Improving EASI Model via Machine Learning and Regression Techniques

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***Abstract*—We propose an approach to the interpretation of natural 12-lead Electrocardiography (ECG) is the standard tool for heart disease diagnose but measuring all 12 leads is often awkward and restricted by patient movement. In 1988, Gordon Dower has introduced the EASI-lead monitoring system that can reduce the number of electrodes from 10 downto 5 and also increases mobility of patients. In order to gain all 12-lead ECG back from the EASI-lead system, Dower's equation was proposed then. Ever since various attempts have been explored to improve the synthesis accuracy. To find the best transfer function for synthesizing the 12-lead ECG from EASI-lead system, this paper presents a number of Machine Learning techniques including Support Vector Regression (SVR) and Artificial Neural Network (ANN). The experiments were conducted to compare the results from those Machine Learning methods to those of Linear Regression, Polynomial Regression, and Dower's methods. The results have shown that the best performance amongst those methods with the least Root Mean Square Error (RMSE) values were obtained by SVR using spherical kernel function followed ANN, 3rd-order Polynomial Regression, Linear Regression and Dower's equation, respectively.**

***Index Terms*—12-Lead ECG System; ANN; Dower's Method; EASI Electrodes; Linear Regression; Polynomial Regression; SVR.**

I. Introduction

The conventional 12-lead electrocardiogram (ECG) is a representation of the electrical activity of the heart, recorded from electrodes on the body surface, and used for diagnosing other cardiac disorders. The standard 12-lead ECG signals are Lead I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6 signals. Typically for measuring 12-lead ECG requires 9 electrodes to be positioned strategically on the body and one extra electrode to be linked to ground [1,2] as shown in Figure 1(left).

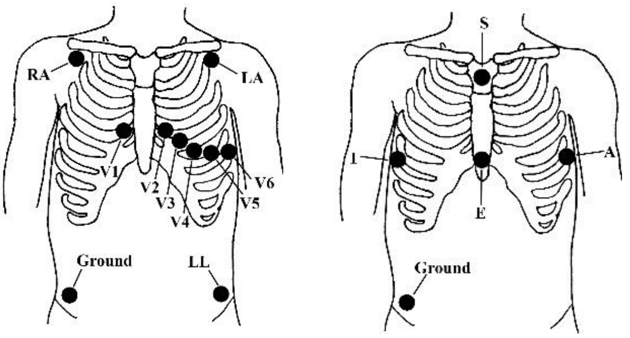


Figure 1: Standard 12-lead ECG System (left) vs. EASI-lead System (right)

Typically, the ordinary 12-lead cannot measure ECG signal for 24 hours because it would be sensitive to noise and artifact while moving body. There must be a way to reduce the number of electrodes, resulting in less sensitive to noise while moving body.

The evolution of ECG systems with number of electrodes reduction started in the 1940s [3], but the earliest notable work on 12-lead ECG system derivation occurred in 1968 [4] with the launch of a 12-lead ECG derived from the spatial vectorcardiography previously introduced by Frank [5]. Reducing the quantity of leads from the original 12-lead ECG yielding fewer measurement electrodes and consequently less number of wires, is possible by deriving the missing signals from the actual measured electrodes.

Until 1988, EASI-lead system has been introduced and developed by Dower and his team [6]. It is a quasi-orthogonal system, accommodating only 5 electrodes as shown in Figure 1(right). The electrodes are positioned at the upper sternum for **S** electrode, at the lower sternum for **E** electrode and at the left and right mid-axillary lines for **A** and **I** electrodes, respectively, while the final electrode can be placed at any position for ground. The advantage of EASI-lead system is less sensitive to noise and increases mobility of patients.

After the derivation method of 12-lead ECG system with Dower's equation via EASI electrodes has been presented, various improvements on coefficients in Dower's equation have been investigated ever since.

In 2002, Feild and his team [7] presented the improvement on 12-lead ECG derivation using **E**, **A**, **S** and **I** signals as input data via new EASI coefficients. This has been done by using larger data set.

