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DIABETES PREDICTION USING SENSORS BY ANALYSING SKIN TEMPERATURE

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Abstract

Diabetes is a type of metabolic disease identified by unstable blood glucose level due to the defect in the human body and the body does not make insulin. Diabetes is created due to the defect in the metabolism of converting glucose to energy in the blood. Type 1 diabetes is caused due to lack of generation of insulin in human blood and Type 2 diabetes is caused due to resistance to insulin action, which leads to several other diseases like foot ulcer and severe wounds in the human foot or other parts of the body. The main aim of the research study presented here is to diagnose Type 2 diabetes. While the traditional method of identifying diabetes does not provide effective results, more reliable and research on this perspective has gained potential importance. Based on the analysis noted down from the heat changes in the human foot, we present a study to diagnose diabetes is done in the human body is done using TEG sensors. Imbalanced glucose level affects the performance of the nerves system, which leads to slower response for temperature change in the foot surface. The study in this paper uses Thermo Electric Generator (TEG) sensor to analyse the temperature changes in the foot, which could represent the level of diabetes caused in the patient body. The signals extracted from the TEG sensor were collected and processed using signal analysis algorithm using MATLAB software. The results obtained were more promising and compared with several other existing schemes. The result was analysed using physicians who have agreed on the inference obtained using the study.

Keywords: Diabetes, TEG Sensor, Type 1 diabetes, Type 2 diabetes, MATLAB

1. Introduction

Diabetes is a metabolic disease, which is caused due to an increase in blood glucose level. About 5.1% of the global population were affected by diabetes disease. International Diabetes Federation shows that 12% of the total expenditure was spent over the medication for diabetes, which is 5% of the total expenditure on health care. Diabetic care is one of the important issues faced by most of the developing countries. Diabetes is classified as Type 1 and Type 2, where the former one is identified in children's and the later in adults. Due to the severe complication of diabetes disease, the cost of medication increases. Increase in blood glucose level leads to nerve damage and damage in extremities of the body, which in turn leads to a severe foot-related problem. Non-invasive methods were used to monitor the hydration of the skin of the affected user [1]. A low cost medical embedded system is designed to monitor diabetic peripheral neuropathy. On the contrary, there are ensemble learning algorithm provides rule sets with weight precision of 94.2% and hybrid system is provided to perform diagnosis over diabetes disease, which provides the second opinion for lay users. [2]

There are several body composition changes, which could be noted for early detection of Type 2 diabetes. The major role player for reducing diabetes is to maintain proper food cycle, which helps to reduce the effect of diabetes disease. We focus on to present our research study and early detection on Type 2 diabetes only and we mean the same, wherever we have mentioned about it. It should be noted that current diagnosing system analyses the diabetic foot with clinical sensory tools and the results of foot severity are mostly measured manually [3]. To automate the process of diabetes diagnosis a new approach was followed to measure the heat of the human foot. Metkar and Girigoswami [4] mentioned that the approach presents the used of TEG sensor, which extracts the signals for prediction of diabetes from the human foot. Infrared thermography and other techniques to measure the temperature of the foot is under development to identify the destructions in foot plantar temperature disturbance [5].

Sweat gland malfunctioning is an important symptom to diagnose pre-diabetics in a clinical manner [6]. The traditional method of identifying the diabetes foot was based on sensory testing on foot, which shows the sensation of the patient's foot. According to Shearman and Pal [7], the results were diagnosed by the rate of sensory power on the affected foot of the patient. Some of the tests for analysing the foot sensation are Semmes-Weinstein monofilament testing pinprick sensation and vibration analysis.

Most of the traditional testing methods lack accuracy because of variability in the sensing pattern of the patients. Hence, detection of foot diabetes is still lacking, and researchers present on diagnosis using different approaches. Thermal analysis over the patient foot is the quantitative method to analyse and diagnose the foot diabetes in early stages [8]. By analysing the thermal response by the affected foot, the level, the work has measured the significance of the damage caused due to diabetes. The diabetes disease reduces the thermal response of the foot thus by applying cold stress; recovery of heat by the foot gets longer when the patient is affected by diabetes disease. The recovery speed of the foot can be handled as a measure to scale the effect of diabetes disease in the patient body.

