables—in this study 22 for the left arm/left foot lead reversal and 16 for each of the different precordial lead reversals. Each network was trained and tested using the 10,906 ECGs with correct lead placement and 10,906 ECGs with the appropriate lead reversal.

For each lead reversal, the data set was divided into 2 parts: a training set and a test set. The training set was used to adjust the connection weights, whereas the test set was used to assess the performance. In order to obtain as reliable performance as possible, a cross-validation procedure was used. The data set was randomly divided into equal parts, and each of the different parts was used once as a test set, while training was performed on the remaining parts of the data. We used threefold cross-validation to decide when to terminate learning in order to avoid ''overtraining'' and eightfold cross-validation to train the networks and assess their performance. Performance was studied in the separate test set, and the results are the mean values from 10 different runs; that is, each ECG was in the test set 10 times. During the training process, the connection weights between the neurons were adjusted using the backpropagation algorithm. In order to attain very high specificity, the networks were trained to identify ECGs with correct lead placement with highest possible accuracy. This was done during the training session by means of presenting these ECGs 300 to 500 times more often to the networks than the ECGs with a lead reversal. All calculations were performed using the JETNET 3.0 package.[12]

The interpretation program developed at the Glasgow Royal Infirmary contains criteria for the detection of precordial lead reversals.[13] These criteria were applied to the correct ECGs and the ECGs with computer-generated precordial lead reversals. The performance of each of the criteria was compared to that of the neural networks. There are no published criteria for the detection of left arm/left foot lead reversal.

Sensitivities and specificities of the neural networks and the conventional criteria for detection of lead reversals are presented in Table II. The networks used QRS and T-wave measurements only as inputs (Table III). The addition of P-wave data to the input variables failed to improve the performance of the networks. The specificities of the networks and the conventional criteria were very high for all lead reversals. Also, the sensitivities were generally high for the networks, ranging between 44.5% and 83.0%, while the sensitivities for the conventional criteria were much lower, ranging between 0.1% and 10.0%.

Figures 2 to 4 show examples of ECGs that have been misinterpreted by the conventional interpretation program as a result of lead reversals that were not detected. The ECGs presented were among the 208 ECGs with lead reversals found in the original database of 11,423 ECGs. The cases in the figures were all detected as lead reversals by the neural networks developed on the larger database.

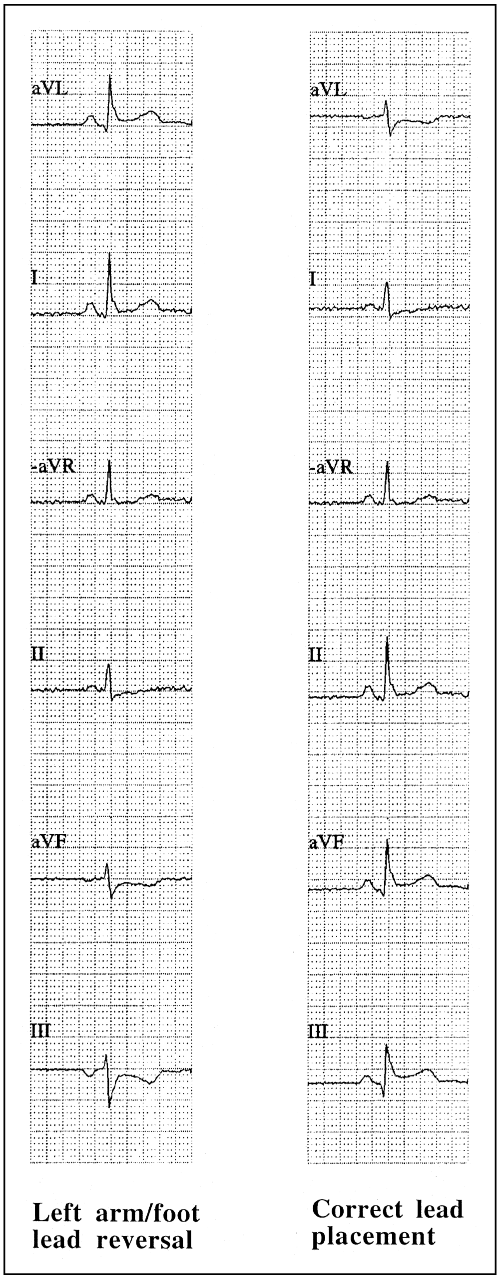


**FIGURE 3. ECG with a left arm/left foot lead reversal with ST depressions in the inferior leads *(left)*. ECG with correct lead placement *(right)*. There are ST elevations in the inferior leads, consistent with acute myocardial injury.**