Later, during 2010-2014, Oleksy and his team [8, 9, 10] introduced various machine learning and regression methods as opposed to Dower's equation, to synthesize the standard ECG signals from EASI lead system. Nonetheless, their experimental result seemed to compare among only those of Linear Regression against those with Feild's EASI coefficients and lastly those of the original Dower's equation. The dataset conducted in this work has been obtained from Physionet Database [11].

Recently, the Nonlinear Regression methodology has been proposed as the synthesis approach to derive the 12-lead ECG signals from EASI leads. This yielded to less error compared to the previous Dower's and Linear methods.

This paper attempted to refine the primary EASI ECG model and achieve the finest result for deriving 12-lead ECG signals. Five different methods have been explored here. The first is the original Dower's Method. Then two common regression approaches were conducted; Linear and Polynomial Regressions. Finally, two effective Machine

Learning techniques; Support Vector Regression (SVR) and Artificial Neural Network (ANN) were studied.

II. METHODOLOGY

The following subsections briefly revise the basic concepts of all five machine learning and regression approaches used in this work.

A. Dower's Method

The synthesis method implemented in Dower's method used paired signals **A-I**, **E-S** and **A-S** derived as a weighted linear sum of these 3 base signals as in the Equation (1).

- Lead **A-I** projects the heart's electrical activity in a direction of left-to-right.
- Lead **E-S** projects the heart's electrical activity in a direction of caudal-to-cranial. This lead also contains a considerable anterior-posterior component.
- Lead **A-S** projects the heart's electrical activity both in directions of left-to-right and caudal-to-cranial. This lead also contains a small anterior-posterior component.

$$L_{Derived} = a(A-I) + b(E-S) + c(A-S) \tag{1}$$

where

$L_{Derived}$ is states any surface ECG lead;

a, b, and c are empirical coefficients, elaborated by Dower, which can be positive or negative values with up to 3 decimal points of accuracy.

B. Linear Regression

Linear Regression [12] is the longest-established and most acknowledged predictive model. In the early 18th Century, Gauss introduced the means of reducing the sum of the squared error to fit a straight line, resulting as a linear function, to a group of data points. A Linear Regression model is the outcome from that process.

The pattern of the function is shown in Equation (2).

$$Y_n = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \tag{2}$$

where:

Y_n is the transfer function of Lead n signal;

n is those 12 standard leads;

β_0 is the constant and β_1 ,..,β_4 are coefficients of X_1,.. X_4 from the fold providing the minimum RMSE of Lead n signal;

X_1,X_2,X_3, and X_4 are Lead **E**, **A**, **S**, and **I**, respectively.

C. Polynomial Regression

Polynomial Regression [13] is a pattern of Linear Regression to place nonlinear data into a least squares Linear Regression model, allowing a single Y variable to be forecasted by fragmented the X variable into various degrees of polynomial function. The pattern of the function is shown in Equation (3).

$$Y_n = \beta_0 + \beta_1 X_1 + \beta_2 {X_2}^2 + \beta_3 {X_3}^3 + .. + \beta_n {X_n}^x \tag{3}$$

where:

Y_n is the target variable;

X_1, X_2,... X_n are the predictor variables;

β_0 is the constant;

β_1, β_2 ,…β_n are the coefficients that multiply the predictor variables.

In Polynomial Regression, different of degrees x variable are sequentially included to the function resulting in the changing of the best fit line shape; i.e. a unswerving line for including degree of 1, a parabola for including degree of 2 and an S-curve for including degree of 3.

The experimental result from the previous research [14], conducted on the comparison of Polynomial Regression with degree 2, 3, 4 and 5, showed that the best performance for deriving 12-lead signals from EASI-lead system on PhysioNet Dataset obtained from the degree 3. Therefore, the 3rd-order Polynomial Regression has been chosen in this paper. The function is shown in Equation (4).