World Health Organisation (WHO)has reported that diabetes patients in developing countries were doubling every year. Diagnosing of early diabetes is impossible due to the lack of trained professionals in developing countries. Therefore, the low cost, effective and false less diagnosing method is required to perform early diagnose of diabetes disease in the developing countries. Several works have been reported and the most recent ones include analysing the thermal images at a low cost and effective diagnosis developing the low-cost diagnosing system is a challenging task to analyse the thermal pattern of the patient foot [9].

The major research focuses on the foot of the patients, which are affected by diabetic peripheral neuropathy. The patients affected by diabetes are most vulnerable to neural damage. 50% of the patients affected by diabetes possess neural damage and 15% of them are affected by foot ulcer during their lifetime. A foot ulcer is the main reason for the cause of lower extremity amputation to the patients affected with diabetes diseases. The way to find advanced causes due to nerve damage or foot ulcer is to develop an early detection system for diabetes disease. Traditional methods followed by the physicians may miss the detection of diabetes in the patient because of the low detection rate in the traditional methods [10]. Only 60% of detection is possible through traditional diagnosis methods. Therefore, the thermal analysis over the patient foot is developed to increase the accuracy of detection of diabetes disease in the early stage. The main theme of analysing the thermal effect of the foot by applying cold stress is followed and the heat recovery pattern is analysed by various thermographic systems. A Peltier sensor-based thermal analyser is used to analyse the thermal effect over the feet to analyse the cause of diabetes in the patient body. Peltier sensors are those, which convert thermal energy into electrical energy.

The rest of the paper is organized as follows. While Section 1has presented some basics, Section 2 highlights the works that exist earlier in the proposed area of research. Section 3 details on the research study carried out, Section 4 elaborates on the study results and analysis and finally, Section 5 highlights the conclusion and future work.

2. Related Work

Diabetes is a chronic disease, which caused due to the lack of generation of insulin by the pancreas or inefficient utilisation of insulin by human blood. This deficiency leads to type 1 diabetes and further leads to type 2 diabetes in human. Untreated condition of diabetes disease reveals result in severe health complications like nerve dysfunctions, foot diabetes, diabetes retinopathy and increases the risk of early death. Thus, early detection of diabetes plays a vital role in health management to improve the quality of life. If foot diabetes is not found early, it leads to foot amputation for diabetes patient. The work presented focus on analysis of Near-Infrared Images (NIR) of the foot to perform early diagnosis of diabetes. The thermo graphical behaviour of the patient foot will vary based on the level of diabetes in human blood. Pixel intensity matrix platform is used to analyse the NIR images acquired from the patient foot. [11]

Based on studies by Bayareh et al. [12], works reported along with development kit including infrared (IR) sensor were developed to analyse the effects of diabetes in the patient foot. The method proposed by the authors' analyses the characteristics of heat over the foot surface by radiometric technique.

Subsequently each of the frames were analysed pixel by pixel with the sensor reading that is extracted from the heat flow in the patient foot. Three stages of analysis were performed namely the thermal imaging, infrared sensor readings and the bolometric sensor array. A matrix of heat flow is generated from the bolometric sensor. Artificial Intelligence (AI) techniques were applied to the system to analyse the sensor values to diagnose the effect of diabetes on the human foot. The study carried out a method helps in detecting early diabetes using foot thermograph.

More recently, a study using data mining techniques have been adopted for classification of medical images from a large database system. The medical imaging system is one of the leads methods used for health diagnosing by physicians. Therefore, image classification becomes more important in diagnosing the disease in health care application, especially for diabetes detection. Some of the image classification algorithms like k-mean clustering, neural network, Bayesian network and fuzzy logic are widely used in analysing the infected region on the patient body. A system for analysing foot ulcer was developed to identify and classify the foot ulcer wound in a patient's body [13]. Support vector machine was implemented in diagnosing the diabetes disease in the early stage. Along with the support vector machine, an additional explanation module was added, which converts the black box module of SVM to prediction tool of diabetes disease. A comprehensive rue set is developed to increase the accuracy, sensitivity and specificity of detection of diabetes [14].

