Sensor signals processing

A Deep Learning-based System for Automated Sensing of Chronic Kidney Disease

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Abstract—In this article, we propose a new sensing technique for the automated detection of kidney disease. The salivary urea concentration is monitored to detect the disease. A new sensing approach is introduced to monitor the urea levels in the saliva sample. Further, for analyzing the raw signals obtained from the sensor, we have implemented a 1-Dimensional (1-D) deep learning Convolutional Neural Network (CNN) algorithm which is incorporated with a Support Vector Machine (SVM) classifier. The use of CNN-SVM integrated network enhanced the classification accuracy of the model. The proposed model successfully classified the samples with an accuracy of 98.04%.

Index Terms—Ammonia sensor, chronic kidney disease, convolutional neural network, correlation, support vector machine.

I. INTRODUCTION

Saliva is gaining importance as an effective bio-fluid in the clinical diagnosis of diseases. Like blood samples, saliva samples can also be used as a potential diagnostic tool for identifying various diseases [1]. Most of the disease revealing components found in the blood can also be detected in saliva. The non-invasive sample extraction method makes saliva a good choice as a diagnostic aid. Several research activities at various levels have successfully proved disease diagnosis using salivary biomarkers. In this work, we have proposed a new method to detect Chronic Kidney Disease (CKD) from the saliva samples. The assessment of the kidney functioning is generally monitored by measuring the levels of creatinine or urea in the serum. Recent findings show that the urea values in the serum and saliva are positively correlated [2]. Hence, the salivary test can be used as a capable alternative to the blood test for detecting CKD. The salivary urea value ranges from 12 to 70 mg/dL in healthy individuals [3]. An elevated urea level in saliva indicates improper functioning of the kidneys.

There are different methodologies for measuring the urea levels in the body fluids. However, the majority of these approaches are based upon the clinical analysis test which involves massive devices like chemical analyzers. The conventional approaches are not suitable for real-time applications because of their complex detection procedures. Human breath also contains ammonia which can be evaluated to detect CKD non-invasively [4]. However, the concentration of ammonia is significantly low in the breath. Hence, extremely sensitive sensors are required to assess the minute levels of ammonia in the breath. Therefore, a saliva-based diagnosis is actually the better choice and can give superior performance compared to breath-based analysis. A new sensing approach based on salivary diagnosis is presented in this work. We have conducted the statistical analysis to quantify the strength of the relationship between the proposed sensing approach and the traditional urea detection method.

Further, a deep learning CNN-SVM network is implemented for processing the sensor signals. As the sensor response is a time-varying 1-D signal, a 1-D CNN network is implemented in the proposed work. The contemporary research works have shown the capabilities of 1-D CNN to analyze the signals in real-time [5]–[7]. The advantage of using deep learning network is that no extra feature extraction algorithm is required. An SVM classifier is combined with the CNN network for performing the classification operation. The CNN-SVM integrated network can offer better classification accuracy compared to conventional CNN network [8].

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Associate Editor: Julian Gardner
Digital Object Identifier 10.1109/LSENS.2017.0000000

II. METHODOLOGY AND SYSTEM DESIGN

A. Sensing Module

In this work, we have developed and investigated a new sensing approach for analyzing the salivary urea levels. The conventional enzymatic urea transformation process is carried out for hydrolyzing urea to ammonia [9]. Urease enzyme is used for this enzymatic conversion. This enzymatic reaction produces ammonia gas which is then measured by a semiconductor-based gas sensor. The amount of ammonia gas produced will be proportional to the urea concentration in the sample.

The sensing module consists of a specially crafted gas sensing chamber, an Arduino board and an MQ-series ammonia gas sensor. The conversion reaction is carried out inside the gas chamber. This chamber has an inlet valve at the top for dropping the sample, and the urease enzyme is placed below this valve in a small cylindrical beaker. The ammonia gas sensor is mounted inside the gas chamber. The model of the gas chamber is shown in Fig. 1. An MQ-137 ammonia sensor is used for measuring the ammonia gas [7], [10]. The specifications of this sensor are given in Table I. The MQ-137 sensor has a layer of stannic oxide on its surface for absorbing the ammonia gas.

