International Journal of Psychosocial Rehabilitation, Vol. 24, Issue 04, 2020
ISSN: 1475-7192

Automated Sensing of Chronic Kidney Disease Using SVM and Random Forest Algorithm

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ABSTRACT

Chronic kidney disease is a rising health problem and involves a condition that decrease the efficiency of renal functions and that damages the kidney. Chronic kidney disease may be detected with several automated diagnosis system, and these have been classified using various features and classifier combinations. In this project, SVM and Random forest classifiers is proposed for the diagnosis of chronic kidney disease. The classification performances are estimated with different performance metrics. The use of SVM and Random forest integrated network enhanced the classification accuracy of the model. The proposed model successfully classified the samples with a better accuracy.

KEYWORD: *Chronic kidney disease, SVM, Random forest algorithm.*

I. INTRODUCTION

Chronic kidney disease is a kind of kidney disease in which there is slow loss of kidney done a dated of months to years. Primarily there are generally no symptoms; later, symptoms may include leg swelling, feeling tired, vomiting, loss of appetite, and confusion. Problems include an increased risk of heart disease, high blood pressure, bone disease, and anemia. Causes of chronic kidney disease contain diabetes, high blood pressure, glomerulonephritis, and polycystic kidney disease. Risk factors include a family the past of chronic kidney disease. Ultrasound or kidney biopsy may be implemented to determine the underlying cause. Several severity-based staging systems are in use. Screening at-risk people is recommended. Early treatments may include medications to lower blood pressure, blood sugar, and cholesterol. Angiotensin converting enzyme inhibitors (ACEIs) or angiotensin II receptor antagonists (ARBs) is generally risk of heart disease. First-line agents for blood pressure control, as they slow movement of the kidney disease and the risk of heart disease.

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Received: 03 Dec 2019 | Revised: 21 Jan 2020 | Accepted: 18 Feb 2020

FIG.1 NORMAL KIDNEYS

Loop diuretics may be used to control edema and, if needed, to further lower blood pressure. NSAIDs should be avoided.

FIG.2 DISEASED KIDNEY

Other recommended measures include staying active, and certain dietary changes such as a low-salt diet and the right amount of protein.

II. RELATED WORK

Saliva can be collected non-invasive, frequently and without trained personnel. It is a hopeful diagnostic body fluid with clinical use in endocrinology and dentistry. For decades, it is known that saliva has similarly urea, creatinine, and other markers of renal function. Clinical studies have shown that the salivary concentrations of these markers could be suitable for the assessment of kidney function without the need of blood collection. This papergives the clinical and experimental data on the utilization of saliva as a diagnostic fluid in nephrology and reveals out the merits, pitfalls, practicalnecessities and future outlook for the use of saliva as a novel latent diagnostic bio fluid [1]. Breath Volatile Organic Compounds (VOC’s) study is a non-invasive tool to assess information about health status. This study aims to study exhaled breath of Chronic Kidney Disease (CKD), Diabetes Mellitus (DM) and Healthy Subjects (HS), using electronic nose (e-nose) and Gas Chromatography Quadruple Time-Of-Flight Mass spectrometry (GC/Q-TOF-MS).

Breath samples were gathered from 44 volunteers containing 14 females and 30 males. Urine samples were also gathered to measure Creatinine level (CL) by UV–via Spectrophotometry as reference method. GC/Q-TOF-MS was used to diagnose the volatile organic composites that were recognized in the respired breath of CKD, DM, and healthy subjects at diverse CL concentrations. The e-nose dataset was treated by Principal Component Analysis (PCA), Support Vector Machines (SVMs), Hierarchical Cluster Analysis (HCA) and Partial Least Squares-regression (PLS-regression). PLS model revealed a connection between breath and urinary CL. The projected results display that e-nose created on chemical gas sensors in binding with pattern recognition methods could include the basis of inexpensive and non-invasive diagnosis to differentiate between breath of CKD, DM patients and healthy controls based on breath VOC's analysis [2].Primary detection of the motor faults is useful and artificial neural networks are broadly used for this method. The characteristic systems usually encapsulate two distinct blocks: feature extraction and classification. Such constant and hand-crafted arrangements may be a suboptimal choice and need a major computational cost that will avoid their usage for real-time applications. Here, we introduced a fast and correct motor condition observing and early fault-detection system using 1-D convolutional neural networks that has an inherent adaptive plan to fuse the feature extraction and classification phases of the motor fault finding into a single learning body.

The proposed method is linearly appropriate to the raw data (signal), and, thus, rejects the need for a various feature extraction algorithm resulting in more efficient systems in terms of both speed and hardware [3].A method to detect Chronic Kidney Disease (CKD) from the saliva samples. The assessment of the kidney functioning is generally observed 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.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. An elevated urea level in saliva indicates improper functioning of the kidneys.

