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Optimal Diagnosis of AMI by Artificial Neural Network & Data Envelopment Analysis

T.B. Ramkumar[1] and K.S. Deepthi[2]

Abstract

Optimization of diagnostic efficiency by mathematic modeling rather than logic is getting momentum in the medical spectrum using computer data analysis. Effective evaluation of disease diagnosis is considered to be one of the research problems getting relief and reduction of cost. Thus the diagnosis of Acute Myocardial Infarction (AMI) by DEA-ANN method is a significant development received by Physician as well as R&D of Pharmaceuticals. This study proposes an optimization criterion of diagnosis by BCC method of Data Envelopment Analysis (DEA) and Artificial Neural Network. ANN is used as a logical tool to optimize the decision developed by DEA. Tables and graphs were provided for the optimization diagnosis of 100 patients and conclusions were made on the final diagnosis.

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[1] Calicut University.

[2] Calicut University.

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1 Introduction

DEA is a technique of nonparametric optimization of LPP on multiple inputs and outputs (Farell 1957). Charnes (1987), Norman and Stoker (1991).Cooper et al.(2000) provide sufficient details on DEA showing the efficiency and application of this method. CCR model by Charnes et al. and later BCC model by Banker were the basic models of DEA. Artificial neural networks can be used to support Physicians for analyzing and make sense on complex clinical data across a broad range of medical applications. Several researchers Er, Yumusak and Temurtas presented a comparative chest disease diagnosis which was realized by using multilayer, probabilistic, learning vector optimization, and generalized regression.

Gil, Johnsson, Garicia, Paya and Fernandez worked out some artificial neural network models as a tool for supporting the medical diagnosis of urological dysfunctions. Altunay, Telatar, Erogul and Aydur analyzed the uroflowmetric data and assisted physicians on their diagnosis. They introduced an expert pre-diagnosis system for automatically evaluating possible symptoms w r to the uroflow signals. The system used artificial neural networks (ANN) and produced a pre-diagnostic result.

Monadjemi and Moallem investigated application of artificial neural networks in typical disease diagnosis.

2 Preliminary Notes

2.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is methodology based upon an interesting application of linear programming. It was originally developed for performance measurement. It has been successfully employed for assessing the relative performance of a set of firms that use a variety of identical inputs to produce a variety of identical output.

DEA is a linear programming based technique for measuring the performance efficiency of organizational units which are termed Decision-making unit (DMU). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs DMUs. DEA has been successfully applied to measure the performance efficiency of all these kinds of DMUs.

The performance of DMUs is assessed in DEA using the concept of efficiency or productivity, which is the ratio of total outputs to total inputs.

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}}$$

Efficiencies estimated using DEA are relative, that is, relative to the best performing DMU (or DMUs if there is more than one best performing DMUs). The best performing DMU is assigned an efficiency score of unity or 100 percent, and the performance of other DMUs vary, between 0 and 100 percent relative to this best performance.

Banker in 1984 developed a model to estimate the pure technical efficiency of decision making units with reference to the efficient frontier. It identifies whether a DMU is operating in increasing, decreasing or constant returns to scale.

The corresponding to each DMU we can formulate LPP in the dual form:

$$\min \theta - \varepsilon\{\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\}$$

$$\text{s.t.} \quad \theta x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = 0, \quad i = 1, 2, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0}, \quad r = 1, 2, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1, \quad j = 1, 2, \ldots, n$$

$$\lambda_j, s_r^+, s_i^- \geq 0, \quad j = 1, 2, \ldots, n, \quad i = 1, 2, \ldots, m, \quad r = 1, 2, \ldots, s$$

A unit is BCC-efficient if and only if θ*= 1 and all slacks are zero. The envelopment surface in BCC model is variable returns to scale and this is the result of the presence of the convexity constraint ($\sum \lambda_j = 1$) in the dual equivalently, the presence of u_o, which is an unconstrained variable, in the primal problem. Inefficient units are projected to the efficient frontier, first by reducing their input, and then by accommodating the slack variables if any.

