iCardo 2.0: Association of Hyperkalemia with NYHA Class IV Heart Failure Patient using T wave Morphology of ECG

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***Abstract*—Potassium plays a vital role in heart's normal functioning. Potassium homeostasis disorder can elevate the risk of heart failure, and acute treatment may not be tolrated in long term. Hyperkalemia and cardiac failure are linked through a viscous cycle. In this study the association of blood potassium level to heart failure has been scrutinized with the help of BIDMC Congestive Heart Failure dataset. The dataset contains ECG recordings of 15 subjects of NYHA Class III-IV patients. Eleven of them were men between the ages of 22 and 71, while four were women between the ages of 54 and 63. T wave morphology of ECG recording can quantify the information of blood potassium level and this concept is already well validated. Here, in this work threshold for amplitude of T was set to 10 mm of height and the concept has been authenticated using MIT-BIH Normal Sinus Rhythm database. Based on the T wave morphology 12 out of 15 subjects of BIDMS dataset were found to be hyperkalemic while 2 were not hyperkalemic, and one subject did not exhibit a distinguishable T wave, making it impossible to determine whether he was hyperkalemic or not. Overall, 93% of heart failure patients in the database are hyperkalemic, indicating a strong link between the two conditions. In future integration of this approach with machine learning is possible.**

***Index Terms*—T wave, heart failure, hyperkalemia, Potassium level**

I. Introduction

Cardiovascular disease is the major reason for death worldwide according to a report of the World Health Organization (WHO). It has been observed that serum potassium level and heart failure are viscously related and sometimes medicine like spironolactone used to treat heart failure causes hyperkalemia [1] and vice versa. The patient in the intensive care unit would benefit greatly if serum potassium could be measured using an ECG. Heart failure is a clinical syndrome in which cardiac muscle weakens and ultimately fails to pump blood to the body that arises gradually or sudden (i.e due to myocardial infarction). According to the research of the American Heart Association, almost 4 out of 10 heart failure patients develop hyperkalemia, and many patients have recurrent hyperkalemia episodes [2]. Heart failure is classified into four stages by the American Heart Association which complements the classification of the New York Heart Association (NYHA). These are the four classes: Class I: Regular exercise does not result in any symptoms, Class II: At rest, comfortable, but mild symptoms during routine activity, such as fatigue, dyspnea Class III: Asymptomatic at rest but with strong symptoms during daily activity Class IV: Severe signs of physical activity limitation that persist even when at rest. In this study, we have found the association of hyperkalemia with class IV heart failure patients using the T wave morphology of ECG. Homeostasis of potassium level in blood is very important in different pathological cases especially in case of chronic or acute heart failure. The monitoring is also very important in kidney renal diseases. As per study report, the potassium level outside the range of 4.1 to 4.7 millimoles per liter is associated with an increased mortality rate [3]. A non-invasive or semi-invasive method for potassium level monitoring can be extremely useful in the intensive care unit for the patient of chronic kidney disease or heart failure. The effect of potassium level on electrocardiography is well known for long ago [4]. Serum potassium level in the body is measured by a blood test that is an invasive method and it also takes a considerable amount of time. Potassium concentration measured using ECG can be very useful for patients in the critical care unit as doctors can continuously monitor the patient's potassium level in blood. The smart healthcare monitoring for hyperkalemia is shown in Fig. 1.

The smart healthcare allows the patients to have better medical facilities through remote monitoring [5]. With the development of healthcare technologies, consumer awareness of their health is rising. The need for remote medical treatment is being advocated more than ever to improve the quality care. The fundamental components of smart healthcare includes connected health and e-health. The sensors collects the patient data to store at the cloud which may be accessible through mobile applications [6]. The ECG monitoring of critical care patient could be possible with smart healthcare system for hyperkalemia detection. It would allow to take preventive actions for possible cardiac failure of the patient. In the Paper, the association of hyperkalemia is explored with heart failure with T wave morphology and the QRS complex.

