SCIREA Journal of Medicine

http://www.scirea.org/journal/PM

April 1, 2018

Volume 2, Issue 1, February 2018

Transformation of the Davenport Diagram to a Computerized Artificial Neural Network

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Abstract

The Davenport diagram, which illustrates the interactions of pH, bicarbonate and pCO_2 as related to respiratory/metabolic phases of acidosis/alkalosis was transformed into a computerized neural network. This transformation enables computer-assisted prediction of acidosis/alkalosis subtypes on the basis of any two factors from pH, bicarbonate and pCO_2. Furthermore, this neural network can eventually be trained to predict changes in acid-base balance on the basis of additional factors; illustrating the utility of neural network analysis as a dynamic predictive tool in healthcare.

Keywords: Davenport diagram, neural network, nomogram, acidosis, alkalosis

Introduction

Many artificial intelligence techniques are useful tools in healthcare. Among these are computerized artificial neural networks, which facilitate prediction of outcomes based upon two or more independent variables. A simple, yet flexible application of neural network analysis is the development of a neural network based upon a nomogram. These nomogram transformations can expand the utility of the nomogram, since additional factors can be used to train the computer to modify predictions beyond the capability of the basic two-dimensional nomogram. Examples of these transformations have been published previously [1,2]. The purpose of this report is to illustrate a neural network transformation based upon the Davenport diagram as a template.

Methods

The Davenport diagram illustrates the interactions of pH, bicarbonate and pCO_2 as related to respiratory/metabolic phases of acidosis/alkalosis [3]. While there are many variants of this diagram, the various subtypes of respiratory/metabolic phases of acidosis/alkalosis are illustrated in Figure 1 [4]. Points from each acidosis/alkalosis subtype area, including areas of transition between these subtypes were entered into a Microsoft Excel™ (Redmond, WA) spreadsheet, where the independent variables for pH, bicarbonate and pCO_2 were linked to the corresponding acidosis/alkalosis subtype as the dependent category variable for prediction (a total of 160 points). Since any two independent variables in will define a region in the diagram as with any nomogram, two variables were presented for training of the network. Additional variables, such as changes in pCO_2, may be added to enhance the dynamic predictive power of the network, which is an important property of the Davenport diagram [1]. A segment of this spreadsheet is shown in Table 1. For transformation into a neural network, the software package NeuralTools 7 was obtained from Palisade Corporation (Ithaca, New York). This program utilizes the Microsoft Excel™ spreadsheet as the interface for data entry and analysis.

Results

Following training and software-based testing of the network, points not in the database were used to assess the predictive utility of the network. Points were selected from the various acidosis/alkalosis subtypes within the diagram and the neural network predictions were obtained. Examples are shown in Table 2. Note that in each case, the network predicted the correct acidosis/alkalosis subtype defined in the diagram.

Discussion

While the transformation of the diagram into a neural network was successful, as noted previously, additional independent variables can expand the utility of this predictive tool. There are many factors that can alter acid/base balance. Since pCO_2 is one of the features of the Davenport diagram, this is the next logical element for extending the utility of the neural network [1]. Additional factors are renal function and drug therapy [5,6]. With additional data, clinicians can modify and retrain this neural network to enhance the utility of the network.

Acknowledgements

The author wishes to thank the Global Consortium for Life Systems Research for their input into this work and intramural support from the University of the Pacific.

