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# Analysis of Epilepsy using Approximate Entropy Algorithm

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**Abstract –** *Degree of anomaly in EEG based brainwave signal picked up during seizure is found to be most severe. There are various methods of detecting epilepsy in patients. The algorithm used here for detection of epilepsy is called Approximate Entropy (ApEn). This algorithm helps to identify irregularity and unpredictability in EEG signal. Our work gives ApEn based measure for the anomalous characteristic present in the EEG brain waves. The proposed critical and quantitative analysis clearly distinguishes between EEG waves of epileptic and non-epileptic subjects.*

***Key Words*: *EEG, Epilepsy, Approximate Entropy (ApEn***)

## 1. INTRODUCTION

Brainwaves are the rhythmic neural activity found in human nervous system. This activity is measured by the diagnostic process called electroencephalography (EEG). EEG signals are also used for analysis and identification of cerebral diseases in patients. Epilepsy occurs mainly due to irregularity in human brain activities. Though small percentage of people in society suffers from it, but if detected at early age, it may be cured. Epilepsy causes frequent seizures in patients. Abnormal variations in EEG frequency bear sign of epilepsy in the patient. The ApEn algorithm is apt for detection of epilepsy, probably present in a person. ApEn algorithm fulfils the objective of epilepsy detection in our case.

ApEn is a time-based function and helps measure the unpredictability and irregularity in EEG signal [1]. ApEn can classify complex systems even when the system contains deterministic, chaotic and stochastic process in it [2]. The other methods for analyzing epileptic signals from EEG are Discrete Wavelet Transform (DWT), Lomb-Scargle Periodogram, Cosine Similarity Measure, etc. These methods are based on calculation of the energy which may not result in accurate detection, since high signal energy is not always the distinguishing characteristic for epileptic signals.

EEG measures neural oscillations that occur as a result of the voltage fluctuations due to ionic (Na+ & K+) discharges of the brain neurons [3]. The neurons pass information through the process of discharging and accepting these ions through synapses. This electrical activity generates brainwaves. EEG is non-invasive method of measuring brainwaves. There are invasive methods also for measuring brain activity called as electrocorticography.

Alaa Eldeen Mahmoud Helal *et. al.* proposed Lomb-Scargle Periodogram and Cosine Similarity Measure together to detect the probable existence of epileptic natured signal in EEG [4]. The Lomb-Scargle Periodogram was used to measure instantaneous increase in the energy of an EEG waveform. The power spectrum of the signal was considered in this case. The Cosine Similarity Measure was used to measure the cosine of the angle between a normal and an elliptic EEG wave. This similarity measure is mainly used for high dimension positive spaces. Tiny changes were observed in the angle by precise increment or decrement in its cosine value in case of two dissimilar waves.

Kamath and Chandrakar proposed two quantifiers from nonlinear dynamics and chaos theory. The qualifiers were Central tendency measure (CTM) and Higuchi fractal dimension (HFD) [5]. CTM was used to quantify the degree of variability and HFD was used to quantify complexity of the signals [5].

## 2. OVERVIEW

Epilepsy is a type of neurological disorder which results in seizures. The EEG based recordings of epileptic events are characterized by spike and wave patterns. ApEn algorithm analyses these wave patterns and displays output regarding presence of epileptic trend in patient. For any brainwave picked up through the EEG electrodes, corresponding numeric ApEn value may be deduced. The spike and wave patterns occur due to the repolarization and depolarization of the ionic sodium and potassium channels in human brain. Proper and timely diagnosis of epileptic trend in a patient helps to control the disease with medication. Though epilepsy and related seizure does not kill a patient directly, but the trauma and accidents caused during the seizure may be life threatening. Through prolonged medication, the severity of seizure and fatality in a patient can be controlled.

Approximate Entropy algorithm uses large amount of data. ApEn is an offline process and with good computational facilities, it can accurately analyze probable epileptic trend in a patient. The results are also subject to the accuracy of the experimental conditions during the state of recording. Our work offers a unique approach using ApEn leading to the ease of qualitative detection of epilepsy in a patient.

