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# NEURAL NETWORK APPROACH FOR ESTIMATION OF LACTATE

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**Abstract**

Lactate is cleared from the body by transporting it to the liver. This process of the body requires adequate amounts of oxygen. Due to certain ailments such as heart failure, respiratory dysfunctions,or severe infection, there is a shortage of oxygen supply. This leads to inefficient elimination of lactate and hence abnormal accumulation of lactate in the blood. To provide timely intervention, lactate needs to be monitored in a non-invasive manner in a critical care scenario. This manuscript describes a method of predicting lactate using fixed wavelength in the near-infrared region. We have selected wavelengths namely 2299, 2285, 2259, 2225, and 2129nm which correspond to theabsorption peaks and valleys of lactate.We have performed a comparative analysis of partial least square regression and principal component analysis-artificial neural network for regression analysis. We obtained a root mean square error of 2.02 mg/dL with partial least square regression and aroot mean square error of 0.15 mg/dL with principal component analysis-artificial neural network. Hence, theartificial neural network can be employed to predate lactate for medical applications.

There is a buildup of lactate in the body when it generates the required energy by the anaerobic pathway. The body clears the tissue lactate by carrying it tothe liver where it either gets oxidized to carbon dioxide or transformed to glucose through cyclic process. This process requires adequate amounts of oxygensupply. However in conditions such as hypoxia where there is a shortage of oxygen due to underlying conditions such as heart failure, respiratory dysfunctions, or severe infection. In such conditions, lactate elimination is hindered. This leads to the accumulationof lactate in the blood beyond normal allowable levels. The normal levels in the human blood of lactate are less than 2mmol/L(18.02mg/dL). The above conditioncan lead to lactic acidosis due to altered pH levels as a result of high lactate concentrations in the blood. There can be other life-threateningconditions such as difficulty in breathing, confusion, and even coma [1]. Lactate concentrations higher than 4 mmol/L have been found in myocardial infarction [2], cardiac arrest [3], circulatory failure [4,5] ,and emergency traumasituations [6,7]. Hence a robust, continuous and non invasive method is of paramount importance in critical care scenarios.

Earlier investigations have shown the viability of Near Infrared (NIR) radiation for in-vitro lactate prediction [8,9]. In one study, ultraviolet(UV)/visible,NIR and Mid Infrared (MIR) radiation were used to estimate lactate contained in phosphate-buffered saline (PBS) in the concentration range of 0 to 20 mmol/L. Regression analysis were done using Partial Least Squares Regression (PLSR) and leave-one-out cross-validation gave a root mean squareerror of cross- validation of 1.59, 0.89, and 0.49 mmol/L for UV/visible, NIR,and MIR region respectively [10]. In this work we are attempting to bring out theefficacy near infrared region for lactate estimation by using reduced wavelengthsinstead of the entire absorption spectra. Earlier research works have reportedabsorption signature of lactate in combination band [11,12]. This workcarefullyselects wavelengths at the reported absorption peaks and valleys which lactatehas. These wavelengths are found to correlate with concentration changes inlactate in the sample. The selected wavelengths are 2299, 2285, 2259, 2225,2129nm. Reduction of wavelengths points reduces the computing and memoryresources required to build estimation models.

Near infrared spectra were recorded of 64 laboratory samples in the rangeof 2050-2350nm using spectrophotometer (Model V-770 by Jasco, Japan). Thelaboratory samples contained glucose, ascorbate, urea, lactate, and alanine inaqueous solution. These above compounds were used as they resemble the bloodtissue. The concentration of alanine was made to vary from 10 to 28 mg/dL,concentration of urea was made to vary from 11 to 20 mg/dL, concentration oflactate was made to vary from 12 to 22 mg/dL, concentration of glucose wasmade to vary from 70 to 280 mg/dL and concentration of ascorbate was madeto vary from 2 to 5 mg/dL. All the compounds used were of analytical grade(Sigma Aldrich Ltd.). A quartz cuvette was used as a sample holder which hada path length of 1mm.

Partial least square regression (PLSR) and Principal Component AnalysisArtifcial Neural Network (PCA-ANN) were used for regression analysis. Forthe first regression analysis PLSR was implemented on the recorded data usingParLeS 3.1 software[13], which uses orthogonalizedPLSR algorithm. The second regression analysis PCA-ANN, needs PCA algorithm to be applied on theinput data which is done using MATLAB R2021b. The data is centered beforepassing through PCA algorithm. The Statistics and Machine Learning Toolboxis necessary to run the PCA in MATLAB R2021b. The toolbox leverages theSingular value decomposition (SVD)

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algorithm to implement the PCA. The preprocessed data by PCA is fed as input to the ANN for the purpose of machinelearning. The algorithm used to train the network is Levenberg-Marquardtback propagation algorithm. This is a part of the neural network fitting application which is bundled along with MATLAB R2021b. The tan-sigmoid transferfunction is used as an activation function for the hidden layer and the linearactivation function is used in the output layer. The created ANN is a shallownetwork, as it contains only one hidden layer, an input layer and an output layer.The scores on the principal components are given as input to the neural network. The input layer contains 3 neurons, hidden layer contains 5 neurons andthe output layer contains one neuron. For Both the Regression analysis, 57 ofthe 64 samples were used as calibration/training dataset. The rest 7 sampleswere used for validation of the created models where lactate was estimated inthe unknown samples.

The table 1 shows the analysis done using the above outlined methods. Thefrst approach using PLSR we extracted 4 factors to model the data. TheRoot Mean Square Error(RMSE) for prediction of lactate on the 7 validationsamples was 2.02 mg/dL. In the second approach, namely PCA-ANN 3 principalcomponents were extracted from the input spectral data which explained 99.97%of variance. These were then fed as input to the ANN. The lactate estimationon the validation set gave a RMSE of 0.15 mg/dL.Table 1: Estimation of lactate using the PLSR and PCA-ANN The PLSR method employed above is a multivariate method which models the linear relationships between the block of predictor variables (absorption signatures) andthe block of response variables (sample concentrations). However, there maybe many underlying non-linear effects occurring in the sample such as nonlineardetector response, stray light, sample turbidity, and multiple scattering due toin homogeneities in the sample, shifts in the width and positions the absorption bands due to variations in sample temperature and composition [14]. ThePCA-ANN is able to model the linear as well as the non-linear relationshipbetween predictor variables and response variables. The above results indicatethat PCA-ANN approach enhances the accuracy of estimation methodology andis a superior method as compared to PLSR.

| Sr. no. | Actual Concentration in mg/dL | | | | | **Estimated lactate by PCA-ANN in mg/dL** | **Estimated lactate by PLSR in mg/dL** |
|---|---|---|---|---|---|---|---|
| | **Urea** | **Glucose** | **Ascorbate** | **Analine** | **Lactate** | | |
| 1 | 20 | 70 | 5 | 28 | 12 | 11.93 | 13.96 |
| 2 | 20 | 100 | 5 | 10 | 12 | 12.09 | 14.27 |
| 3 | 11 | 200 | 2 | 10 | 22 | 22.12 | 20.12 |
| 4 | 11 | 280 | 5 | 28 | 12 | 11.94 | 14.76 |
| 5 | 20 | 280 | 5 | 28 | 22 | 21.69 | 22.93 |
| 6 | 20 | 200 | 2 | 28 | 12 | 12.16 | 11.46 |
| 7 | 11 | 100 | 5 | 10 | 12 | 12.08 | 14.68 |

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