The schematic diagram of the sensor circuit is shown in Fig. 2. The load resistance R_L in the circuit is adjustable. R_L is selected as 47KΩ to get the maximum sensing competency. The sensor needs a circuit voltage and a heater voltage for its functioning. The Arduino controller board is interfaced with the sensor circuit for receiving the signals. As we have applied a new sensing approach, the proposed sensing module has been tested by passing ammonia gas into the chamber. Ammonia gas is injected into the gas chamber through the inlet valve, and the response of the sensor is observed on a digital signal oscilloscope. The output voltage of the ammonia sensor showed

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Table 1: Specifications of the Ammonia Gas Sensor

Parameter Name	Circuit voltage	Heating voltage	Load resistance	Heater resistance	Heating consumption	Standard temperature	Humidity	Sensing resistance	Ammonia detection range	Analog output voltage
Values	5±0.2V	5±0.2V	Adjustable	31Ω±5%	≤800mW	10-45^{o}C	<95% RH	2-15KΩ	5-500ppm	0-5V

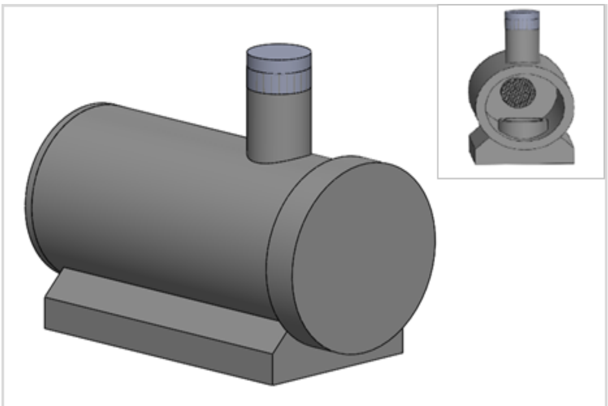

Fig. 1: The model of the gas sensing chamber (internal view of the chamber is shown in the inset)

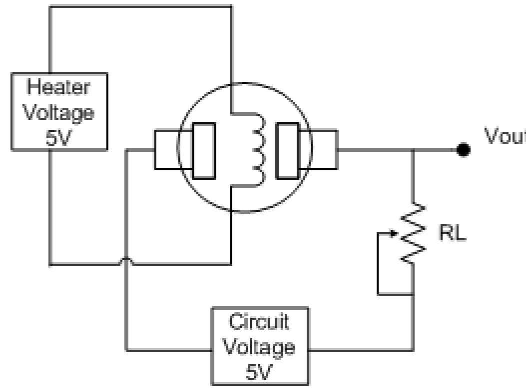

Fig. 2: Schematic diagram of the detection circuit with sensor

Fig. 3: Photograph of the experimental setup (sensing unit is shown in the inset)

variations with changes in ammonia gas concentration within the gas chamber. The sensor response is recorded for varying levels of gas concentration. The photograph of the experimental setup and sensing unit is shown in Fig. 3.

B. Sample Collection and Testing

The samples for this experimental study are collected from 102 participants, including 40 healthy volunteers and 62 individuals with kidney disease. The purpose of this research work is informed to the participants before the analysis, and written consent is obtained from them. For the testing, 1 ml of unstimulated saliva is collected from every participant in a graduated test tube. The saliva samples are collected using spitting method with the help of medical personnel.

Testing is performed by dropping the sample through the input opening of the chamber. Depending on the amount of ammonia gas produced, the electrical conductivity of the gas sensor changes. This variation in the conductivity is transformed to an analog voltage using an electrical circuit. The sensor response for a test sample is shown in Fig. 4. From the experimental analysis, we have observed that the sensor produces a voltage of 0.62-0.93V for healthy subjects. As the urea concentration in saliva will be more in kidney patients, the sensor showed higher voltage values in CKD subjects. The output voltage values are above 0.93V in CKD subjects. As the sensor is operated under its standard working condition, we observed that the humidity is not affecting the sensor performance. We need to consider the humidity variations if the sensor is operated outside its standard working condition. The effect of humidity can be compensated by using humidity sensors and by correcting the sensor signal accordingly [11]. This study has been carried out in accordance with the ethical norms of the Declaration of Helsinki.