$$\begin{aligned} Y_n = {} & \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 \\ & + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 + \beta_{11} x_1^2 \\ & + \beta_{12} x_2^2 + \beta_{13} x_3^2 + \beta_{14} x_4^2 + \beta_{15} x_1^3 + \beta_{16} x_2^3 + \beta_{17} x_3^3 \\ & + \beta_{18} x_4^3 + \beta_{19} x_1^2 x_2 + \beta_{20} x_1^2 x_3 + \beta_{21} x_1^2 x_4 + \beta_{22} x_2^2 x_1 \\ & + \beta_{23} x_2^2 x_3 + \beta_{24} x_2^2 x_4 + \beta_{25} x_3^2 x_1 + \beta_{26} x_3^2 x_2 + \beta_{27} x_3^2 x_4 \\ & + \beta_{28} x_4^2 x_1 + \beta_{29} x_4^2 x_2 + \beta_{30} x_4^2 x_3 + \beta_{31} x_1 x_2 x_3 + \beta_{32} x_1 x_2 x_4 \\ & + \beta_{33} x_1 x_3 x_4 \end{aligned} \tag{4}$$

where:

Y_n is the transfer function of Lead n signal;

n is those 12 standard leads;

β_0 is the constant and β_0 ,..,β_{33} are coefficients of X_1,.. X_4 from the fold providing the minimum RMSE of Lead n signal;

X_1, X_2,X_3, and X_4 are Lead **E**, **A**, **S**, and **I**, respectively.

D. Support Vector Regression (SVR)

Support Vector Regression [15, 16] in the past, has been used to resolve nonlinear problems. The basic concept behind SVR is to project input data into higher dimensional space to map nonlinearity in original data as to perform linear in higher dimensional space using a kernel function and build the separated hyper plane. The SVR function is shown in Equation (5).

$$f(X) = \langle W \cdot \mathrm{K}(X) \rangle + b \tag{5}$$

where:

W is the weight vector;

X is the input column vector;

K is the kernel function for mapping data to higher dimension;

b is the bias value.

The dataset used to train with SVR is $\{(X_i, Y_i)\}_{i=1}^{l}$, $X \in \mathbb{R}^n$, $Y \in \mathbb{R}$ where X_i is the input data vector, Y_i is the desired output vector, X is the input space, Y is the output space.

"Support Vector", from Figure 2, is all of those of input data X_i that gives value of $f(X)$ function within $\pm\varepsilon$ interval, where the deviation (ε) is known as "Loss Function" in the function.

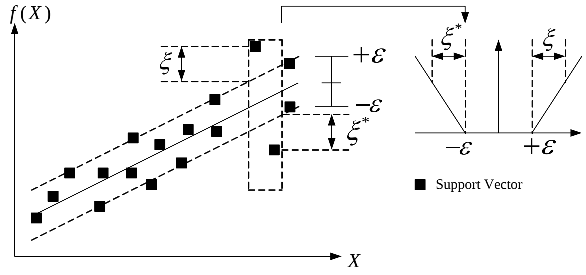


Figure 2: Soft Margin $\varepsilon -$ Insensitive in Linear SVR.

From Figure 2, the optimization was used to find weight vector (W) as in Equations (6-8).

$$\min_{W,\xi_i,\xi_i^*} \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{l}(\xi_i, +\xi_i^*) \quad (6)$$

Subject to:

$$\left.\begin{matrix} Y_i - \langle W \cdot K(X, X_i)\rangle - b \leq \varepsilon + \xi_i \\ \langle W \cdot K(X, X_i)\rangle + b - Y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{matrix}\right\}$$

where:
C is a constant;
W is weight vector acquired by solving with optimization problem as in Equation (7).

$$W = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(X_i) \quad (7)$$

Substitute Equation (7) into Equation (5), the function $f(X)$ can be written as in Equation (8).

$$f(X) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(X, X_i) + b \quad (8)$$

where;
$K(X, X_i)$ is a kernel mapping function between X and X_i.

The performance of SVR is majorly dependent on kernel function being used. RBF, ERBF and Spherical Kernels have been explored and tested in the past experiment [17]. It has been found the best of kernel function is Spherical Kernel for mapping input data to a higher dimension as in Equation (9). The parameter ε was set to 0.001 and parameter C was set to 5,000.

$$K_{Spherical}(X, X_i) = 1 - \frac{3}{2}\left(\frac{\|X - X_i\|}{\sigma}\right) + \frac{1}{2}\left(\frac{\|X - X_i\|}{\sigma}\right)^3 \quad (9)$$

where: σ is the bandwidth of the kernel function.