The conventional enzymatic urea transformation process is carried out for hydrolyzing urea to ammonia. 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 ofammonia gas produced will be proportional to the urea concentrationin 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. Thi schamber 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. An MQ-137ammonia sensor is used for measuring the ammonia gas.

The specifications of this sensor are given. The MQ-137sensor has a layer of stannic oxide on its surface for absorbing theammonia gas.The schematic diagram of the sensor circuit is shown.The load resistance RL in the circuit is adjustable. RL is selected as47K to get the maximum sensing competency. The sensor needs acircuit voltage and a heater voltage for its functioning. The Arduinocontroller board is interfaced with the sensor circuit for receiving thesignals. As we have applied a new sensing approach, the proposedsensing module has been tested by passing ammonia gas into thechamber. Ammonia gas is injected into the gas chamber through theinlet valve, and the response of the sensor is observed on a digitalsignal oscilloscope. The output voltage of the ammonia sensor showed.

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. 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. 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 classificationlayer in the conventional CNN. The optimal features obtained after convolution and down-sampling operations are fed to the classifier. The features are classified with a Radial Basis Function (RBF) kernel based SVM classifier.

III. PROPOSED SYSTEM

Diagnosing a disease is a complex task in several existing medical expert systems, Identifying a disease is based on the patient symptoms and other details that are given as input to the system. Random Forest is one of the classification technique used to analyze chronic kidney disease. Chronic kidney disease

Raw signal is one of the signals used for the proposed model. The proposed methodshows the Random Forest Classification is greatest proper classifier for Chronic Kidney Disease among all classifiers like SVM .With these proposed method an Diagnosis system is established to produce outcomes to end users.

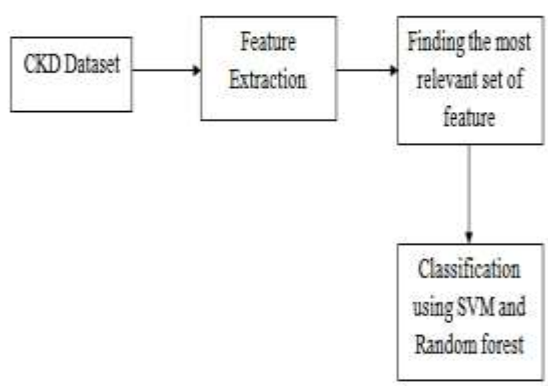

FIG.3 BLOCK DIAGRAM

In preprocessing section, the input image may be in different size, contains noise and it may be in different color combination. These parameters want to be modified according to the necessity of the process. Image noise is most apparent in image regions with low signal level such as shadow regions or below exposed images. There are so many types of noise like salt and pepper noise, film grains etc., All these noise are removed by using filtering algorithms. The first step of every image processing application is image acquisition or image capturing. The images of leaves are captured by using the camera and it will store it in some formats like .PNG, .JPG, .JPEG etc. The selected features represent the uniqueness of the images for defining a class. The features are extracted to classify the kidney images.

Feature extraction is the most important part of this project. The properties standard deviation, entropy, contrast etc are extracted from the image and are used to train the dataset for the classification. Image processing is the study and manipulation of graphical images from sources such as photographs and videos. There are three main steps in image processing; first, is the change of captured images into binary values that a computer can process; second, is the image enhancement and data compression; and the third is the output step that consists of the show the processed image. The most important part of this segmentation method is delay of feature space. But in real images, noise is corrupting the image data or image usually contains of textured segments. This phase is the extraction of the sensed insect pest from the image. The output image which was found at the end of the earlier phase was used in this phase. The image pixel values of the output image will be scanned both horizontally and vertically to determine the coordinates in the image. The width and altitude of the extracted image was determined by using its initial and ending coordinates. Support Vector Machine (SVM) classifier was used to identify the normal or abnormal images by extracting six categories of texture features. The optimal features were specific for the classification task with the help of differential evolution feature selection.

CLASSIFICATION

RANDOM FOREST ALGORITHM

Random decision forests is an ensemble learning process for differentiating, regression and unique tasks that maneuver by avoiding a multitude of decision trees at training time and producing the class that is the method of the classes (classification) or mean prediction (regression) of the separate trees. Random decision forests correct for decision trees custom of over fitting to their training set. Random forest algorithm constructs multiple decision trees to act as an ensemble of classification and regression process. A number of decision trees are constructed using random subsets of the training data sets. A large collection of decision trees provide higher accuracy of results. The runtime of the algorithm is comparatively fast and also accommodates missing data. Random forest randomizes the algorithm and not the training data set. The decision class is the mode of classes generated by decision trees.