Measuring of acetone level in the human breath is the effective method for early diagnosis of diabetes and used as a daily monitoring process for diabetes patients. Analysing along with other traditional methods like human blood analysing system, acetone analysis over human breath has provided more merits like non-invasive, inexpensive and more accurate results leading to an accurate diagnosis. A nanosensor with K2W7O22 was developed to measure the acetone value from the human breath.

The results presented using these sensors show that the nanosensor can effectively analyse the presence of acetone in human breath even at trace level at normal room temperature. Ferroelectric and semiconducting technologies were adopted in nanosensor analysis to improve the detection rate of acetone in human breath. The level of acetone in human breath levels the presence of diabetes in human blood. Nano sensor-based diabetes analysis has been identified to produces positive results, which leads to the development of smart devices to analyse the early stages of diabetes in the human body. [15]

Increase in the development of a decision support system based on domain knowledge is an effective way to diagnose health issues like diabetes and heart diseases. Classical ontology does not provide more data for disease diagnosis but fuzzy ontology can generate effective data and knowledge about the diseases with uncertainty. The five-layer fuzzy system was introduced to diagnose early diabetes in human. A fuzzy diabetes ontology is framed to generate knowledge about diabetes with uncertainties. The five layers named fuzzy knowledge layer, group layer, group domain layer, relation layer and domain layer are generated to develop an expert fuzzy system. The semantic decision support agent was developed along with the fuzzy system to develop efficient knowledge about the disease [16].

Work reported using Self Organising Map (SOM)was developed using the non-invasive method by collecting information from the diabetes patients about self-care, condition of health and economic issues. Here the data analysis is performed to generate SOM, which produces two risk groups of developing diabetes foot. The groups provide knowledge about the present health condition and possibilities of occurrence of diabetes foot and the information collected is helpful in providing medical attention towards prevention of type 2 diabetes disease. The study results by Ferreira et al. [17] with linear discrimination analysis was used to validate the correctness of the data collected in the groups through statistical analysis over the dominant variable. A diabetic foot ulcer is a severe disease caused due to improper diagnosis of type 2 diabetes disease, which can lead to foot amputation. A foot ulcer can occur in any part of the leg in any shape, colour, and patterns based on the effect of ulcer in foot pathology. Current diagnosis methods for foot ulcer takes more time and cost to diagnose the effect of ulcer in the foot [18]. Fully convolution network is framed to analyse the collected foot image to provide knowledge about the cause and effect of foot ulcer on diabetes patients. 705 images of foot ulcer images were provided to the network for effective diagnosing in a clinical approach. Henceforth, the authors have developed a two-layer convolution network is developed to segment the ulcer cell from the surrounding normal skin from foot image.

Research on foot diabetes provides an economic burden over the quality of life providing physical impairments in the patients' life. Detection of diabetes should be performed in order to overcome the occurrence of wound, ulceration and amputation. A cross-sectional study of over 44 volunteers with type 2 diabetes is performed. Foot plantar thermal images are collected from the participants using a high-resolution infrared camera. Three segments of the foot are concentrated they are first finger, fifth finger and the heel. From the collected three results the output with higher temperature asymmetry is collected for analysing foot diabetes risk.

The generated result is then compared with the Body Mass Index (BMI) and a fat mass ratio of the concerned patient. It shows that the BMI and body fat mass ratio plays a vital role in the risk of type 2 diabetes in the patient [19]. This also increases the probability of cause of foot ulcer in the patient foot. The foot ulcer may result in removing of total foot because the foot ulcer will totally damage the foot tissues may lead to an early death. The foot ulcer can develop even applying improper pressure on the foot and due to ageing factor, gender and location of the patient residence. Chan vase algorithm is evolved to analyse the diabetes foot ulcer based on the foot temperature of the patient. The temperature of the patient foot is measured using an IR thermal camera for an effective finding of disease [20].