C. Deep Learning Module

A deep learning CNN-SVM algorithm is implemented for computing and classifying the features automatically from the output signal of the sensor. The CNN algorithm is a well-known deep learning approach which is commonly used for processing 2-D signals [12], [13]. We have implemented the proposed network by modifying the architecture of the conventional CNN network to suite to 1-D signals. The CNN network consists of convolution and pooling layers followed by classification layers. Initially, the convolution operation is performed on the sensor analog voltage signal and the kernel. The feature map is obtained as:

$$c_i(n) = \sum_{m=-p}^{p} x(m+1)k(q-m+1) \quad (1)$$

where x and k represent the input and the kernel function with length p and q respectively.

After the convolution operation, a pooling function is applied for down-sampling the dimension of the feature map. A max-pooling layer is used in this work. These two operations are repeatedly performed to obtain the reduced feature map from the raw signal. The fully connected Multilayer Perceptron (MLP) is the classification layer in the conventional CNN [14]. In the proposed network, we

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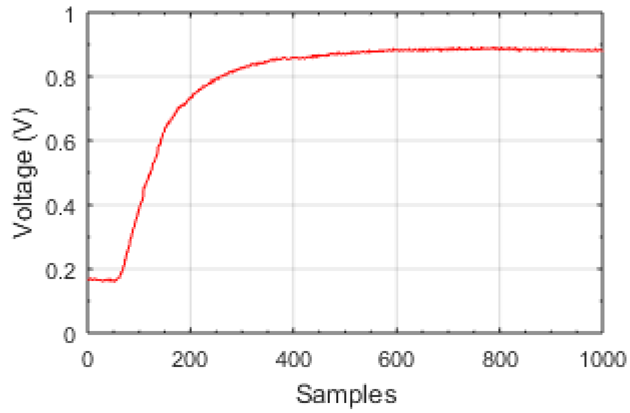

Fig. 4: Sensor response graph showing the voltage output signal for a test sample

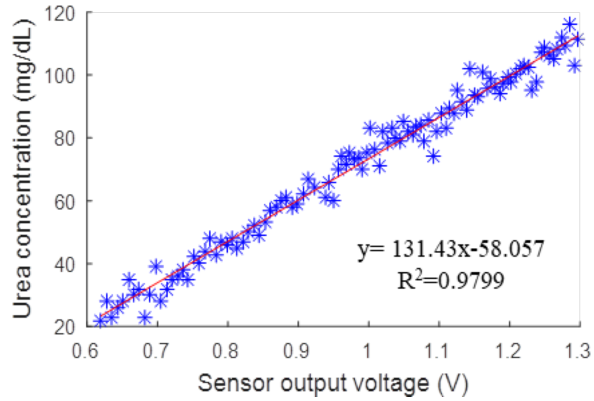

Fig. 5: Scatter plot and regression equation showing the relationship between the proposed sensor output voltage and the urea concentration in the saliva sample

have used an SVM classifier instead of the MLP layer. As SVM is a better classifier, it is able to deliver better classification accuracy [15].

III. RESULTS AND DISCUSSION

The sensor readings are recorded for 1000 samples. The clinical trials are conducted at the Medical health center, and the simulations are carried out at the Bio-signal processing laboratory. The modeling and simulation of the algorithms are done in Matlab 9.2 environment.

A. Validation of the Sensing Module

In clinical practice, urea concentration in the body fluids is measured using chemical analyzers. In the proposed approach, we have monitored the urea concentration by transforming it into ammonia gas. Therefore, the concentration of ammonia gas produced in this conversion process will be directly proportional to the urea concentration in the sample. Accordingly, to estimate the degree of correlation between the values obtained using the proposed sensing method and the values obtained using the traditional urea detection method, we have performed Pearson's correlation analysis. For this analysis, the urea concentration is measured in all the 102 participants using the usual clinical analysis method. We have used Beckman Coulter AU680 chemistry analyzer for urea estimation. A correlation coefficient of r = 0.9898 is obtained in our analysis. This indicates that there is a strong positive correlation between these two values.

Regression analysis is also performed to find how the values are numerically related to each other. The scatter plot diagram representing the relationship between the observed sensor output voltage values and the urea concentration levels in the saliva sample are illustrated in Fig. 5. The obtained regression line equation is y = 131.43x-58.057. Using this equation, it is possible to predict the urea levels by substituting the measured voltage values in the derived regression line equation. The coefficient of determination R^2 is obtained as 0.9799. This means that 97.99% of the values can be predicted by the independent variable.