E. *Artificial Neural Network (ANN)*

Earlier, Artificial Neural Network [18, 19] has been used for synthesis 5 signals (V1, V3, V4, V5 and V6) from 3 leads (Leads I, II and V2) of the standard 12-lead ECG signals [20].

However, in this paper, an ensemble of N multi-layer feedforward ANN trained via a supervised back-propagation algorithm was utilized. Every independant ANN comprises of a single input layer with 4 input neurons (Lead **E**, **A**, **S** and **I** in this case), a single output layer with 12 output neurons (12 derived signals), 4 hidden layers and N ranges from 10 to 60 neurons per each hidden layer. The activation function type use a linear activation function for the output neurons and chosen sigmoid transfer function for the hidden layer is shown in Equation (10).

$$f(n) = \frac{2}{1 + exp^{(-2n)}} - 1 \quad (10)$$

III. Research Experiments

The experiments have been conducted to compare synthesis methodologies for synthesizing the 12-lead ECG from EASI-lead system. All dataset, used in this work, are obtained from Physionet Database consisting of each signal to shuffle data sets in order to prevent over fitting and using five-fold cross-validation, to find the best parameter. The following steps present how to derive the transfer function;

1. The total dataset from Physionet has been into two parts (90:10). The former '90%' part was used as "Train Data" to find constant, coefficients, kernel parameters of SVR and nodes for ANN while the latter '10%' part was used as "Blind Test Data".
2. As five-fold cross-validation was utilized in this work, the first 90% dataset was then divided into 5 equal parts/folds. Each round a single fold is used for testing, leaving the other 4 folds for training. In the n^th round, fold#n is used for testing while the remaining folds are used for training. For instance, in the 2^nd round, fold#2 is used for testing while fold#1 and folds#3-5 are used for training. In total 5 rounds are processed. To find the average errors in the regression of each fold, the Root Mean Squared Error (RMSE) [21] in the Equation (11) is used.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \quad (11)$$

   where:
   A_t is the real value in time t;
   F_t is the predicted value in time t;
   n is the number of samples of testing set in each fold.

3. From all 5 folds, the RMSE value of the Lead I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6 signals are considered. In order to find the transfer function of each signal, the fold that provides the minimum RMSE value of that signal must be identified. Then the constant, coefficients, parameter σ and number of hidden layers from that fold will be substituted into the equation of Dower's method in Equation (1), Linear Regression in Equation (2), 3^rd-order Polynomial Regression in Equation (4), SVR with Spherical Kernel Function in Equation (8) and ANN in Equation (10).
4. After obtaining the transfer function models for each signal is tested with Blind Test Data of 10% to find RMSE values.
5. Finally the big test in order to evaluate these transfer functions can then be started. By feeding the data set into these 12 transfer functions to get the calculated Lead n signals, the RMSE values of each lead signal can be determined from the calculated signals and the ones from the Physionet Dataset.

IV. Result Comparison

The experiments with 5-fold cross-validation to find RMSE values between five different methodologies (Dower's method, Linear Regression, 3^rd Degree Polynomial

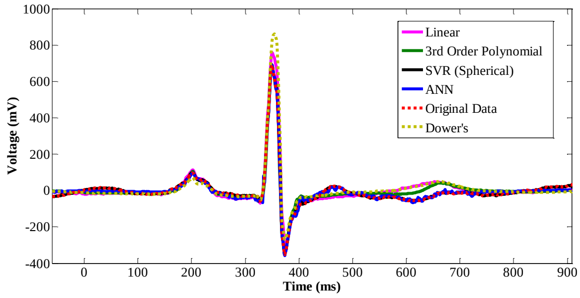
Regression, SVR with Spherical Kernel Function and ANN) and the original signals from PhysioNet Database for all 12 leads provided the following results listed in Table 1.

The highlighted values in Table 1 showed the minimum RMSE values amongst 5 folds for each of 12 leads. The constant, coefficients, parameter σ and the number of hidden layers from those folds with the minimum of RMSE value was then used for deriving 12-signal ECG. The transfer function models for each signal is tested with Blind Test Data to find RMSE value.

