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Proceeding Paper

Design and Implementation of a IoT based Smart Digestive Health Monitoring device for Identification of Digestive Conditions†

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Abstract: Over the past few decades, there has been a significant rise in the wearable healthcare technologies that have been playing a major role all over the world in monitoring health and alerting individuals during deviation from their normal health conditions and assisting them to stay fit and healthy. Due to the modern lifestyle and consumption of unhealthy food products, there's been an adverse effect on digestive health standards. In this work, a wearable device with textile electrodes is designed and developed to analyze the digestive conditions namely, pre-prandial and post-prandial using Electrogastrogram (EGG) signals. Further, the proposed device is comprised of textile electrodes as a sensor, Analog to Digital Converter (ADC) with Programmable Gain Amplifier (PGA), Microcontroller with inbuilt Wireless Fidelity (WiFi) module and Internet of Things (IoT) cloud platform. Also, the EGG signals are acquired under two different conditions namely, pre-prandial and post-prandial conditions, and then the Long Short Term Memory (LSTM) deep learning model is utilized to classify pre-prandial and post-prandial EGG signals to identify the eating habits of normal individuals. Results demonstrate that the proposed approach is capable of classifying the pre-prandial and post-prandial EGG signals, which, in turn, identify the fasting or ingestion state of the normal individuals.

Keywords: Bio-signal acquisition; Electrogastrograms; Fast Fourier Transform; Internet of Things; Pre-prandial and Post-prandial conditions

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1. Introduction

In general, intaking food on a regular basis is essential for a healthy digestive system. However, the people with different age groups are more subjected to a sedentary lifestyle. Further, they prefer to consume highly processed foods, spicy foods, or taking excessive meals without hunger, skipping meals, eating at unusual times, and eating before sleep [1]. Also, the problems with sleep are associated with digestive disorders either as a form of symptom or a cause [2]. Digestive disorders, otherwise, known as gastrointestinal (GI) tract disorders are impairments and diseases linked to the Gastrointestinal (GI) tract of the human body. These GI tract disorders are linked to the abnormal eating habits and unhealthy lifestyles. Overall, leading to most of the digestive disorders such as Gastroesophageal Reflux Disease (GERD) [1], chronic diarrhea, and major gastrointestinal cancers namely Colorectal Cancer (CRC), Esophageal Cancer (EC), Pancreatic Cancer (PC) [3], functional dyspepsia etc. These are some of the serious digestive disorders observed mostly in people worldwide and thus, can lead to complications as time progresses.

According to survey report in 2019 [4], in the 6174 participants, 8.2% of the participants had GERD The disease is prevalent in urban areas (11.1%) than rural areas (5.1%). Furthermore, the GERD is a very common chronic disease in India and can lead to serious chronic diseases like adenocarcinoma if left unnoticed. The common methods of diagnosing digestive disorders include lab tests, imaging tests, endoscopic methods etc. Also, the imaging tests includes colorectal transit study, Computerized Tomography (CT) scan, defecography, Magnetic Resonance Imaging (MRI) scan, ultrasound scanning etc. The common imaging method used in digestive diagnostics is computerized tomography. In CT, cross sectional imagery using X ray method is used to detect an accurate reading of the organ's histology. According to the study conducted by Herbert L. Fred [5], the method is very much expensive and the amount of dosage of radiation during a test is extremely high. The prolonged use of the device is extremely dangerous for the patient. Endoscopic procedures involve colonoscopy, endoscopic retrograde cholangiopancreatography and sigmoidoscopy. Endoscopy is the visual examination of the digestive tract using a camera placed at the tip of a flexible tube and the tube is inserted through the mouth or the anal orifice. Therefore, it can cause extreme discomfort for the patient during the procedure. Blockages due to the flexibility and maneuverability limitations of the tube can also lead to complications and extreme discomfort for the patient. Moreover, it can be used for histological test of the gut lining as it only gives imagery as results [6]. These limitations can affect the accuracy of the diagnostics. To prevent such problems the non-invasive method of electrogastrogram (EGG) is used.