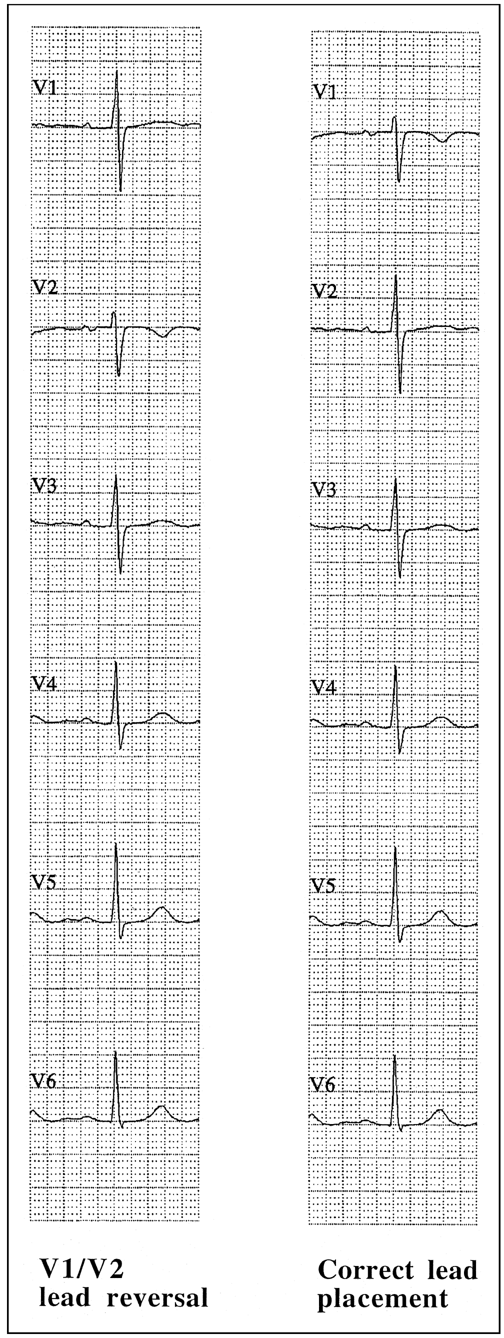


**FIGURE 4. ECG with a reversal of $V_1/V_2$ *(left)*. This gives an impression of loss of R-wave amplitude and septal ST changes suggesting ischemic heart disease, according to the interpretation program. ECG with correct lead placement *(right)*. The lead reversal was not detected by the interpretation program that incorporates conventional criteria for detection of near-neighbor lead reversals but was found by the neural network.**

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The results clearly demonstrate that artificial neural networks can be used to detect lead reversals in the 12-lead ECG with very high specificity and in most cases high sensitivity. Lead reversals were found in nearly 2% (208 of 11,432) of the ECGs in this study and, considering that an estimated 300 million ECGs are recorded annually in the world, approximately 6 million of these may be recorded with a lead reversal. Most are not detected today, especially for the left arm/left foot lead reversal, as well as some precordial lead reversals under study in this paper.

In this study, 208 ECGs with a lead reversal were found in the database, 116 of 194 belonging to 1 of the types under study in this paper or 47 of 194 to 1 of the lead reversals involving the right/left arm leads or 31 of 194 the right arm/foot leads, which were studied earlier.[1,4] These 8 types of lead reversal represent >90% of all the lead reversals found in our database; this could probably be true for other settings as well. The results from this and earlier studies demonstrate that approximately 75% of these lead reversals could be detected by artificial neural networks, in combination with an algorithm for detection of the right arm/right foot lead reversal. There are many other types of lead reversal, and each of them may occur, although infrequently. Neural networks have not been developed for the specific detection of each of those different types, but many of them would be detected by the networks developed for the most common lead reversals.

With a few exceptions, electrocardiography and cardiology textbooks do not cover lead reversals or their implications. The right arm/right foot lead reversal, which is relatively common, as well as the lead reversals under study in this paper, are generally not presented at all, whereas the very rare right arm/left foot,[14] left arm/right foot,[15] and clockwise/counterclockwise[16] lead reversals have been described.

How might these neural networks be used in clinical routine? We believe that the electrocardiograph presents a warning, based on neural network outputs, and can be used to advise the technician to check the cables. The recording is interrupted, and no ECG complexes or ECG interpretation are presented. The technician must either then confirm that the leads are correctly placed or correct the leads before the recording can be completed. With this approach, lead reversals could easily be corrected and a false detection by the neural networks would not cause much inconvenience.