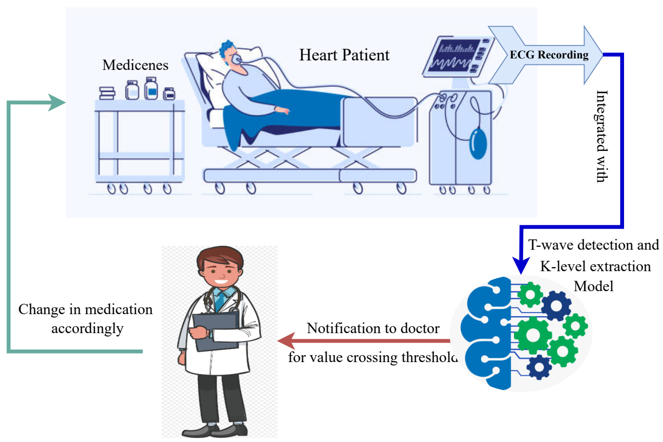

Fig. 1. Hyperkalemia monitoring with Smart Healthcare System

The organization of the paper is as follows:

II. Background Theory

The correlation of hyperkalemia with heart failure is not explored much in the literature. The electrocardiographic effect of hyperkalemia is observed as a narrow-based and peaked T-wave. Blood potassium levels in patients receiving hemodialysis can be gauged using changes in T-wave morphology [7] [8]. At an early stage or in NYHA class I patient, it is very difficult to identify the cardiac failure due to its initial phase and yield no visible symptom. In Class II patients only, mild symptoms are visible but most of the patients avoid it as it does not have a powerful impact on the lifestyle or day-to-day activity but in class III and IV, symptoms are visible and inevitable. Mostly patients of this group kept under observation in an intensive care unit where the patient is continuously connected to continuous ECG monitor. ECG can further be used to extract potassium level in the blood that will eliminate the need of blood test and it will also make the continuous monitoring of potassium level possible. With the known potassium level of the patient, doctors can keep better track of the heart's health and this will also helpful to prevent the worst condition. It may further have its scope in treatment of kidney renal disease or for patient on haemodialysis.

A. *Role of Potassium in Regulation of Cardiac Activity*

Potassium helps in triggering of heart to squeeze blood through the body and it helps the heart to beat more healthily. It also contributes in maintaining resting potential and action potential in cardiomyocyte along with other ions like sodium, calcium, magnesium, etc. Normal potassium level lies between 3.0 to 5.5 mEq/L, if it lies between 5.1 to 6.0 it is considered as a case of mild hyperkalemia if it is between 6.1 to 7.0 mEq/L it is a case of moderate hyperkalemia and if levels are greater than 7.0 mEq/L then it reflects severe hyperkalemia. Resting membrane potential is the voltage or charge difference across cell membranes. When the cell is at rest, a series of ion fluxes through specific channels in the membrane of cardiomyocytes form an action potential which is an electrical stimulus that causes heart contraction. It is comprised of 5 phases (0-4) as shown in the Fig. 2. Ions are propelled across cell membranes by two main forces: chemical potential, which causes an ion to move along its concentration gradient, and electrical potential, which causes an ion to move away from other ions with similar charges. The gradients in ionic concentration and charge differences between the inside and exterior of cardiomyocytes are maintained in part by ion channels. Due to the continual leakage of K^+ through the cell, the resting potential of a cardiomyocyte is -90 mV, as shown in Fig. 3. The resting phase is Phase 4. At the resting phase, Na+ and Ca^{+2} channels are closed. The depolarization of cardiac muscle cells or pacemaker cells is referred to as phase 0. The Trans-membrane Potential (TMP) rises above 90 mV during this period when an action potential in a pacemaker cell is triggered. As TMP reaches the threshold potential, or -70 mV, Na+ channels open one by one and leak into the cell, raising TMP. At this point, enough Na^+ channels have opened quickly to produce a self-sustaining inward Na^+ current. The TMP quickly depolarizes to 0 mV and remains just above 0 mV for a brief period known as overshoot due to this high Na^+ current. L-type (long opening) Ca^{+2} channels open when TMP is higher than -40 mV, causing a slow but constant influx of Ca^{+2} down its concentration gradient. Phase 0 is an early re-polarization phase, and TMP is marginally positive during this phase. A few K^+ channels momentarily open, and TMP recovers to 0 mV in response to a K^+ outflow. Phase 1 is early polarisation phase. Phase 2 is known as the plateau phase, during which L-type Ca^+ channels are still open and a tiny, steady inward influx of Ca^{+2} is present. In the excitation-contraction coupling mechanism, this current is important. K^+ leaks out through delayed rectifier K^+ channels along its concentration gradient. These two counter currents are electrically balanced throughout this period, and TMP is kept at a plateau just below 0 mV. Phase 3, also known as Repolarization: In order to get the cell ready for a fresh cycle of depolarization, Ca^{+2} channels are gradually inactivated during this phase. Persistent K+ outflow is now outpacing Ca^{+2} input, and membrane potential is returned to resting potential, which is -90 mV. Normal transmembrane ionic concentration gradients are reestablished as Na^+ and Ca^{+2} return to the external environment while K^+ stays inside the cell. The following effects could occur if the extracellular fluid contains too much potassium: First, it reduces the heart rate and causes the heart to enlarge and become flaccid. Next, it lowers the resting membrane potential of cardiac muscle fibres. As this membrane potential falls, the strength of the action potential likewise does so, weakening the heart's ability to contract. Larger amounts can also prevent the atrioventricular (A-V) node from transmitting the cardiac impulse from the atria to the ventricles.