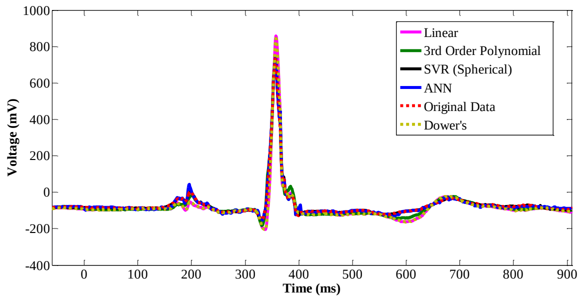
Plots of all 12 signals measured using standard 12-lead ECG method, derived using EASI-lead system by Dower's Method, Linear Regression, 3rd-order Polynomial Regression, ANN and SVR are shown in Figure 3(a-l).

Table 1
RMSE (mV)

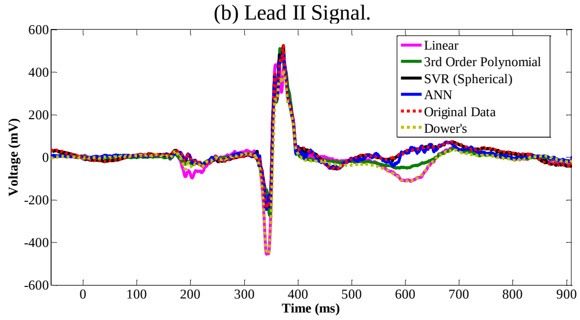
	Signals	Fold#1	Fold#2	Fold#3	Fold#4	Fold#5
Dower's Method	I	33.608	30.026	29.693	30.993	28.152
	II	34.885	31.966	30.140	35.927	34.266
	III	54.207	47.657	42.845	54.354	46.284
	aVR	25.672	24.062	24.508	24.917	25.700
	aVL	40.243	35.191	32.393	38.959	32.672
	aVF	44.897	40.078	36.279	46.002	40.899
	V1	27.421	25.007	25.286	29.801	23.904
	V2	41.022	37.179	37.895	44.646	41.476
	V3	50.933	46.322	44.833	52.422	43.699
	V4	53.287	50.880	56.162	64.026	55.620
	V5	31.169	30.070	29.124	34.890	31.224
	V6	23.477	19.720	17.422	19.670	18.782
Linear Regression	I	24.380	23.373	25.086	26.846	23.861
	II	40.678	37.272	35.344	41.899	40.131
	III	47.419	42.953	40.908	51.353	44.795
	aVR	23.714	22.505	22.823	24.059	24.254
	aVL	31.746	29.126	28.967	35.214	29.755
	aVF	42.462	38.477	36.111	44.901	40.819
	V1	20.115	17.880	20.466	27.402	20.187
	V2	40.981	37.045	37.696	44.856	41.359
	V3	48.055	44.943	44.525	51.549	44.171
	V4	54.586	50.523	55.933	63.799	55.354
	V5	24.043	22.057	23.111	29.470	25.179
	V6	10.954	10.418	9.750	11.955	9.857
3rd-order Polynomial Regression	I	17.379	16.317	18.023	17.639	17.048
	II	28.369	27.776	28.404	28.935	27.767
	III	30.080	28.788	29.954	29.751	28.641
	aVR	18.089	17.655	18.479	18.785	18.048
	aVL	20.055	18.831	20.232	19.719	19.045
	aVF	27.916	27.084	27.763	27.989	26.889
	V1	10.840	10.844	13.231	12.229	10.678
	V2	23.665	22.462	23.680	24.776	24.169
	V3	29.356	29.651	27.100	30.229	29.983
	V4	37.434	34.822	36.892	35.951	36.219
	V5	15.996	14.881	18.403	16.401	16.135
	V6	6.052	5.691	5.524	5.793	5.999
ANN Method.	I	15.531	9.701	8.750	11.049	12.214
	II	15.057	11.920	10.991	13.882	16.181
	III	21.757	15.570	18.367	18.204	12.575
	aVR	10.120	10.029	10.836	9.781	9.596
	aVL	14.087	10.589	10.880	14.257	11.826
	aVF	14.302	16.003	15.173	14.232	13.011
	V1	5.862	5.144	5.667	5.705	4.872
	V2	12.278	12.235	15.370	12.922	12.814
	V3	10.987	14.442	14.943	16.975	14.379
	V4	25.985	21.524	25.205	23.915	28.019
	V5	9.917	7.056	9.527	9.061	7.904
	V6	3.964	3.974	4.515	5.809	5.198
SVR using Spherical Kernel	I	3.836	3.351	4.191	3.454	3.259
	II	6.352	6.995	7.666	4.444	4.280
	III	8.827	7.420	7.739	6.043	5.994
	aVR	5.803	6.391	7.003	4.060	3.910
	aVL	5.688	4.011	4.049	4.189	4.024
	aVF	7.924	7.619	8.155	5.357	5.276
	V1	2.257	2.384	4.534	2.390	2.707
	V2	4.908	5.269	7.252	5.597	5.427
	V3	6.482	7.102	5.225	7.098	5.050
	V4	10.287	9.880	9.105	9.316	9.802
	V5	4.480	3.552	6.412	4.190	4.708
	V6	2.656	4.743	5.500	2.763	1.884