2.2 Artificial Neural Network

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. A subgroup of processing element is called a layer in the network.

In medicine, ANN is widely used for modeling, data analysis and diagnostic classification. The most common ANN model used in clinical medicine is the multi-layered perceptron (MLP). The most widely used connection pattern is the back propagation neural network which have been proved to be useful in modeling input-output relationship while the most commonly used transfer function are linear, log sigmoid and tan-sigmoid. ANN sequencing with a powerful structure, is a popular non-parametric technique of step by step programming - training, back propagation and evaluation of numerical data set.

In ANN, initially the weights on all the interconnections are set to be small random numbers which are initialized randomly to values between -1 and +1. The network then is presented with a training data set, which provides inputs and desired outputs to the network. Weight training in ANNs is usually formulated as minimization of an error function by iteratively adjusting connection weights. The probability of successful convergence will depend on the weight initialization scheme. For this reason back propagation can only be applied on networks with differentiable activation functions such as sigmoid function.

Sigmoid function, $f(x) = \dfrac{1}{1+e^{-\sum w_i x_i}}$, where w_i is the weights and x_i is the input values. This gives values for hidden neurons and output neurons. At each training cycle, the error is calculated, and the weights are changed in the direction that minimizes the error. This process of changing the weights or updating the weights is called training. New weights are calculated by the formula

$$\Delta w(t) = -\varepsilon \frac{\partial E}{\partial wt} + \alpha\, \Delta w_{t-1}, \quad \varepsilon = \text{learning rate}, \ \alpha = \text{momentum}$$

All weights are kept until the end of training. Of all the possible outputs in the output layer, only one neuron will fire whose value is closer to 1.

3 Main Results

3.1 Data Analysis

DEA model was applied to find optimum patients (Affected AMI) for a given set of 6 clinical and behavioral findings (1 Hypertension, 2 DM, 3, Smoking 4, Cholesterol 5, Hereditary Disease 6, Nil (None of the 5 parameters) as DMU (I) and one DMU (O) - ECG as output in BCCI Model. A successive DEA was performed with ECG as input (I) and the Lipid Hypothesis (TC, TG, LDL, HDL, VLDL) as outputs (O). Further DEA analysis is performed on BCCI model with Lipid parameters as input (I) and Final Diagnosis as output (O).

BCC Model aims to reducing the input amounts by as much as possible while satisfying at least the present output levels which is called input-oriented model. Input-oriented model is preferred because many DMUs have particular orders to fill and hence the input quantities appear to be the primary decision variables. BCC model is based on the assumption of variable returns to scale (VRS). The VRS assumption is appropriate when all DMUs are operating at an optimal scale.

3.1.2 Optimization of Diagnostic Efficiency

The outcome of DEA toolbox from DEA-Solver is used to find optimum diagnosis as shown below:

In Table 1 shows, BP, DM, SMK, CHL had high influence on ECG findings. For the combined set of 100 DMU average score is 69% with SD 26 % indicating lack of optimum detection criteria achieved.

Table 1: Average and Standard deviation in 1st DEA Report

DMU	1--50	51--100	1--100
No. of DMUs	50	50	100
Average Score	0.76	0.62	0.69
SD	0.25	0.27	0.26

Table 2: Relative Efficiency

1--50		51--100	
Peer set	Frequency to other DMUs	Peer set	Frequency to other DMUs
P4	16	P56	3
P16	0	P69	9
P21	21	P75	15
P32	29	P78	0
		P87	28
		P92	30

For the first set of 50 DMUs 4 patients with co-morbid symptoms were diagnosed as in the projections with no bias. In all 46 other cases error is found in the projections (output) with respect to the conditions of patients. 16 patients reach optimum output only if the condition of P4 is realized. Similarly 21 patients required P21 conditions and 29 patients need P32 conditions to reach better outcome.

For the Second set of 50 DMUs 6 patients with basic symptoms were efficiently diagnosed as its projections with no error. In all 44 other cases, error is found on projections with respect to the factors. 3 patients reach optimum conclusion only if conditions of P56 is realized. Similarly 9 patients required P69 conditions and 28 patients need P87 conditions, 30 needed P92 conditions.