Study through visual examination by the clinicians is mainly based on the size and healing status of the wound on the foot. Thus, a quantitative and cost-effective method was developed to analyse the patients wound even by the caretakers in the home environment. This has also provided an active role in acceleration in healing of the wound, reducing the travelling cost and reduces health care expenses. The algorithm works by the processing of the wound image taken from a smartphone. Accelerated mean shift algorithm is utilised to perform image segmentation over images captured using a smartphone. The outline of the foot is determined using the skin colour and the wound boundary was detected through connected region detection method. Finally, the affected region within the wound boundary was analysed using red, yellow and black colour evaluation model. The healing status of the wound is quantitatively assessed based on-time records of the patient [21].

3. Research Study

Early diagnoses of diabetes are important research to reduce the health care cost. The diabetes diseases initially lead to a foot ulcer, wound and foot amputation, which may further lead to loss of a foot or even to an early death. A non-invasive and simple method is required for early diagnosis of diabetes even in-patient friendly clinics or in-home environment. We present our research study by using TEG sensor, which would be a non-invasive scheme. TEG sensors used to record the heat from the foot of the patients to diagnose the level of diabetes in their body.

The TEG sensor is placed on the left and right leg foot, rapid signals were collected, and the recorded signal is processed using discrete wavelet transformation and spectrum analysis algorithm. The result of the algorithm was applied to the regression model to calculate diabetes value from the patient's foot signal. Figure 1 shows the block diagram of the method followed to measure diabetes value-form patient foot using TEG Sensor. As inferred from Fig. 1, we present a TEG sensor for diabetes detection, while rest other blocks that exist in the workflow were predominantly used in the many other areas of research [22]. The foot temperature was measured using a TEG sensor, which accurately measures the heat values, which were proceeded using the basic process of Instrumentation Amplifier.

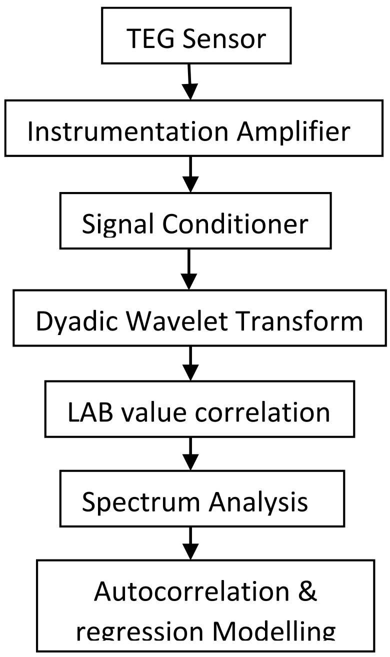

Fig. 1. Proposed architecture diagram.

The TEG sensor works using see beck effect, which converts the heat energy into electrical energy. The generation of electrical energy varies based on the surface of the heat where it has been placed. The TEG sensor placed over the feet absorbs heat from the foot and the heat source is converted to an electrical source. By measuring the generated electrical pulse heat on the foot can be measured. The TEG sensor is connected to the instrumentation amplifier. While earlier amplifiers like AD620 and others have higher superimposing waves, we preferred the ACS712 amplifier, which is more advantageous for integration with other devices [23]. Instrumentation amplifier possesses additional buffers than normal differential amplifiers.

The TEG sensor and Instrumentation amplifier circuits are shown in Figs. 2 and 3. The additional buffers help to match the input impedance of the amplifier for every stage. Instrumentation amplifiers provide advantages like low offset voltage, higher common-mode rejection ratio, high input resistance and high gain.

$$\text{Voltage gain (AV)} = \left(\frac{v_0}{v_2 - v_1}\right) = \left(1 + \frac{2R_1}{R_g}\right) * \frac{R_3}{R_2} \tag{1}$$

The output voltage generated from the TEG sensor will be low thus the voltage signal amplified using instrumentation amplifier and the output signal of the instrumentation amplifier is provided to signal conditioner circuit. The signal conditioner converts the signal into a readable format of conventional instrumentation devices. The signal was then recorded using signal recording tools and applied to the MATLAB algorithms.