Electrogastrogram (EGG) is an electrical signal which gives electrical activity of stomach and can be recorded with the help of a non-invasive technique called Electrogastrography by placing electrodes over the surface of the stomach. With the use of EGG signals, the digestive disorders can be detected in an effective manner [7]. In this era of smart technology, the health parameters related to Electrocardiogram (ECG), blood pressure, heart rate, oxygen level saturation are measured [8]. While surfing various literatures, it is evident that the EGG shall be used for the purpose of scientific research and only few researches are carried out in practical point. So, need of EGG tracking as a health parameter with the use of real-time Internet of Things technology is highly beneficial and helps individuals to be alert and able to take care of people with digestive disorders.

EGG involves measurement of the electrical rhythm of the stomach. In a healthy person, the cycle would be 3 cycles per minute. This frequency can either increase or decrease based on the disorders associated with the system. Further, the increase in frequency is known as Tachygastria and the decrease in frequency is known as Bradygastria. Also, the increase and decrease in the frequency can be measured and detected by using Artificial Intelligence systems especially by learning methods. In a study conducted by Raihan et al. [4], the use of various AI algorithms including support vector machine (SVM), K-Nearest Neighbor (KNN) and Logistic Regression (LR) was utilized. In machine learning, the computer possesses the ability to learn without any background programming and the ML algorithm is set to find patterns in data. Furthermore, Electrogastrogram (EGG) signals can be abnormal by being slower or faster than the normal rate. Therefore, the machine learning algorithm can be used to detect the changes in the pattern and provide an accurate result which can differentiate the normal and the abnormal EGG signals.

2. Literature Survey

Due to poor electrical activity of stomach, majority of people are suffering from digestive disorders. Gopu et al. (2008) have proposed a method of recording electrogastrogram signals to avoid use of endoscopy by using cutaneous Ag-AgCl electrodes and a Signal Conditioning Unit to improve signal quality and filtered to remove noise and converted digital output is sent to microcontroller [9]. A method presented by Haddab et al. (2009) represents the EGG signal acquisition and using neural networks for noise filtering of motion artefacts with actual signal and then, transmitting to medical care unit through GSM communication [10]. In contrast to passive electrode system for the acquiring of electrogastrogram signals, an active electrode setup is proposed by Gopu et al. (2010) shown a higher sensitivity and reliability that helped in diagnosis of gastric disorders such as ulcers and dyspepsia through preprocessing using Principal Component Analysis (PCA) with support of wavelet transform for analysis [11].

Gharibans et al. (2018) discussed that EGG signals can be recorded using multi-channel system of wearable type and also used some signal processing methods for the removal of artefacts overtaking the limitations of the single channel measurement and presence of signal artefacts that resulted in inconsistency of data reliability. This proposed approach shows an increased scope in diagnosing and treating GI disorders in an effective manner [12]. Development of both two and three electrodes system and a comparison made by Alagumariappan et al. (2018) for recording of electrical activity of stomach in which three electrode system shown a higher information content ensuring progression in the accurate diagnosis of any abnormalities related to electrogastrogram signals [16]. Gharibans et al. (2019) revealed that abnormality in gastrointestinal function is a multifactorial and potential cause of the gastroparesis and functional dyspepsia for which non-invasive cutaneous high-resolution recording of EGG helps in identification of those above-mentioned symptoms [14].

Several researchers have extracted features from acquired EGG signals and classified various digestive diseases [15-19]. Alagumariappan et al. (2020) have discussed the role of electrogastrogram in prior detection of digestion abnormalities in diagnosing Type 2 Diabetes with the help of extracting features by pre-processing the recorded EGG signals using Empirical Mode Decomposition and generic algorithms in picking up good features and relating all these features with digestive system's mobility [15]. A user-friendly, non-invasive and wearable approach for monitoring gastrointestinal problems is proposed by Kumar et al. (2020) used LabVIEW software for analyzing signals and moving average algorithm in MATLAB for accurate electro-gastrographic extremities [16]. A study conducted by Paramasivam et al. (2021) explores that there is a positive impact of yoga asanas on the process of digestion is identified through Fast Fourier Transform (FFT) by recording EEG signals before and after yoga for which normal frequency range of EGG signals is aligned with post-yoga recorded signals [17].