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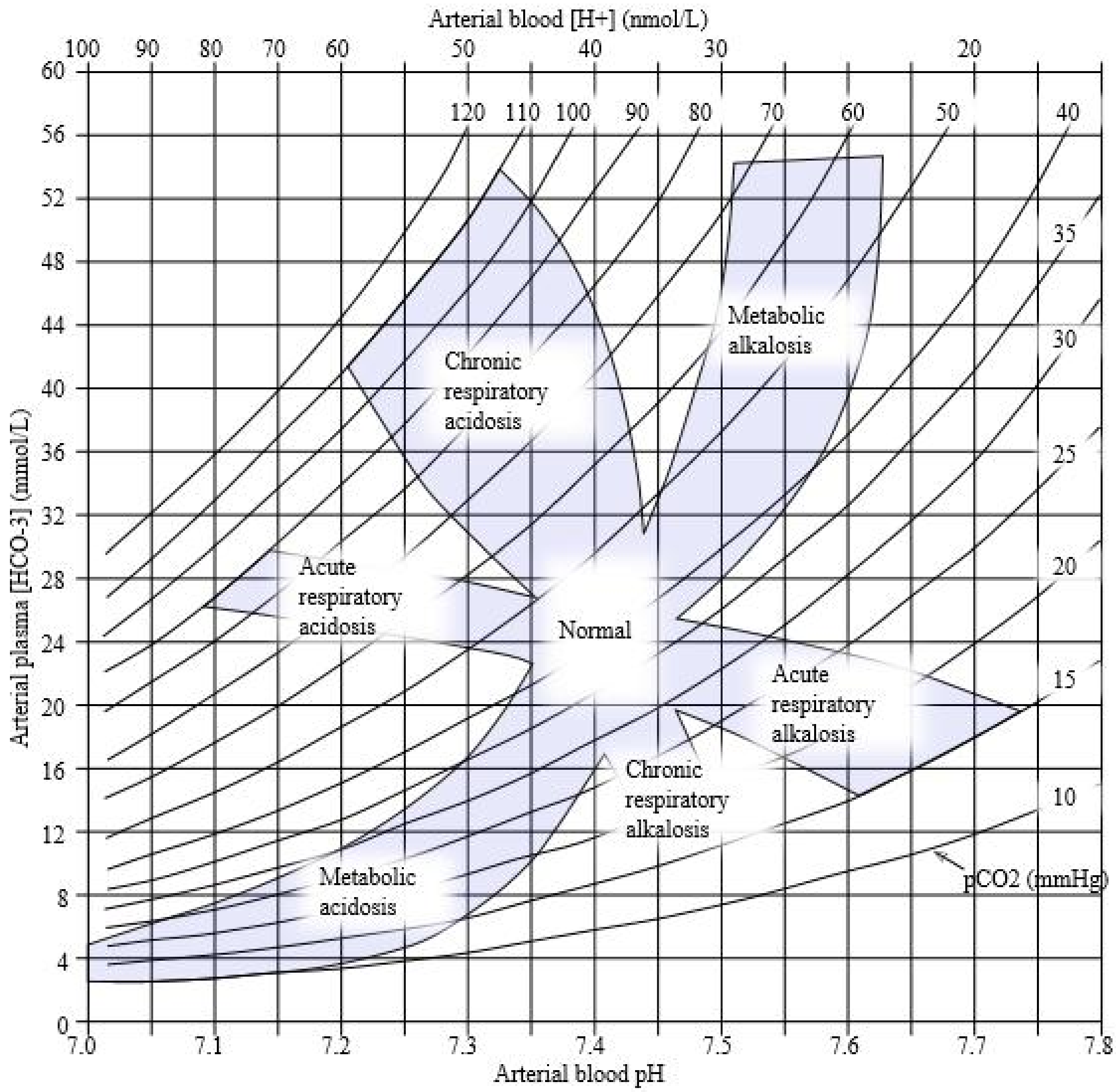

Figure 1. The Davenport Nomogram illustrating the relationship of arterial blood pH, bicarbonate and pCO_2 in the characterization of respiratory/metabolic acidosis/alkalosis. (adapted from Wikipedia, [4])

https://en.wikipedia.org/wiki/Acid%E2%80%93base_homeostasis#/media/File:Acid-base_nomogram.svg

HCO_3^-	pH	Physiologic Status
54	7.6	Metabolic Alkalosis
48	7.5	Metabolic Alkalosis
54	7.325	Chronic Respiratory Acidosis
28	7.35	Chronic Respiratory Acidosis
26	7.1	Acute Respiratory Acidosis
23	7.34	Acute Respiratory Acidosis
11	7.2	Metabolic Acidosis
6	7.3	Metabolic Acidosis
14	7.49	Chronic Respiratory Alkalosis
16	7.48	Chronic Respiratory Alkalosis
20	7.74	Acute Respiratory Alkalosis
25	7.5	Acute Respiratory Alkalosis
36	7.45	Chr Resp Acid to Met Alk
40	7.45	Chr Resp Acid to Met Alk
32	7.175	Acute Resp Acid to Chr Resp Acid
34	7.2	Acute Resp Acid to Chr Resp Acid
20	7.25	Acute Resp Acid to Met Acid
20	7.3	Acute Resp Acid to Met Acid
12	7.4	Met Acid to Chr Resp Alk
8	7.4	Met Acid to Chr Resp Alk
16	7.5	Acute Resp Alk to Chr Resp Alk
13	7.55	Acute Resp Alk to Chr Resp Alk

20	7.525	Acute Resp Alk to Met Alk
32	7.58	Acute Resp Alk to Met Alk
22	7.38	Normal
22	7.4	Normal
22	7.42	Normal

Table 1. Sample points from the nomogram arranged as a dataset in Excel. A physiologic state between metabolic/respiratory acidosis/alkalosis is represented as one physiologic state ***to*** another. Acid = acidosis, alk = alkalosis, chr = chronic, met = metabolic, resp = respiratory.

HCO_3-	**pH**	**Predicted Physiologic Status**
40	7.3	Chronic Respiratory Acidosis
46	7.55	Metabolic Alkalosis
26	7.25	Acute Respiratory Acidosis
14	7.35	Metabolic Acidosis
18	7.45	Chronic Respiratory Alkalosis
18	7.65	Acute Respiratory Alkalosis
32	7.7	Acute Resp Alk to Met Alk
50	7.45	Chr Resp Acid to Met Alk

Table 2. Predictions of physiologic status based upon neural network analysis. Input values (HCO_3^- and pH) not in the dataset were used to test predictions. For abbreviations, see Table 1.