For the combined set of 100 DMU average score is 69% with SD 26% indicating lack of optimum detection criteria.

Findings on DEA-2 BCCI Model

44 patients with rank 1 and score 1 in two sets of the BCCI model were considered as DMUs and applying BCCI-DEA model Taking ECG as input (I) and Lipid parameters as outputs (O).

In Table 2 shows, at 2nd stage of DEA, on average the Lipid and ECG parameter estimates are in normal values but SD indicate fluctuation leads to risk or high risk category.

Table 3: Average scores with SD Factor in 2nd DEA Report

	ECG	TC	TG	LDL	HDL	VLDL
Average	1.75	193.41<200	123.80<150	126.09 (100—129)	43.32< 45	24.52 <32
SD	1.43	36.51	60.40	35.17	22.04	12.23

For the 44 patients on average the Lipid and ECG parameter estimates are in normal values but SD indicate fluctuation leads to risk or high risk category. There is high correlation between (TC & LDL) and (TG & VLDL).

Table 4: Total Average and SD of 44 Patients

No. of DMUs	Average	SD
44	0.44	0.42

Average DMU is only 44% with very high SD 42% implying non reaching optimum criteria.

Table 5: Frequency in Reference set

Peer Set	Frequency to Other DMUs
P8	12
P17	16
P20	2
P22	27
P27	7
P28	10
P51	5

For the DEA of 44 DMUs 8 patients with symptoms were diagnosed alike the projections with maximum efficiency. In all 36 other cases error is found on projections with respect to the factors. 12 patients each attains optimum conclusion only if conditions of P8 is realized. Similarly, 16 patients required P17 conditions, 2 patients need P20 conditions, 27 patients need P22 conditions, 7 patients need P27 conditions, 10 patients need P28 conditions and 5 patients need P51 conditions for real projection.

Findings on DEA-3 BCCI Model

14 patients with rank 1 and score 1 in above DMUs are considered as DMUs of this analysis and applying BCCI -DEA model. Taking Lipid parameters as inputs (I) and Final Diagnosis as output (O) performance efficiency is detected.

Table 6: Average score with SD of Factors in 3rd DEA Report

	TC	TG	LDL	HDL	VLDL	DIAGNOSIS
Average	197.36<200	144.14<150	119.79 (100—129)	48.79 (45—59)	28.86<32	1.29
SD	37.52	75.39	37.81	37.06	14.92	0.699

Based on averages diagnosis of 1-Unstable Angina or 3-Acute Myocardial Infarction is developed in patients with lipid parameters falls in normal or risk factor ranges. Thus more optimum assessment is required. There is high correlation between (TC & DIAGNOSIS) and (TG & VLDL).

Table 7: Total Average and SD of 14 Patients

No. of DMUs	Average	SD
14	0.98	0.034

Average DMU is 98% with only 3% SD indicating a good criterion for diagnosing levels of AMI is achieved. Also P29 reaches optimum without reference of any other patient level. Showing that it is optimum diagnosis for Unstable Angina. Also 4 patients can reach optimum by enhancing P49 condition leading to Unstable Angina. 2 patients each realize the same outcome in-coordination with conditions of P51 and P72.

Table 8. Frequency in Reference set

Peer Set	P29	P49	P51	P72
Frequency to other DMUs	0	4	2	2

From the data set 14 DMUs 10 are optimum patients with score 1 and remaining 4 are not optimum but it can be reached optimum by re-assessment of the parameters. From the data set of 14 DMUs 10 are efficient with Rank and Score 1 and in the remaining 4 a minimum score of 87% is achieved with 2 more had a high score of 95% and 98%.

As the diagnosis of outcome by applying DEA technique:

Unstable Angina is ascertained not from ECG in 6 out of 8 cases as ECG is normal within limits. But either TC, TG or LDL (one of them) will be high along with increased of HDL ensures Unstable Angina. Also Acute Myocardial Infarction is distinguished with 1-St Elevation In 2, 3, Avf with a habit of smoking having high TC, TG, & LDL. Increased risk is also partly seeing among them and VLDL rate is indicating medication.