B. Feature Extraction and Classification

In the present study, we have implemented a five-layer deep learning CNN network. A 1-D Gaussian kernel is used for the convolution operation [8]. The optimal features obtained after convolution and down-sampling operations are fed to the classifier. Algorithm 1 explains the steps involved in the proposed learning network. The features are classified with a Radial Basis Function (RBF) kernel-based SVM classifier. The samples are predicted by the classifier based on the decision function:

$$f(x) = \sum_{i=1}^{p} \alpha_i L_i \ exp \frac{(- \parallel x_i - x \parallel^2)}{2\sigma^2} + b \tag{2}$$

where α_i corresponds to the Lagrange multiplier, L_i is the class label, and σ represents the kernel width.

Algorithm 1 Feature Extraction and Classification

Steps:
1: Obtain the sensor data
2: Initialize the kernel k_r
3: **for** each signal x_i do
$i \leftarrow 1$
4: **while** i=1 to 5, repeat steps 5 to 7
5: Perform convolution of input and kernel
$c_i(n) = Conv(x_i, k_r)$
6: Apply max pooling to down-sample the signal
$C_i = max(c_i*)$
7: $i \leftarrow i + 1$
8: **end while**
9: **end for**
10: Train the SVM classifier
α=SVM train(x, L_i), where x_i is input and L_i is class label

C. Performance Evaluation of the Model and Clinical Validation

The performance of the proposed model is validated using the k-fold cross-validation process, where k is set to 10. The major performance evaluation parameters are calculated for the proposed model. Table II summarizes the obtained performance parameter values. The Matthews Correlation Coefficient (MCC) and F1 score values give valuable information about the performance and classification accuracy of the model. The proposed model successfully classified

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Table 2: Performance Metrics Values Obtained for the Proposed Model

Performance Parameters	Accuracy	Sensitivity	Specificity	F1 Score	Precision	MCC	False Positive Rate	False Negative Rate	Computation Time
Values	98.04%	96.25%	99.19%	0.975	0.987	0.959	0.008	0.037	1.94s

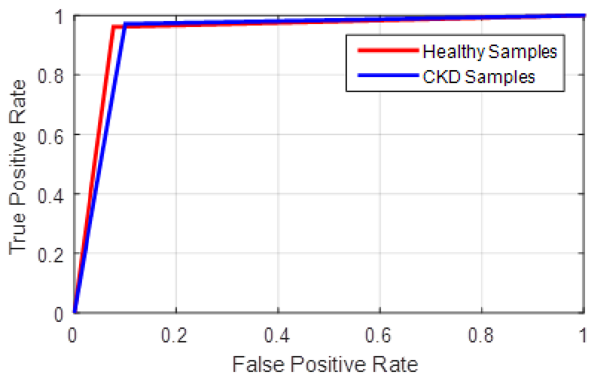

Fig. 6: ROC plot of the proposed model

the test samples with an accuracy of 98.04%. We have plotted the Receiver Operating Characteristic (ROC) curve to determine how good the proposed model can separate normal and CKD samples. Fig. 6 shows the obtained ROC plot. The Area Under the Curve (AUC) of 0.975 and 0.971 are obtained for healthy and CKD samples respectively. This shows that the proposed model can deliver high classification accuracy. The proposed network has taken 0.79s for extracting features, and 1.15s for classification operation. The analysis is performed in an 8^{th} generation 2.2GHz clock speed Intel processor machine.

To validate our analysis results, we have performed the clinical trials at the medical center. In clinical practice, CKD is detected by calculating the Glomerular Filtration Rate (GFR) value [16]. The GFR value will be less than 90mL/min for kidney patients. We achieved a good correlation for the results obtained by the proposed approach and the clinical validation results. The performance evaluation and validation results show that the proposed method can be used to detect CKD non-invasively.

IV. CONCLUSION

In this article, we have proposed and investigated a new sensing model for prompt and accurate diagnosis of CKD. The raw sensor signal is directly given to the deep learning algorithm for predictive decision making. The proposed 1-D CNN-SVM algorithm extracted features directly from the raw signal and successfully classified the samples with an accuracy of 98.04%. The proposed sensing approach is tested and validated by the physician. We have performed the statistical analysis to determine how well the proposed sensing method values and traditional urea estimation values are correlated. A positive correlation is observed between the two values with r and R^2 values of 0.9898 and 0.9799 respectively. The experimental evaluation results show that the proposed sensing module can be successfully used with the capabilities of deep learning techniques for detecting CKD more effectively than traditional methods.

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