In the process of depolarization and re-polarization mineral ions play a very important role. Cardiomyocytes have membrane potential known as pre-potential since these cells are generated by atrioventricular node (AV) as a backup mechanism. At the peak of each impulse I_k (current due to potassium ion) begins and brings about re-polarization. I_k then declines and a channel that can pass Na^+ and K^+ gets activated. Two types of Ca^+ channels are present in the heart, first T (transient) channel and L (long-lasting) channel. Opening of T channels completes and I_{Ca} (calcium current) due to the opening of L cause impulse.

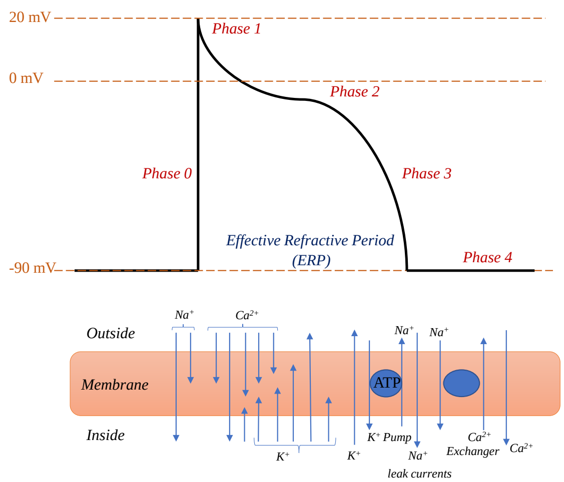

Fig. 2. Ventricular Action Potential

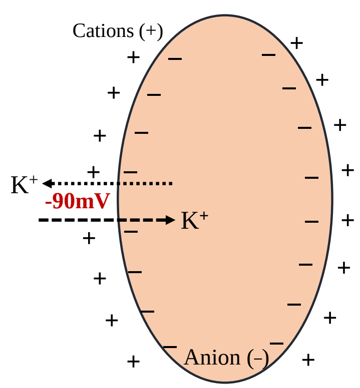

Fig. 3. Resting Potential of the cell

B. Characteristics of ECG Signal

ECG is one of the non-invasive, inexpensive clinical tests, and it has great clinical importance for experimental studies. It helps to have the knowledge about the heart and also about clinically significant mechanical and metabolic issues. It also allows forecasting some of the preventable catastrophes. Small pacemaker cells within the myocardium of the heart oscillate periodically and are in charge of the heart's rhythmic contraction at any given moment. These cells also generate electrical impulses, which are recorded as an ECG signal. This signal is a compilation of all signals generated by the heart because of its automaticity and conductivity. It has an ample amount of information about the heart, which is very useful in diagnosis. Along with the pacemaker cells, the heart also have specialized conduction tissue, and working heart muscle, which act as functioning cables for the electrical signal sent by the pacemaker cells. Heart rhythm originated from the Sinoatrial node(SA node) also known as the sinus node. If the Sinoatrial node fails, the atrioventricular node (AV node) take over the pacemaker function. Cardiac activation is technically termed as depolarization, in this state heart contract to pump blood in the body and electrical impulse spread in atrial and ventricles. Return of the cardiac to their resting state is termed as re-polarization followed by depolarization. The direction of depolarization is the same for individual cells or fiber but in the entire myocardium, it propagates from endocardium to epicardium whereas during re-polarization it travels from epicardium to endocardium. When the ventricles are stimulated and depolarize, the depolarizing electrical current is recorded by the ECG as a QRS complex and a P wave, respectively. When the atria are stimulated and repolarize, the ECG records a ST segment, T wave, and U wave. Atrial re-polarization is usually obscured by ventricular potentials.