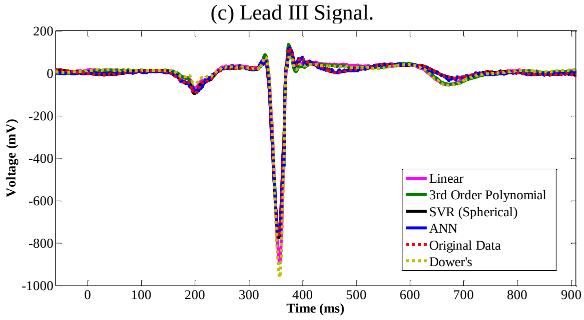
(a) Lead I Signal.



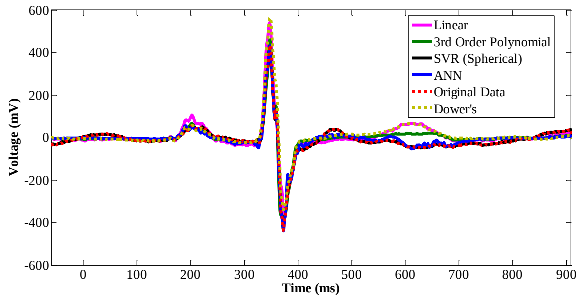
(b) Lead II Signal.



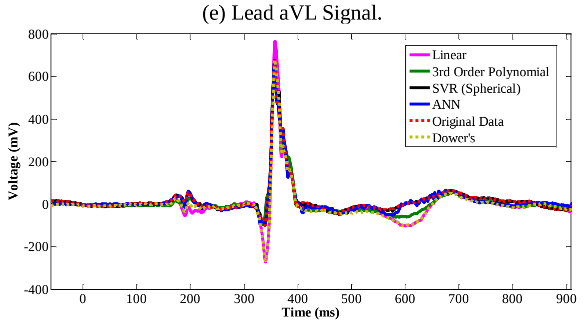
(c) Lead III Signal.



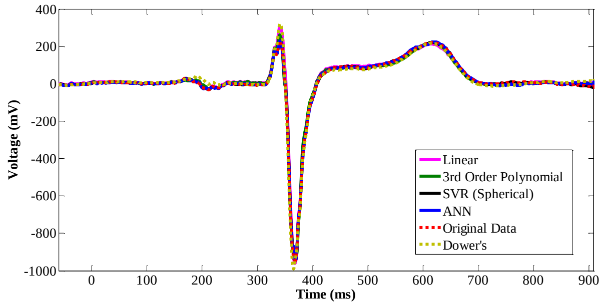
(d) Lead aVR Signal.



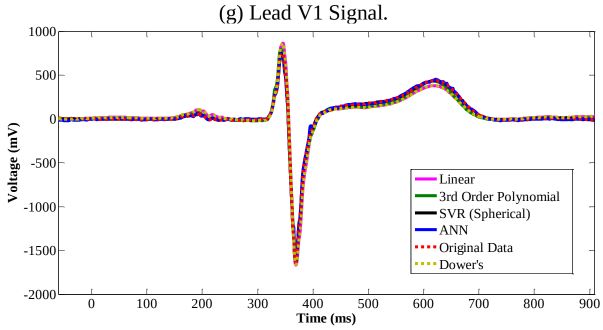
(e) Lead aVL Signal.