The standard traditional methods involving mean and variance do not give accurate results when the volume of data set and the number of data points increases. In such cases, Approximate Entropy provides far more efficiency. Hence, ApEn is a far better method than DWT for analyzing big EEG

data sets. The main contribution of this work is development of proper ApEn algorithm and to logically decide the threshold value for detection of epileptic trend in a patient. The analysis also proves that this method is more efficient due to its ease of detection and high diagnostic accuracy.

## 3. METHODOLOGY

In this section, various steps of ApEn algorithm are detailed. The test data set is same as mentioned in the research paper of Andrzejak *et. al.* [6]. The data set comprises EEG data of four subjects in normal state as well as during seizures [6]. Seizure data is available only for epileptic patients. For every patient, EEG data is collected over 100 single channels. Each of the recorded 100 channel continuous EEG data stream is first sampled using sampling frequency of 173.61 Hz. Each sampled data stream is cut for 23.6 second long sequences that comprise 4097 points [3]. The EEG signals of two non epileptic and two epileptic subjects are considered here under certain pre defined medical test conditions. The four test conditions are

A] Normally relaxed eyes closed
B] Normally relaxed eyes open
C] Non-seizure (epileptogenic region) - invasive
D] During seizures (for epileptic patients only)

Among the 4 conditions mentioned above, condition C is invasive whereas A, B and D are non-invasive type [4]. The first two subjects (sub1 and sub 2) are non-epileptic. For these two subjects, EEG data are recorded for conditions A, B and C, whereas for the epileptic subjects 3 and 4, EEG data for all four conditions (A to D) are recorded. These facts are tabulated in Table 1. For each patient, for each condition, at first, 100 data streams of 23.6 seconds duration each are generated. Then ApEn value is calculated for each of these 100 segments. Finally, for each patient, for each condition, the calculated 100 ApEn values are plotted in one graph with x axis being the integer value of the data segment. This data segment value ranges from 1 to100. Finally, integration of this ApEn plot gives us the 'unified ApEn value' for that subject for that particular condition. The steps of this particular algorithm and the related mathematical treatment are given below in this section itself.

**Table -1: Subject Type and Data Set for ApEn Plots**

| Sub. No. | Subject Type | Test Conditions | | | |
|---|---|---|---|---|---|
| | | A | B | C | D |
| Sub. 1 | Non-Epileptic | √ | √ | √ | NA |
| Sub. 2 | Non-Epileptic | √ | √ | √ | NA |
| Sub. 3 | Epileptic | √ | √ | √ | √ |
| Sub. 4 | Epileptic | √ | √ | √ | √ |

The Approximate Entropy algorithm actually an anomaly measure of the EEG brainwave signal. It is a time-based function which provides with a single value corresponding to the number of similar patterns observed in the signal. The mathematics behind our ApEn algorithm is as follows:

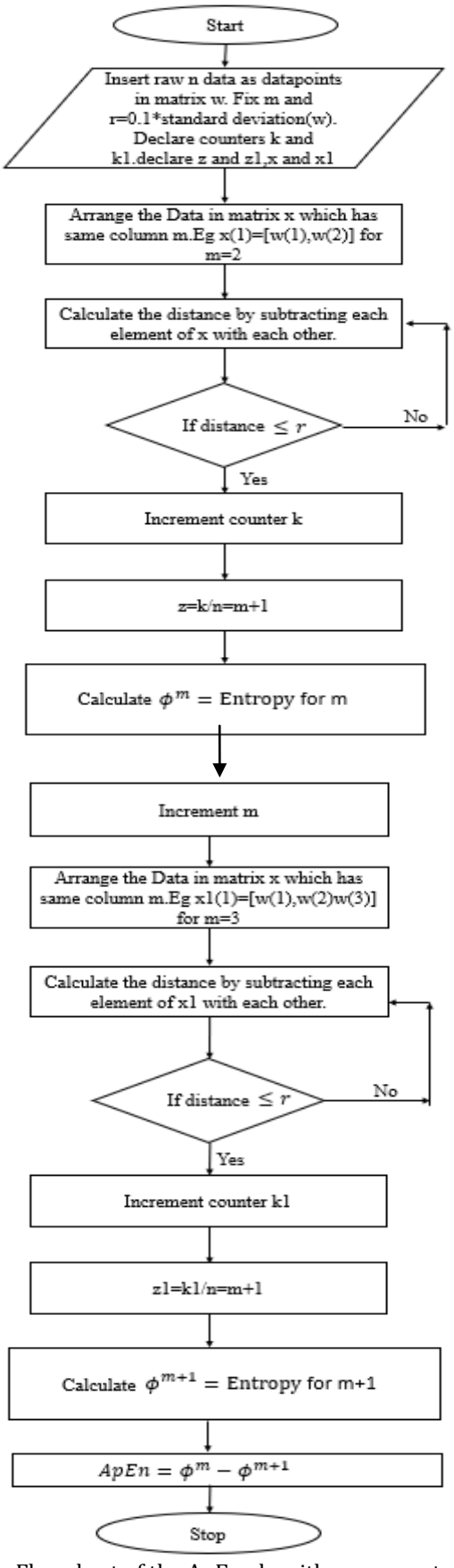


**Fig-1:** Flowchart of the ApEn algorithm pressented here

**Step 1:** The recorded signal is stored in the form of a matrix 'W'. Matrix 'W' contains 'n' number of points. In this case n= 4097. This raw data is measured after equal periods of time.
**Step 2:** Let 'm' be a value for the length of subsequence matrix. 'm' is any positive integer. 'r' is the level of the noise filter. Value of r = (0.1*standard deviation of 'W' matrix)
**Step 3:** Let 'X' be a subsequence vector matrix of 'W' such that,

$$x[1]=\{w[1],w[2]\}$$
$$x[2]=\{w[2],w[3]\}$$
$$x[3]=\{w[3],w[4]\} \quad (1)$$
$$\vdots$$
$$x[n-m+1]=\{w[n-1],w[n]\}$$

**Step 4:** Compare $w(i)$ with $w(j)$ to find the distance between vectors $w(i)$ and $w(j)$.

$$d[x(i),x(j)]=\max\left|w(i)-w(j)\right|, \quad (2)$$

where $k=1, \quad 1<d[x(i),x(j)]<n-m$

and $k=0, \quad otherwise$

**Step 5:** Using the above vector sequence we construct,

$c_i^m(r)=$ Number of x(j) such that

$$d[x(i),x(j])\le r/(n-m+1) \quad (3)$$

This function basically computes the average of all the distances that satisfies step 4. In equation (2), $w(i)$ and $w(j)$ are scalar values whereas $d[x(i),x(j])$ is the distance between the vectors.

**Step 6:** The $\phi^m(r)$ correlation is calculated next

$$\phi^m(r)=(n-m+1)^{-1}\sum_{i=1}^{n-m+1}\log(c_i^m(r)) \quad (4)$$

**Step 7:** Repeat now the steps 2 to step 6 for $m=m+1$

**Step 8:** As a result of Step 7 we will get $\phi^{m+1}(r)$

$$\phi^{m+1}(r)=(n-m+1)^{-1}\sum_{i=1}^{n-m+1}\log(c_i^m(r)) \quad (5)$$

**Step 9:** Approximate Entropy ApEn in next defined as,

$$ApEn=\phi^m(r)-\phi^{m+1}(r) \quad (6)$$

Approximate Entropy is widely used for the analysis of large EEG data especially in the cases of neuro-physical diseases such as epilepsy, schizophrenia, addiction, etc. Fig 2, shown at the top of the right-side column in this page illustrates that maximum value of ApEn would indicate most complex signal [7]. So, white noise has highest complexity followed by chirp and then sine wave signal.