C. Data Description

The dataset from Physionet has been utilised to obtain the ECG in this paper. The MIT-BIH Normal Sinus Rhythm database is used for code validation. Included in this were 18 patients who had been referred to Boston Beth Israel Hospital Deaconess Medical Center and had no discernible arrhythmias. Out of the 18 subjects, 13 were women between the ages of 20 and 50, and 5 were men between the ages of 26 and 45. The BIDMC congestive heart failure database [9], which contains 15 records of congestive heart failure patients with NYHA classes III-IV, is utilised to determine the relationship between hyperkalemia and congestive heart failure. This includes 4 women, aged 54 to 63, and 11 males, aged 22 to 71, who are NYHA Class III-IV patients with severe congestive heart failure. Each recording lasts for around 20 hours and contains two lead ECG signals recorded at a rate of 250 samples per second with a resolution of 12 bits across 10 mv. At Beth Israel Deaconess Medical Center, formerly Boston Beth Israel Hospital, ambulatory ECG recorders are used to make the original recordings. The range of the recording bandwidth is roughly 0.1 Hz to 40 Hz.

III. Proposed Methodology of iCardo 2.0

The paper proposes the correlation of hyperkalemia with heart failure using T wave from ECG. This work essentially comprised of three steps. The first step is to pre-process the noise-filled ambulatory ECG data that was downloaded from Physionet. Second, information is extracted from the given ECG signal using feature extraction techniques, and the third is to classify the hyperkalemic patient. The code is subsequently validated through MIT-BIH Normal Sinus Rhythm Database. The properties of the BIDMS congestive heart failure database are utilised to show the interrelationship between hyperkalemia and congestive heart failure.

ECG signal taken from the physionet is recorded from the Holter monitor hence contains noise like electronic noise, motion artifact, etc. One of the original recorded signal is shown in Fig. 4. The pre-processing of these ECG is very important to remove these noises to have meaningful ECG signal. It helps to equalize the inputs to make it more suitable for further analysis. Figure 5 displays a screenshot of a pre-processed electrocardiogram signal. The detailed step-wise process of the proposed methodology including pre-processing steps are shown in Fig. 6.

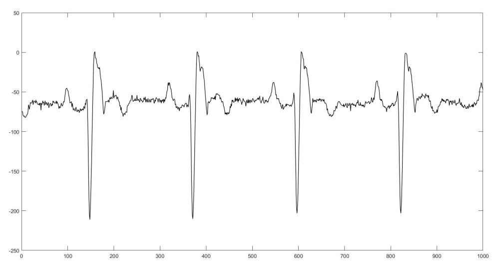

Fig. 4. Raw ECG Signal

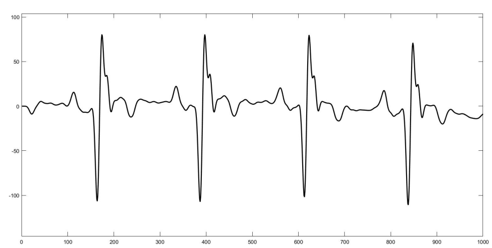

Fig. 5. Pre-Processed Signal

Normally baseline contains low-frequency artifact noise that is known as Baseline Wander (BW) [10]. It has a non-linear and non-stationary nature. It is removed by using wavelet decomposition up to the ninth level. The wavelet filters are utilised to transfer the signal into the frequency domain and to remove the 60 Hz tones from the previously filtered signal. A bandpass filter is designed with quality factor 35 and running on 300 Hz frequency. High-frequency noise is reduced using a low pass filter, and the smooth filter has been employed to improve the signal's visual clarity.

A. Feature Extraction

The feature extraction process is one if the crucial stage to have the precise detection of any machine learning model [11]. The paper uses the extraction of ECG signal features for predicting a heart disease. The extraction of accurate and quick ECG features has been investigated for a long time, and many cutting-edge procedures and transformations have been suggested. Fig. 7 displays the time-series characteristics of an ECG signal.