SUPPORT VECTOR MACHINE

In machine learning, support-vector machines remaindirected learning models with connected learning algorithms that evaluate data used for classification and multivariate analysis. Given a set of training examples, each marked as fitting to one or the other of two categories, an SVM training algorithm builds a model that allocates new examples to one category or the opposite, making it a non-probabilistic binary linear classifier (although methods like Platt scaling exist to use SVM during a probabilistic classification setting). An SVM model is a demonstration of the examples as points in space, mapped so that the examples of the isolated categories are divided by a perfect gap that is as widespread as possible. New examples are then mapped into that very same space and predicted to belong to a category supported on the side of the gap on which they fall.In addition to accomplishment linear differentiation, SVMs can capably perform a non-linear classification using what's called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.When data are unlabeled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The support-vector bunching algorithm relates the data of support vectors, developedwithin the support vector machines algorithm, to categorize unlabeled data, and is oneamong theforemost widely used clustering algorithms in industrial applications. Support Vector Machine a linear model for classification and regression is Support Vector Machine (SVM) that can be used to solve both linear and nonlinear problems. The algorithm classifies data using a hyper plane. In this algorithm, each data item will be plotted as some extent in n-dimensional space (where n is that the number of features) with the worth of every feature being the value of a particular coordinate. Classification will be performed by finding the right hyper-plane which can differentiate the two classes efficiently.

IV. IMPLEMENTATION

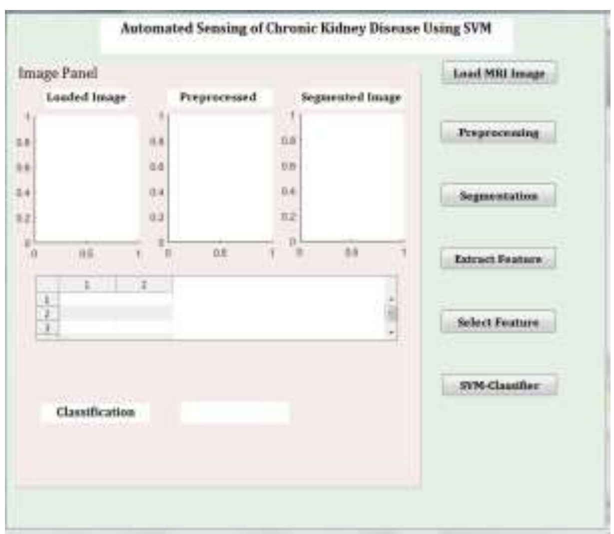

FIG.4 GUI

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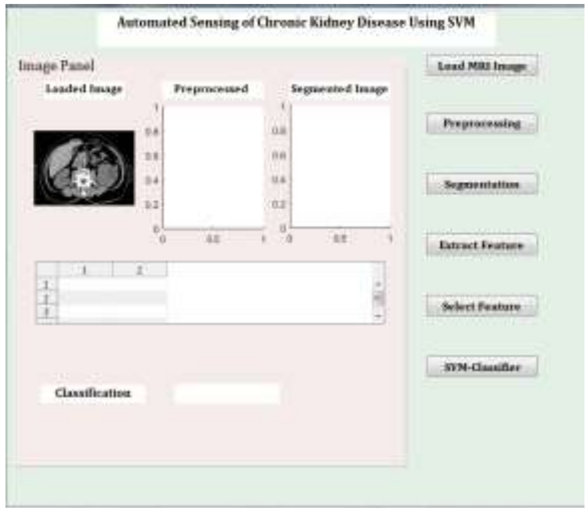