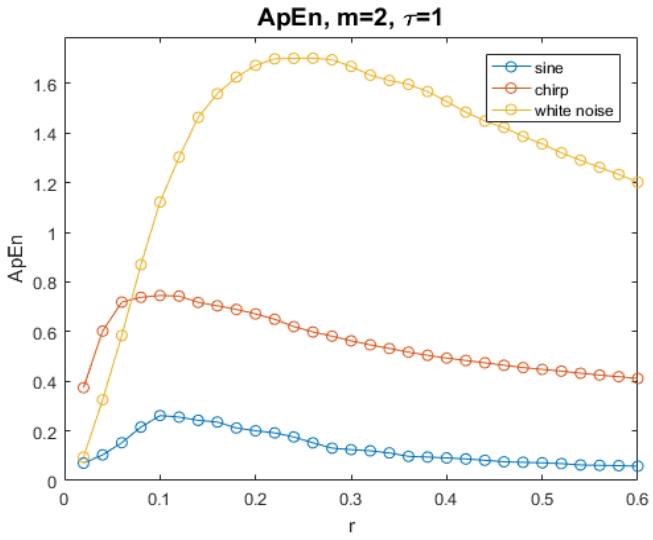


**Fig-2**: Average figure of the approximate entropy ApEn value for Sine, Chirp, and White noise inputs [7]

## 4. RESULTS AND DISCUSSION

The ApEn analysis is performed on the EEG signals picked up from four different subjects. Each set of EEG contains 100 channel continuous time brainwave signals. Then the signals are sampled and discrete data sequences are produced. These sequences are used in ApEn algorithm.

For two non-epileptic subjects, EEG data are picked up for conditions A, B and C each as mentioned in Table 1. Hence, there are total 6 data sets picked up from non-epileptic subjects. For epileptic subjects, EEG data are picked up for all four conditions, Table 1. It means, for epileptic subjects, total 8 sets of data can be obtained. Totally there are 14 data sets on which ApEn algorithm can be tested. But, for ease of demonstration under this section, we have taken only four judiciously chosen data sets. Epilepsy detection inference is drawn from these four data sets after ApEn based analysis.

The four EEG data sets with darker and bigger tick marks (√) in Table 1 are those data sets for which integrated ApEn waveform are generated. The integrated ApEn waveforms obtained for these four chosen sets of EEG data which are picked up from four different subjects under four different medical test conditions are analyzed here in this section. For non-epileptic subject 1, EEG data set of condition A is considered. This is the 'Normally relaxed eyes closed' condition. Next, for another non-epileptic subject 2, EEG data set with condition B is considered. This is 'Normally relaxed eyes open' condition. These two integrated ApEn waves are shown in figure 3 and figure 4 respectively. Next, for subject 3 who is an epileptic subject, EEG data is invasively picked up from the epileptogenic region of the brain under normally relaxed condition. Finally, for the 4th subject who is epileptic, EEG data are picked up non-invasively during seizure. The integrated ApEn wave generated for subject 3 and subject 4 are shown in figure 5 and figure 6 respectively. From design of experiment point of view, it can be observed that the degree of stimuli applied to the subjects is increased from the first to the fourth data set.

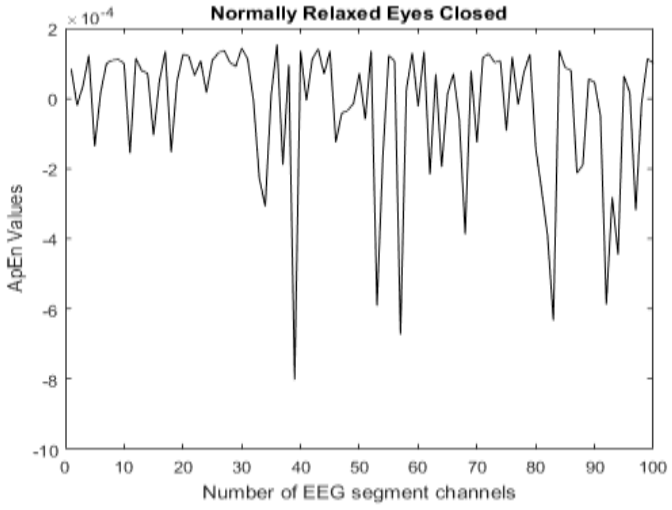


**Fig-3**: Integrated ApEn waveform for 100 channels EEG segments for non-epileptic subject 1, with closed eyes

### A. Non Epileptic Subject 1 – Relaxed & Eyes Closed

This is the first integrated ApEn waveform generated for a non-epileptic subject under completely relaxed condition. The eyes of the subject were also closed during EEG recording. Hence, very less or no external stimuli were administered to the subject. The integrated ApEn waveform is shown in figure 3 above. The integrated ApEn wave shows minimal variation and hence the overall ApEn value of the signal is lowest amongst all four sets of observed data. The count 1 to 100 in the x-axis indicates the 100 channels which are used for EEG wave pick up. For this reason, no reading is registered for the value 0 in any of the graphs.