The objective of this work is to design and develop an Internet of Things based smart wearable device to alert/notify the persons once they skipped their food habits on time. In this paper, the proposed work is organized into four different sections. The first section deals with brief introduction about digestion process, its associated electrical signals and the techniques used to assess the progress of digestion. Further, the section 2 deals with literatures relevant to EGG techniques, objective and organization of the research paper. The section 3 explains the proposed methodology and the section 4 focuses on results and its analyses. The conclusions arrived through analysis are presented in section 5.

3. Methodology

In this work, a wearable device fabricated with three textile electrodes is designed and developed. Further, the digestive conditions namely pre-prandial and post-prandial using EGG signals are analyzed. Figure 1 shows an overall block diagram of the proposed approach.

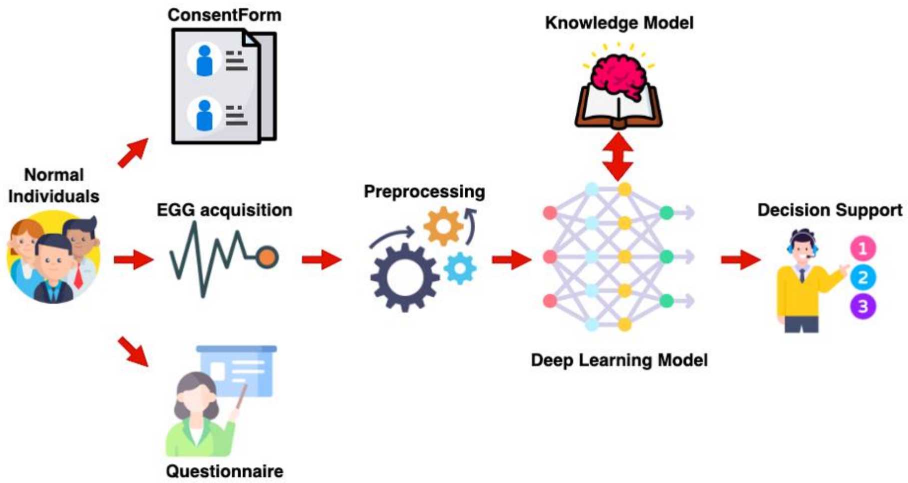


Figure 1. Overall block diagram of the proposed approach.

In the proposed approach, the participants without any previous history of digestive health complications are selected. Furthermore, the two different things namely consent form and questionnaires are obtained from the participants. The experimental procedures are explained clearly and informed consent are obtained whereas the questionnaires are obtained to ensure whether the participants aren't having any medical complications. After obtaining informed consent and questionnaires, the participants are selected for EGG signal acquisition. Also, the EGG signals are acquired from selected participants for two different conditions namely pre-prandial and post prandial conditions. These acquired EGG signals are preprocessed and the unwanted frequency components are removed. Further, the preprocessed pre-prandial and post-prandial EGG signals are given to deep learning model for learning process. Once the deep learning model is trained, the model provides decision support about the digestive habits namely pre-prandial and post-prandial conditions.

3.1. Proposed EGG device

Figure 2 shows the block diagram for proposed device. The proposed device is a wearable device which is used to monitor the digestive habits namely pre-prandial and post-prandial conditions effectively which leads to healthy life.

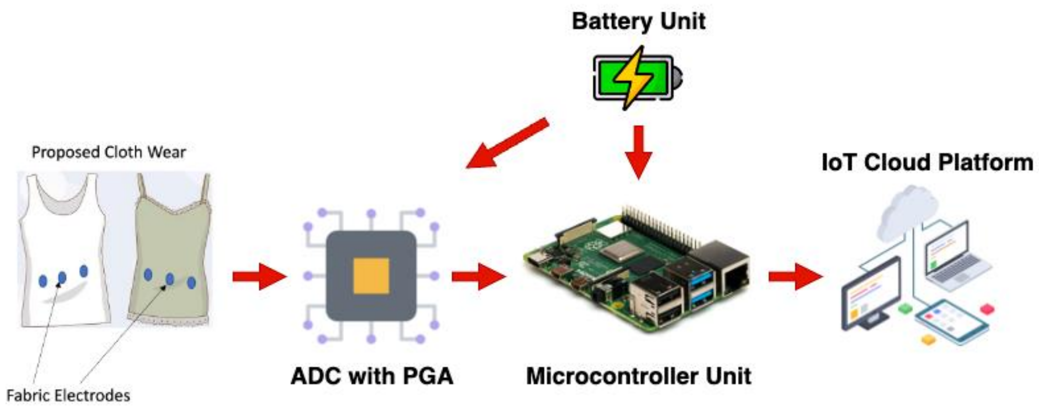


Figure 2. Block diagram of the proposed wearable device.