Mainly wavelet transformation and algorithms based on wavelet transform are used to detect various ECG features [12]. Both the frequency and time domains of the wavelet transform can be localised [13]. It can be used to create algorithms that quickly identify aberrant heartbeats. A method to select the best mother wavelet from a set of orthogonal and bi-orthogonal wavelet filter banks has been devised by [14] which as based on a correlation with the ECG signal. The positive predictivity of the QRS complex can be achieved upto 98% by utilizing Daubechies wavelets. The multi-resolution wavelet transform created by [15] is used to extract ECG signal features (recorded from modified lead II) by denoising the data. It helps to remove the corresponding wavelet coefficient at a scale that is higher than QRS complexes which are further discovered. Each QRS complex is utilised to trace the peaks of an individual wave, including onset and offset of P and T waves. Additionally, a new ECG obfuscation approach for feature extraction and corruption detection is developed using mathematical morphology by [16]. This method uses a cross-correlation-based method to differentiate all ECG features before corrupting those features with additional noise. The competent composite method was also developed by [17] and used for data compression, signal retrieval, and feature extraction of ECG signals. Artificial neural network was used to compress data in such a way that the compression ratio increases as the number of ECG cycles increases while the experimental results (i.e., feature extracted by amplitude, slope, and duration criteria) remain stable and consistent. In order to complete the classification task, important data from the ECG input data can also be extracted using discrete wavelet transformations (DWT). By extracting their features, wavelet transform and neural networks can also be utilised to classify healthy and unhealthy cases in ECG images. Feature extracted is further analyzed using cross-correlation, which gauge the similarity between two signals and captures the information present in the signal.

IV. Result and Discussion

A. T Wave Morphology

T wave represents the net potential of ventricular repolarization, and it is expected to be positive. In healthy people, the T wave typically has an asymmetrical shape. If it is positive then it rises gradually before rising abruptly to the baseline. While in case of negative, it lowers gradually before rising abruptly to the baseline. Symmetrical T wave is observed in some cases of myocardial infarction or hyperkalemia (i.e increased serum potassium level) [18]. Among all the wave components of the ECG signal, the T wave has great potential to be misinterpreted because due to non existence of sharp line between the normal and abnormal T wave. An abnormal pattern in the T wave may also because of other disturbances like noise or artifacts. T wave abnormalities may be classified as primary and secondary abnormality according to independence and dependence on the QRS complex. These abnormalities may be of the result of an abrupt change of heart rate, drugs, toxins, electrolyte abnormality, ischemia serum calcium, and potassium, etc. [19] Normally amplitude of T wave should be 1/8 size of the R wave or less than 2/3 of the R wave