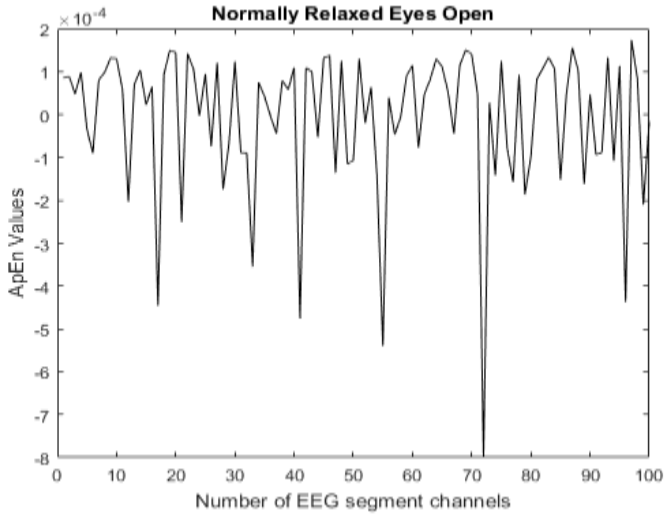


**Fig-4**: Integrated ApEn waveform for 100 channels EEG segments for non-epileptic subject 2, with open eyes

### B. Non Epileptic Subject 2 – Relaxed & Eyes Opened

This is the second integrated ApEn waveform generated for a non-epileptic subject under completely relaxed condition, figure 4. The eyes of the subject were open during recording of the EEG signal in this case. Open eyes indicate

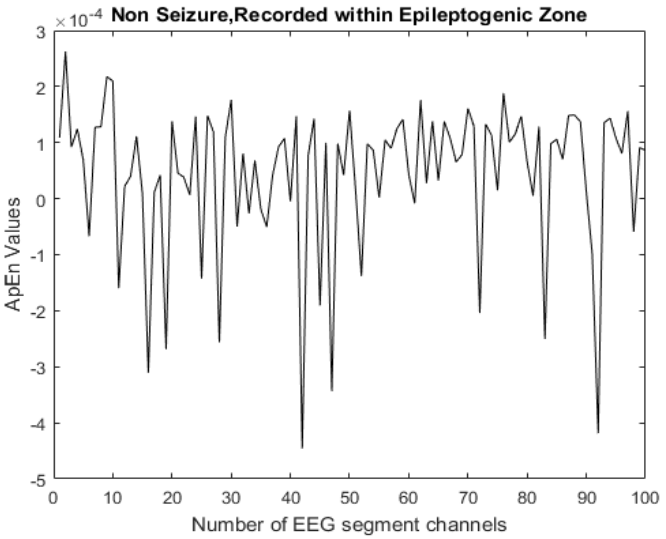


**Fig-5**: Integrated ApEn wave for relaxed epileptic subject 3, EEG picked up invasively from epileptogenic brain region

presence of little amount of natural stimuli during EEG recording. For non-epileptic subjects, random variations are generally not present in EEG waveforms because these subjects do not have seizures. But due to presence of optical stimuli, the ApEn wave of figure 4, is found to have more random variation than that of figure 3. For the same reason, the integrated ApEn value for the wave in figure 4 is higher than that shown in figure 3.

### C. Epileptic Subject 3-Epileptogenic Zone, Nonseizure

Figure 5 above shows the integrated ApEn wave for 100 channel EEG waveforms picked up for an epileptic subject. EEG electrodes were invasively placed in the intracranial epileptogenic brain region while EEG recording. The subject was in relaxed condition with opened eyes. Though the patient is epileptic, during the EEG recording the subject was not having seizure. The integrated ApEn value for epileptic subject 3 is higher than that of non-epileptic subject 2.