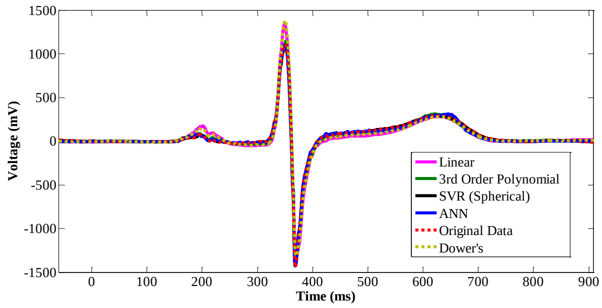
(f) Lead aVF Signal.



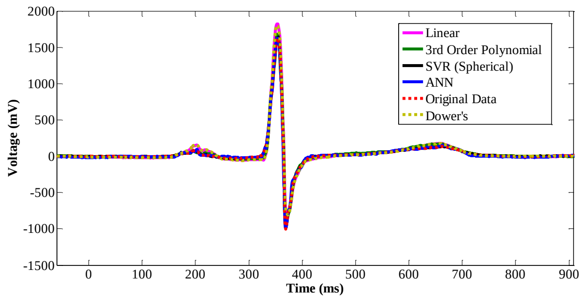
(g) Lead V1 Signal.



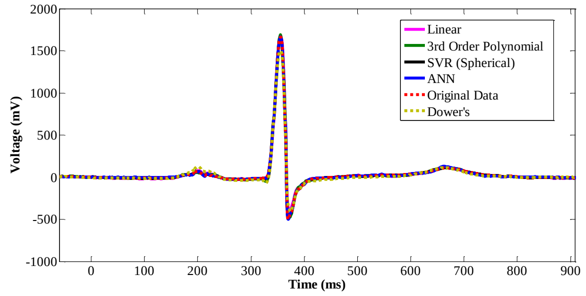
(h) Lead V2 Signal.



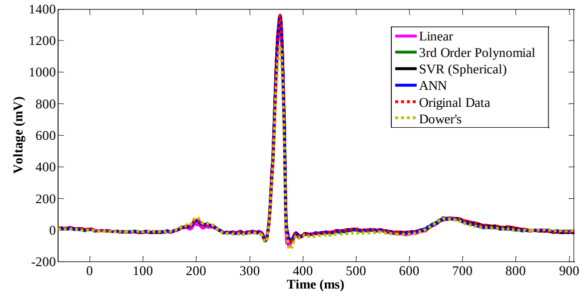
(i) Lead V3 Signal.



(j) Lead V4 Signal.



(k) Lead V5 Signal.



(l) Lead V6 Signal.

Figure 3: Derived VS Original signals of 12-lead ECG.

The average RMSE values for each lead signal with all 5 techniques are listed in Table 2 and depicted in bar graph format in Figure 4.

Table 2
RMSE (mV) tested with Blind Test Data.

Signals	Dower's	Linear	Poly	ANN	SVR
I	35.288	25.665	16.877	10.628	3.608
II	32.476	37.704	26.563	11.930	6.587
III	54.648	46.660	27.867	13.126	7.773
aVR	24.088	22.037	17.375	12.103	4.576
aVL	41.950	32.607	18.582	13.446	4.043
aVF	43.574	40.427	25.881	15.329	7.521
V1	27.438	20.460	12.233	5.763	2.212
V2	40.801	40.807	24.545	14.672	6.331
V3	49.371	47.581	29.865	16.942	6.461
V4	54.262	53.723	36.206	25.997	11.901
V5	35.083	24.579	16.783	11.025	8.558
V6	23.152	12.079	5.876	5.003	3.682
Average	38.511	33.694	21.554	12.997	6.104