The proposed device consists of components such as Textile Electrodes, ADC with programmable gain amplifier, Microcontroller unit, battery unit and Internet of Things cloud platform.

3.1.1. Textile Electrodes

A conductive thread made up of stainless-steel material is utilized in this work to fabricate electrode for EGG signal acquisition. Also, the thread is stitched in three distinct places of the inner wear which forms three fabric electrodes and its position is determined according to three electrode placement protocol suggested by [21]. Furthermore, the wire is tapped from three fabric electrodes and once the inner wear is worn by the individuals, the fabric electrodes pick up the EGG signals. These acquired EGG signals are given to Analog to Digital Converter (ADC) for further process.

3.1.2. ADC with PGA

In this work, ADS1115 based ADC with PGA module is used to convert and amplify the EGG signals with less power consumption. The ADS1115 consumes 150 micro-amps of current. Also, the utilized ADS1115 operates on 2 Volt to 5 Volts and has 4 ADC channels which can perform two differential input operations. In general, the range of the EGG signals are in micro-volts and due to this, it is important to amplify the acquired EGG signals to do further process. The adopted ADC converter with PGA module perform two different operations namely amplification and AD conversion. Firstly, the acquired EGG signals are amplified from micro-volts range to volts range by setting gain of the amplifier through programming. Further, the acquired EGG signals are amplified and are converted from analog to digital and it is fed to the microcontroller unit through Inter-Integrated Circuits (I2C) protocol.

3.1.3. Microcontroller Unit

A Raspberry PI 3 Model B+ based Microcontroller is used to perform computing operations which is portable, consumes less power and can be connected to cloud with the help of Internet connectivity. The preprocessing and deep learning algorithm are coded inside the PI controller using open-source Python programming software. The acquired EGG signals are amplified and preprocessed to remove noises. Further, these preprocessed signals are given to deep LSTM based deep learning model for training and testing process. Also, the PI controller updates the decision support produced by the trained deep learning model to Internet of Things (Internet of Things) cloud platform.

3.1.4. ThingSpeak Internet of Things Cloud Platform:

In general, Internet of Things cloud platforms namely ThingSpeak are used to visualize and analyze the dynamic data remotely. A user account is created in the open source ThingSpeak Internet of Things cloud platform and the individual's food habits namely pre-prandial and post-prandial conditions are monitored. The microcontroller unit access the ThingSpeak user account with the help of write Application Programming Interface (API) key and stores the decision support which can be viewed by the individual or doctor personnel remotely at any time. Also, the day-wise individual's pre-prandial and post-prandial conditions are logged which helps the individuals to lead a healthy life.

3.2. Data Acquisition & Analysis

In this work, the Empirical Mode Decomposition (EMD) technique is used to decompose the acquired pre-prandial and post-prandial EGG signals into multiple components called Intrinsic Mode Functions (IMF's) [15]. The frequency of these IMF's are derived using Fast Fourier Transform (FFT). By analysing the frequency of all the IMF's, the unwanted IMF's are eliminated and remaining IMF's are concatenated which produces a resultant noise free EGG signal. The frequency components of the sampled EGG signal can be extracted using FFT algorithm. Also, in this work, the FFT analysis is used to represent acquired EGG signal in the frequency domain. Further, the FFT of the acquired EGG signal can be computed by the expression (1).

$$f(x) = \sum_{n=0}^{M-1} e^{-2\pi j \frac{xn}{M}} y(n) \tag{1}$$

where f(x) requires a sum of M terms. Also, the frequency with maximum amplitude will be considered as the dominant frequency which is the fundamental frequency of the particular EGG signal.

LSTM is a type of Recurrent Neural Network (RNN) architecture used in deep learning. Recurrent Neural Network (RNN) tends to have the problem of exploding and vanishing gradient; therefore, it is much more difficult to train. This problem occurs when the gradient either becomes too small or too large during back propagation. This happens in the RNN because they have a recurrent connection that allows them to store information from previous time steps. The LSTM is designed specifically to prevent the problem of exploding and vanishing gradient. The LSTM architecture uses two types of nonlinear activation functions namely logistic sigmoid function and the hyperbolic tangent function.