Table 9: Rank Order

Rank	DMU	Score	Diagnosis
1	P78,P6,P8,P72,P51,P49,P27 ,P29	1	Unstable Angina
1	P20,P28	1	Acute Myocardial Infarction
11	P13	0.983016	Unstable Angina
12	P69	0.959308	Unstable Angina
13	P22	0.95225	Unstable Angina
14	P17	0.874884	Unstable Angina

3.2 Performance Evaluation

Neural network toolbox from MathCAD 14 is used to evaluate the performance of the proposed networks.

A typical artificial neural network is proposed to the diagnosis of Acute Myocardial Infarction with suitable hidden layers developed by empirical causes. The input in ANN was fixed from all the possible binary combinations of six variables and optimum was selected as 1, 0, 0, 0, 0, 0 (including the bias neuron with value 1) using method of training, back propagation and validation. Figure1 shows ANN is structured with two step hidden layers -ECG, Lipid Hypothesis with 6 input neurons in the input layer and 1 output neuron in the output layer. Two hidden layers were formulated- ECG (one neuron) and Lipid Hypothesis taken from the Cholesterol derivatives (Five neurons) in each layer for performing the ANN. Considering the whole combinations (64) of 6 digit binary number and applying them to the training data of ANN, inputs are fixed which gives the minimum value of the output value. Thus an input combination of 1, 0, 0, 0, 0, and 0 is selected from the 64 (2^6) combinations of binary number. The inputs of ANN is designed on empirical clinical findings and hence the ANN diagram with an input of 1 0 0 0 0 0 (binary codes), a minimum error with an efficiency of 90 percent is derived.

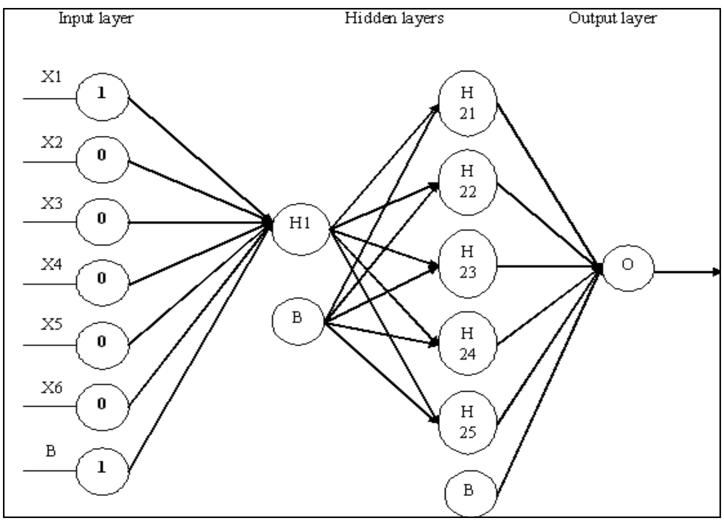

Figure 1: The Architecture of Multi-Layered Neural Network

4 Conclusion

This paper has aimed to evaluate artificial neural network in disease diagnosis. The analysis is based on a DEA that allows for incorporation of multiple Risk Factors inputs and output in determining the relative efficiencies. Artificial neural networks showed significant results in dealing with data represented in clinical symptoms. Results showed that the proposed diagnosis neural network could be useful for identifying the infected person. This paper is aimed to use artificial neural network as a tool to diagnose the gravity of the disease. In DEA Table 9, the data set of 14 DMUs, 10 are efficient with Rank and Score 1 and in the remaining 4 a minimum score of 87% is achieved with 2 more had a high score of 95% and 98% but it can be reached optimum by re-assessment of the parameters. In ANN is developed using 6 inputs and 1 output with intermediate construction of hidden layers of 1 and 5 components. Out of 100 patients examinations an optimum ANN is designed with 90 percent efficiency, with the help of an input combination of 1 0 0 0 0 0.

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