Fig. 2. TEG sensor.

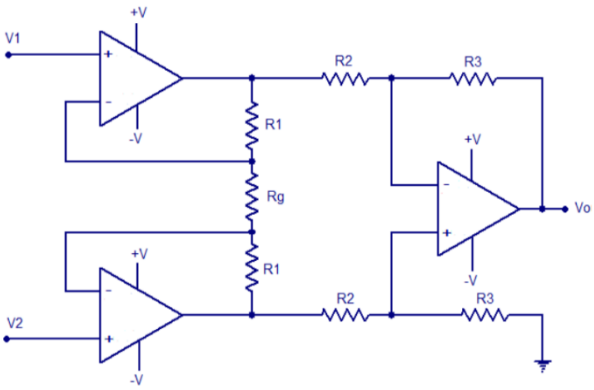

Fig. 3. Instrumentation amplifier.

3.1. Dyadic wavelet transform

Dyadic wavelet transforms [24] divides the input into detailed coefficients and approximate coefficients. These splitted coefficients provide the knowledge about the high and low-frequency signals and provide peak values of the low and high-frequency signal from the input signal. Dyadic wavelet transform is a scaled sample of wavelet transform generated in the ratio of geometric sequence 2. Time of the signal is not sampled. Reconstruction filter bank was used in the dyadic wavelet transform. The dyadic wavelet transform of signal 'f' is defined as:

$$Wf(u, 2^j) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{2^j}} \varphi\left(\frac{t-u}{2^j}\right) dt = f * \bar{\varphi}_{2^j}(u), \tag{2}$$

with

$$\bar{\varphi}_{2^j}(t) = \varphi_{2^j}(-t) = \frac{1}{\sqrt{2^j}} \varphi\left(\frac{-t}{2^j}\right) \tag{3}$$

If Heisenberg boxes cover all the input frequencies then it becomes the stable complete representation n the time-frequency plane, which is a rectangle with a time width σ_t and frequency height σ_w and time-frequency centre, which coincides with the signals (as presented in Fig. 4). Orthogonal and bi-orthogonal wavelet basis along with perfect reconstruction filter banks are used to satisfy the previous conditions in the dyadic wavelet transform. Once the generated wavelet satisfies the previous conditions then fast dyadic wavelet transforms along with reconstruction filter bank and the scaling equation can be applied over input signal.

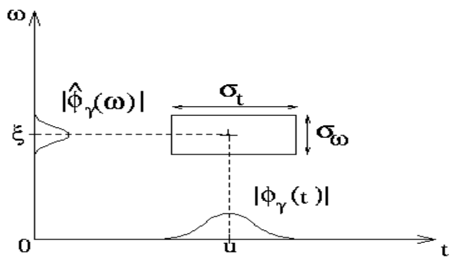

Fig. 4. Heisenberg box representation.

3.2. Spectrum analysis

Spectrum analysis is the process of determining the frequency contents from the continuous-time signal with digital signal processing methods. It determines either the energy spectrum or power spectrum of the input signal. $G_a(t)$ is the input continuous-time signal. $G_a(t)$ is band limited sufficiently, the discrete-time equivalent $g[n]$ should provide good relation with the input continuous-time signal. Frequency spectrum analysis of the input signal provides valuable information based on the source from which, the signal was recorded. Normally the signals are plotted with respect to time but in spectrum analysis, the signal was plotted with respect to frequency. Analysing the amplitude, frequency and phase of the input signal are referred to as frequency spectrum analysis of the signal. To extract this information from the input signal, the signal was analysed, digitized and filtered and plotted in the frequency domain. The spectrum analysis provides the output results like spectrogram, magnitude response plot, probability distribution plot, autocorrelation plot. The spectrogram is the visual representation of the input signal, showing the concentration of information at a frequency at a time. The magnitude response plot represents the magnitude variations of frequency spectra over time. When the signal is in the complex form, it is represented as:

$$a(f)+ib(f) \quad (4)$$

where $i=\sqrt{-1}$ is the imaginary number, then the magnitude of frequency(f) is given by:

$$\sqrt{[a(f)]^2+[b(f)]^2} \quad (5)$$

Probability distribution plot is the statistical function, which groups the values of the signal within the uniform surface area. This plot is utilised to find the range of the input information available in the raw value in the space domain. Autocorrelation is used to compare the sequence signals of the same input to analyse the repetition of the same pattern within the input time sequence. It is used to overcome the loss due to the noise present in the raw signal. These calculations are measured and plotted as a graph, which is discussed in result and discussion.

3.3. Regression analysis

Regression analysis is the statistical model, which is used to analyse the relationship between the variables from the segmented signal. The peak values were extracted along with sample signals and those values were recorded for the study. The level of diabetes in the patient body was measured using regression analysis. The complete results collected from different patients' sample was listed in Table 1.

4. Results and Discussions

The TEG sensor was placed on the right and left leg foot and a series of the signal are recorded. Before the food and after food conditions are placed and the signals were recorded for six patients. The sigma represents standard deviation, Mu represents mean, peak factor, dynamic range, autocorrelation and Diabetes range was recorded and shown in Table 1. The heat flow pattern in the right and left leg shows a major difference in the amplitude. The recorded raw signal poses noise and unwanted signal along with the information signal. Thus, the raw signal was processed using dyadic transformation.

The results extracted were analysed using different dimensions as briefed out earlier. The dataset chosen for the study consisted of 100 records, which were collected over a period. The records were more specific to complaints received from diabetes patients. Each of the individual patient results was carefully analysed and the results were recorded for the study. The results involve the extraction of values using TEG sensors and analysed with the help of MATLAB software. The inference obtained is given to physicians (30 in number) who were skilful enough to validate the results. It is basically assumed that the physicians are well trained and the genuinity of the judgemental study of the physicians is not revealed in this paper. The average results of non-diabetic vs. diabetic patients presented is based on 30 patient results. Configuration type: Non-diabetic (119.32) and diabetic (167.53). We infer that diabetic patients have higher values as compared with non-diabetic patients. The results were listed in Table 1, which presents the different levels of diabetes in each patient, measured using regression mapping.

Table 1. Results for six patients presented with various factors for diabetic detection.

Patient no.	Foot	Duration	Sigma	Mu	Peak factor(Q)	Dynamic range (D)	Auto correlation	Diabetes value
Patient 1	Left foot	Before food	0.106	0.506	5.71	41.86	176.78	169.83
		After food	0.107	0.516	5.55	41.72	176.63	169.75
	Right foot	Before food	0.101	0.536	5.25	24.21	176.49	170.09
		After food	0.054	0.250	11.81	38.41	177.19	172.87
Patient 2	Left foot	Before food	0.053	0.729	2.71	6.29	176.97	172.89
		After food	0.093	0.548	5.09	20.89	176.57	170.56
	Right foot	Before food	0.086	0.568	4.80	15.20	176.68	170.98
		After food	0.085	0.441	5.93	43.46	175.67	171.05
Patient 3	Left foot	Before food	0.1.01	0.494	5.92	42.41	176.50	170.11
		After food	0.107	0.493	11.59	41.51	176.88	169.75
	Right foot	Before food	0.062	0.255	6.03	47.19	176.64	172.41
		After food	0.115	0.485	2.97	41.65	177.016	169.29
Patient 4	Left foot	Before food	0.062	0.707	3.40	7.402	176.66	172.40
		After food	0.069	0.672	2.79	13.78	177.05	171.95
	Right foot	Before food	0.056	0.722	3.37	12.08	176.95	172.75
		After food	0.071	0.674	5.16	8.679	177.02	171.88
Patient 5	Left foot	Before food	0.097	0.543	5.81	17.80	176.35	170.34
		After food	0.106	0.500	5.57	27.60	177.03	169.80
	Right foot	Before food	0.104	0.515	5.32	29.82	177.42	169.92
		After food	0.101	0.531	2.65	23.52	177.35	170.09
Patient 6	Left foot	Before food	0.060	0.734	6.22	6.54	176.99	172.53
		After food	0.108	0.475	2.78	41.72	175.99	169.69
	Right foot	Before food	0.059	0.723	3.25	6.88	176.87	172.56
		After food	0.069	0.683	2.78	13.33	176.94	171.99