FIG.5 LOAD MRI IMAGE

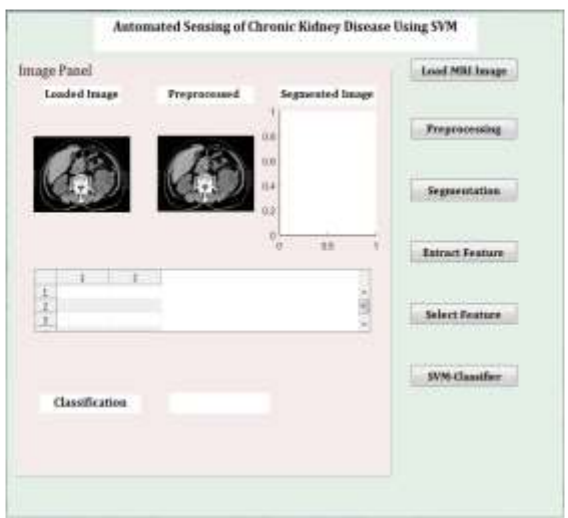

FIG.6 PREPROCESSING

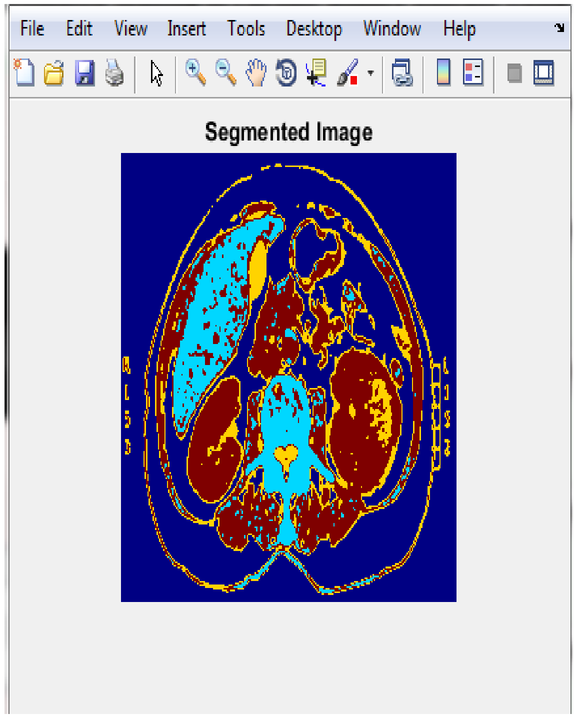

FIG.7 SEGMENTATION

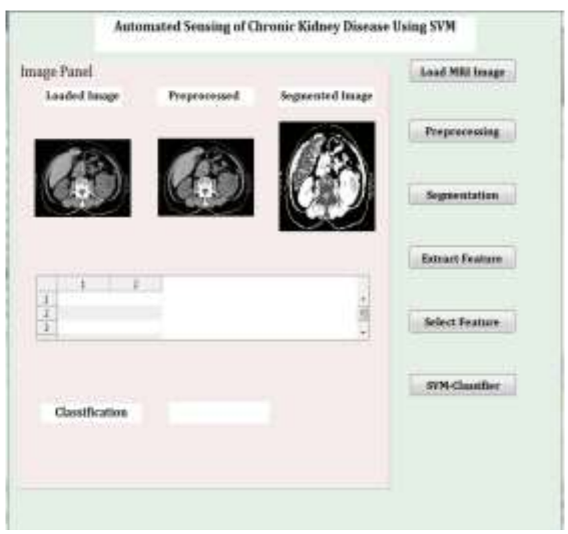

FIG.8EXTRACT FEATURE

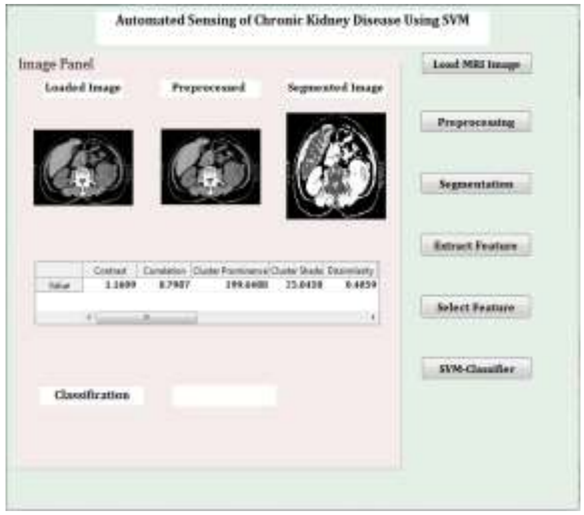

FIG.9 SELECT FEATURE

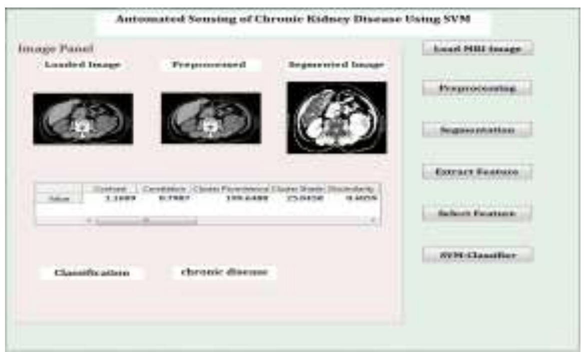

FIG.10 SVM CLASSIFIER

V. CONCLUSION

In this method, the dataset shows input parameters collected from the CKD patients and the models are trained and validated for the given input parameters. Random Forest and Support Vector Deep learning models are constructed to carry out the diagnosis of CKD. The performances of the models are evaluated based on the accuracy of prediction.

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