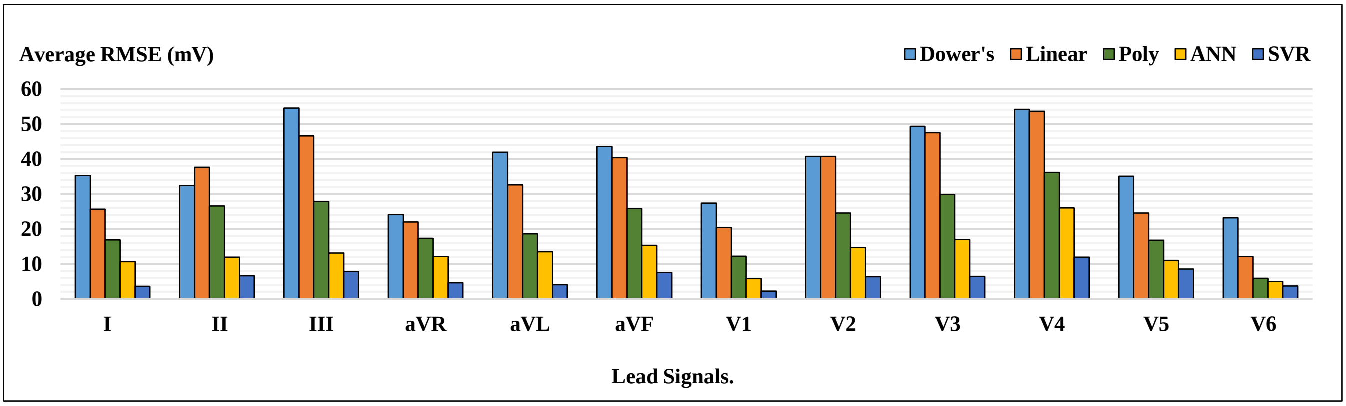


Figure 4: Comparison of Average RMSE Values of 12 Leads Across Five Different Methods with Blind Test Data

Lastly, Figure 5 illustrates the relative of average RMSE value (mV) comparisons for Dower's method, Linear Regression, 3rd-order Polynomial Regression, ANN and SVR techniques.

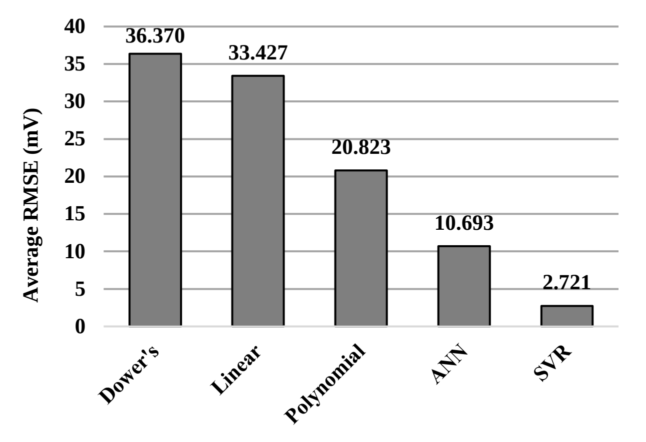


Figure 5: Comparison of Average RMSEs from Dower's method, Linear Regression, 3rd-order Polynomial Regression, ANN and SVR.

V. Conclusion and Future Work

The EASI-lead electrocardiogram (ECG) system, which is fundamental on the dipole hypothesis of vectorcardiography, has offered the possibility of synthesizing the standard 12-lead ECG.

Whereas, previous research introduced the idea of applying nonlinear regression and machine learning techniques for the ECG derivation from EASI system, most if not all of those work have yet shown simply the results from Linear Regression.

This paper has presented and compared various 5 different Machine Learning and Regression techniques to finding transfer function models for deriving the standard 12-lead ECG from 4 measurement signals (**E**, **A**, **S** and **I**) in the EASI-lead system.

The experimental results from Table 2 and very obvious from Figure 5 showed the best performance in this work with least RMSE error values for all signals, was obtained from the SVR method with Spherical Kernel Function followed by ANN, 3rd-order Polynomial Regression, Linear Regression and Dower's method, respectively.

Additionally, from the experiments conducted in this paper, it can be concluded that Machine Learning and Nonlinear equation such as SVR, ANN and Polynomial Regression are much more effective in deriving ECG system than conventional linear equations such as Linear Regression and Dower's method..

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