Table 2 presents the results of diabetic inference with and without TEG sensor along with Machine Learning (ML) approach. For the ML scheme, the unsupervised form of learning is adopted. The results were compared with our own dataset as discussed in the starting of the paragraph. The ratio of training and testing is used is 70% and 30% respectively.

Table 2 provides the conclusion that accuracy value is higher when using the TEG sensor and higher as compared to the ML approach. Table 3 presents the study using the average results presented with the number of evaluators (physicians). It is conclusive that the value slightly drops when the number of physicians increases. Table 3 presents the study on the average of the total number of evaluators as compared with accuracy.

A dyadic decomposition and Haar wavelet transform were applied over the raw signal, which pairs the input values, stores the difference and pass the sum values. This process was repeated continuously thus, pairing up of sum increases to prove the next scale values, which leads to $2n$-1 differences and complete sum for the provided input signal. The unwanted amplitude shifts have been removed and the errorless Discrete Wavelet Transform (DWT) signal was generated for processing. The output signal generated by the DWT is then analysed with the spectrum analyser, which generates spectrogram for the signal, autocorrelation, and probability plot.

And digital values like Mu, sigma, peak factor, dynamic range are generated, which are listed in Table1. The output is imaged in the frequency-time and decibel unit. The intensity frequency at time domain was plotted as a plot, which shows the intensity of the signal at frequency range. Three-dimensional approach of signal visualisation provides more knowledge about the spreading of information over the frequency domain. The autocorrelation is applied to analyse the repeating patterns in the input signal. This process was mainly used to analyse the periodic signal that was hidden by the noise signal. In addition, used for finding the missing fundamental frequency from the signal hidden by the harmonic frequencies. The autocorrelation plot was mapped with autocorrelation time in seconds and respective sequence amplitude. The process was repeated for six more patents and the results were extracted using dyadic wavelet transform and signal analysing algorithm.

Table 2. Accuracy results of non-diabetic and diabetic condition with and without TEG sensor, ML approach.

Factors considered	Left foot		Right foot	
	Before food	After food	Before food	After food
Without TEG	92.1	91.8	91.9	90.8
With TEG	93.2	92.4	92.8	91.7
ML	90.1	89.8	90.2	89.5

Table 3. Accuracy for diabetic patients with TEG sensor.

No. of evaluators	Accuracy	
	Left foot	Right foot
(20)	171.35	170.25
Without TEG	170.97	170.19
With TEG	170.41	169.83
ML	169.21	168.2

5. Conclusions

Diabetic is a major issue in public health. From 50% to 80% of type 2 diabetes is undiagnosed by the traditional diagnosing methods. The aim of this proposed work is to analyse the performance of the disease diagnosis (diabetic prediction) in the foot using TEG sensor. The result generated using the algorithm provides a clear recording of heat transfer in the human foot because of foot diabetes and results were promising and have been agreed by evaluators. The proposal restricts the reliability of the evaluators and we keep working on this aspect in our future work.

Nomenclatures

AV	Voltage gain
D	Dynamic range
F	Frequency
F	Frequency at specified time interval
G_a	Input continuous signal
Q	Peak factor

Greek Symbols

σ_t	Time width
σ_w	Frequency Height

Abbreviations

AI	Artificial Intelligence
BMI	Body Mass Index
DWT	Discrete Wavelet Transform
IR	Infra-Red
ML	Machine Learning
NIR	Near Infra-Red
SOM	Self-Organizing Map
TEG	Thermo Electric Generator
WHO	World Health Organization

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