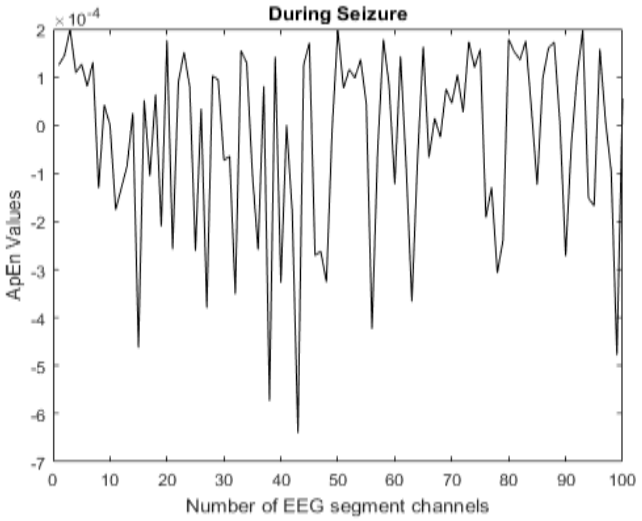


**Fig-6**: Integrated ApEn wave for epileptic subject 4, 100 channel EEG picked up noninvasively during seizure

### D. Epileptic Subject 4 – EEG During Seizure

Figure 6, shown toward the end of previous page shows the integrated ApEn wave for 100 channel noninvasive EEG signals picked up for an epileptic subject during seizure – subject 4. Normal EEG for epileptic subjects shows more random variations than that of non-epileptic subjects. For epileptic subject EEG when the effect of occurring seizure gets added, it results huge amount of random variations in EEG waveforms. The same is depicted in the integrated ApEn waveforms for subject 4, as shown in fig. 6. The integrated ApEn value here is largest among all 4 cases shown in Table 2. It indicates huge amount of variations in EEG wave which is caused by seizure in epileptic patients.

**Table -2:** Estimated integrated ApEn values obtained for all four subjects under four different test conditions

| Sr. No. | Medical Test Condition | Integrated ApEn Value | Inference |
|---|---|---|---|
| 1. | Non-epileptic eyes closed (A) | 2.7259 | Lowest ApEn Value |
| 2. | Non-epileptic eyes open (B) | 2.8384 | Low ApEn Value |
| 3. | Epileptic relaxed (C) | 3.4372 | Higher ApEn Value |
| 4. | Epileptic in seizure (D) | 3.4902 | Highest ApEn Value |

## 5. CONCLUSIONS AND FUTURE SCOPE

The estimated integrated ApEn values shown in Table 2 are for the four different medical test conditions which are mentioned in Table 1. For the medical test condition A, for a relaxed non-epileptic subject with closed eyes, integrated ApEn value is 2.7259. This is lowest integrated ApEn value among all four test conditions. It indicates that for that test condition where the subject is healthy and is without any external stimuli, integrated ApEn value would be lowest. It is because the random variations in this waveform are least. In the next case, for test condition B where the non-epileptic subject has kept his eyes open during EEG pick up, integrated ApEn value has increased little to 2.8384. This slight increment is the result of the optical stimuli administered to the subject during EEG process. In the next case for test condition C which considers an epileptic subject in relaxed state, integrated ApEn value suddenly jumps to 3.4372. This value is considerably higher than that found in under test condition B for non-epileptic subject. Finally, highest degree of randomness and highest ApEn value is estimated for the subject 4 under test condition D where integrated wave is recorded during seizure for an epileptic subject. Table 2 shows ascending order of integrated ApEn values for ascending degree of randomness in picked up EEG signal.

This work presents a unique method for extraction of relevant information from noisy EEG signals. This work also explains the related signal classification algorithm. Approximate Entropy is an algorithm used for fulfilling our objective. Approximate Entropy is the time-based function which measures the irregularity and randomness in EEG signal. The algorithm delivers a single value at the end of processing every data set. From the graphs shown in figure 3 to figure 6 above, we can conclude that increase in value of ApEn indicates higher degree of randomness in EEG wave which in turn indicate presence of higher epileptic signal component in EEG signal. Thus, we can conclude that as the severity of epilepsy increases (from non-epileptic person to an epileptic person) the ApEn value also increases.

The analysis of epilepsy can be further improved if machine learning algorithms are applied to the recorded EEG signals under different medical test conditions. More data can be fed to the system to enhance the learning capability of the system. More precise decision making is possible through enhancement in signal processing algorithms. Machine learning helps in better pattern recognition which in turn helps to achieve higher estimation accuracy.

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