Another approach is the computerized electrocardiographs used today. A statement of suggested lead reversal is presented in the interpretation text. The leads affected by the possible lead reversal are disregarded in the interpretation and are therefore incomplete. This approach has 2 disadvantages. First, the statement in the interpretation text could easily be missed by the technician in the recording situation. Second, a false detection by the interpretation program will result in an incomplete interpretation and the technician cannot change this when checking that the leads are correctly placed. Therefore, no (or almost no) false detections can be accepted using this approach; that is, specificity must be (almost) 100%.

If the specificity is not sufficiently high for the lead reversals, many of the ECGs reported as a case of lead reversal would actually be a correctly recorded ECG. The positive predictive value, though, does not depend on the specificity alone, but on the sensitivity and prevalence for different lead reversals as well. The highest positive predictive value, 79%, has the precordial lead reversal that appeared most often in the database, the interchanging of leads $V_5$/$V_6$, although the specificity was the second lowest among the studied lead reversals.

**Artificial neural networks can be used to recognize lead reversals in the 12-lead ECG at very high specificity, and the sensitivity was much higher than that of a conventional interpretation program. The neural networks developed in this and an earlier study for detection of lead reversals, in combination with an algorithm for the right arm/right foot lead reversal, would recognize approximately 75% of lead reversals encountered in clinical practice.**


**1.** Hedén B, Ohlsson M, Edenbrandt L, Rittner R, Pahlm O, Peterson C. Artificial neural networks for recognition of electrocardiographic lead reversal. *Am J Cardiol* 1995;75:929–933.

**2.** Peberdy MA, Ornato JP. Recognition of electrocardiographic lead misplacement. *Am J Emerg Med* 1993;1:403–405.

**3.** Guijarro-Morales A, Gil-Extremera B, Maldonado-Martin A. ECG diagnostic errors due to improper connection of the right arm and leg cables. *Int J Cardiol* 1991;30:233–235.

**4.** Haisty WK Jr, Pahlm O, Edenbrandt L, Newman K. Recognition of electrocardiographic electrode misplacements involving the ground (right leg) electrode. *Am J Cardiol* 1993;71:1490–1495.

**5.** Cross S, Harrison RF, Lee Kennedy R. Introduction to neural networks. *Lancet* 1995;346:1075–1079.

**6.** Baxt WG. Application of artificial neural networks to clinical medicine. *Lancet* 1995;346:1135–1138.

**7.** Edenbrandt L, Devine B, Macfarlane PW. Classification of electrocardiographic ST-T segments—human expert versus artificial neural network. *Eur Heart J* 1993;14:464–468.

**8.** Farrugia S, Hansen Y, Nickolls P. Implantable cardioverter defibrillator electrocardiogram recognition with a multilayer perceptron. *PACE* 1993;16:228–234.

**9.** Reddy MRS, Edenbrandt L, Svensson J, Haisty WK, Pahlm O. Neural network versus electrocardiographer and conventional computer criteria in diagnosing anterior infarct from the ECG. In: Proceedings of Computers in Cardiology 1992. Los Alamitos, California: IEEE Computer Society Press; 1992:667–670.

**10.** Hedén B, Edenbrandt L, Haisty WK Jr, Pahlm O. Artificial neural networks for the electrocardiographic diagnosis of healed myocardial infarction. *Am J Cardiol* 1994;74:5–8.

**11.** Rumelhart DE, McClelland JL, eds. Parallel Distributed Processing. Vols. 1 and 2. Cambridge, Massachusetts: MIT Press, 1986.

**12.** Peterson C, Rögnvaldsson T, Lönnblad L. JETNET 3.0—A versatile artificial neural network package. *Comp Phys Comm* 1994;81:185–220.

**13.** Macfarlane PW, Lawrie TDV. Comprehensive Electrocardiology Vol. 3. Oxford: Pergamon, 1989:1529–1530.

**14.** Constant J. Learning Electrocardiography. 3rd ed. Boston: Little, Brown, 1987:107–108.

**15.** Marriott HJL. Pearls and Pitfalls in Electrocardiography. Philadelphia: Lea & Febiger, 1990:150–151.

**16.** Hurst JW, Schlant RC, Rackley CE, Sonnenblick EH, Wenger NK, eds. The Heart. 6th ed. New York: McGraw-Hill Book Company; 1986:226.