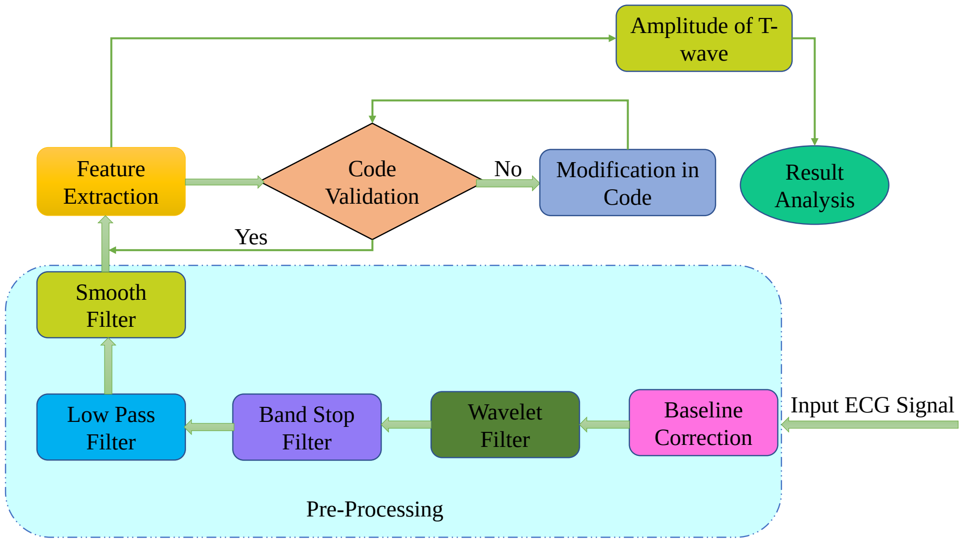

Fig. 6. Proposed iCardo 2.0 Methodology

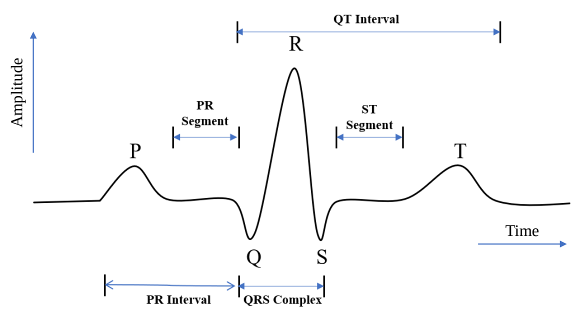

Fig. 7. Normal ECG Signal

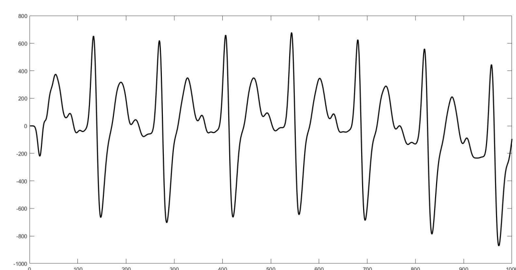

Fig. 8. ECG Signal of subject 11

or less than 10mm height. Tall, peaked or merged T wave indicates hyperkalemia. Association of T with heart failure is already confirmed in [20] and hyperkalemia developed in patients of congestive heart failure on spironolactone [21]. T wave inversion may be normal. Here correlation of hyperkalemia with NYHA class III and class IV patient is done using BIDMC congestive heart failure database. A 10-second segment of the ECG signal has been considered for analysis, the corresponding T value of 15 subjects is tabulated in Table 1. The reported value is average of all values found in 10 second time duration of ECG signal.

It is clear from the Table I that except subject 4 and 7, all other subjects have T wave value more than 10 unit. It is the indication of having increased potassium serum level in blood and are at the high risk. Subject 11 has merged P and T wave or does not have distinguishable T wave (Fig.8), it is merged with QRS complex so that it is difficult to distinguish T wave separately.

According to data shown in Figure 9, it is clear that most of the congestive heart failure subjects are the case of hyperkalemia. T wave morphology would be a promising non-

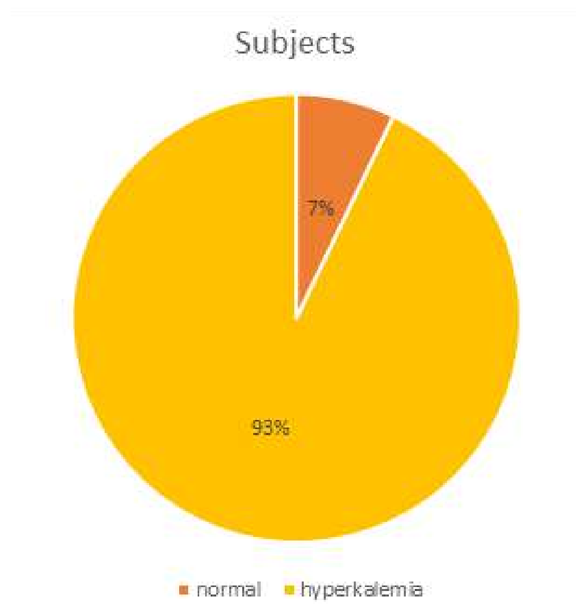

Fig. 9. Hyperkalemia in congestive heart failure patients

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TABLE I
T VALUES OF SUBJECTS

Subjects	T Value
1	-10.7344
2	24.7017
3	53.2922
4	7.0773
5	18.5049
6	-26.7886
7	4.8934
8	-14.8875
9	72.9029
10	-4.7455
11	318.657
12	-12.1046
13	15.7952
14	53.2580
15	-217.564

invasive way to monitor the blood potassium level that could save the life of people who suffers from the congestive heart failure.

V. CONCLUSION

In this study, it has been shown that patients with congestive heart failure has observed with hyperkalemia. This suggests that the hyperkalemia is strongly related to congestive heart failure, as we can say 13 out of 15 subjects have developed hyperkalemia. Further, this non-invasive technique of detecting blood potassium level can be helpful for the patient of kidney failure or renal diseases. In future, the efficient machine learning model may detect CVD with other bio-markers for the diagnosis purpose of critical care patient.

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