The sigmoid activation function converts any x coordinate and converts it into a y coordinate between 0 and 1. This is used as a gate activation function. Further, the sigmoid activation function is given by the expression (2):

$$\sigma(x) = \frac{e^x}{e^x + 1} \tag{2}$$

The hyperbolic tangent function converts any x coordinate value and converts it into a y coordinate value between –1 and 1. Further, the function is given by the expression (3):

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \tanh(x) \tag{3}$$

As the name suggests, there are two types of memory in the LSTM architecture namely long-term memory and short-term memory. The long-term memory is also called as the cell state and it can be modified by arithmetic functions, but there are no weights or biases which can modify the function. The short-term memory is also known as the hidden state. Unlike the long-term memory, the short-term memory has weights and biases that can modify the function. Also, the LSTM architecture consists of memory blocks and these memory blocks are a set of recurrently connected sub-networks. Furthermore, the memory block maintains its state over time and regulate the flow of information. A vanilla LSTM unit is composed of four components such as cell, input gate, output gate and forget gate [22].

3.2.1. Forget gate

This step determines how much of the information must be deleted from its previous cell state. This gate uses the sigmoid activation function for its operation and this is the first block in the LSTM algorithm.

3.2.2. Input gate

This step is used to update the value of previous LSTM cell by combining the input value with its biases and weights and the last LSTM output. This gate also uses the sigmoid activation function for its operations.

3.2.3. Cell

This step combines the values of input value, the input gate value, the forget gate value and the previous cell value.

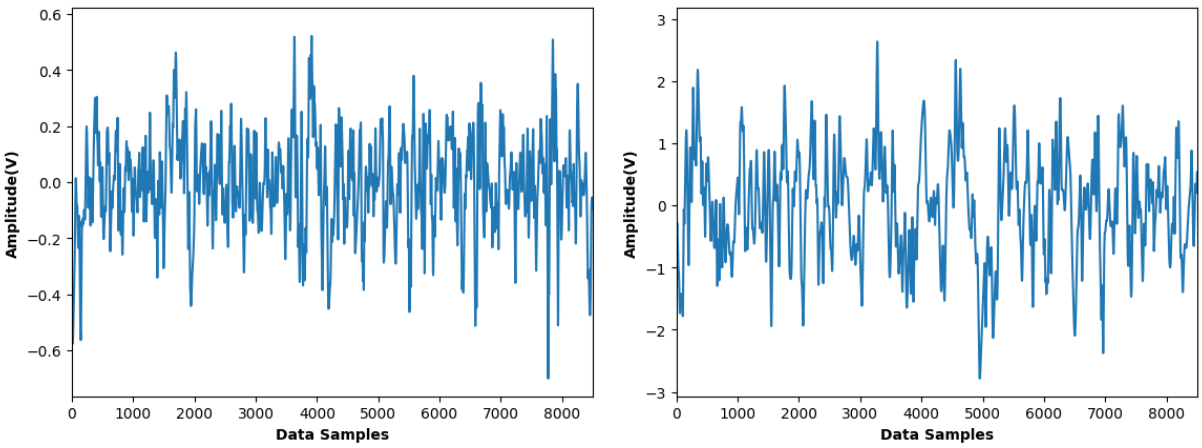
3.2.4. Output gate

This step combines the current input value, the output of the LSTM unit and the cell value of the last LSTM unit.

The input and the output value of the LSTM is combined with the cell values of the last unit and the current unit to get the block input value and the block output value respectively. The values are introduced into the LSTM unit in the form of block input and the output value is received in the form of the block output. In this work, the total of 200 EGG signals are acquired from the normal individuals, out of which 100 EGG signals are acquired under pre-prandial condition and 100 EGG signals are acquired under post-prandial condition. Furthermore, the 80% of the total EGG signals are utilized to train LSTM deep learning model and remaining 20% of the EGG signals are utilized to test the proposed LSTM deep learning model. Also, the proposed deep learning model is incorporated into the developed wearable device and the device updates the decision support to the Internet of Things cloud.

4. Results and Discussion

Figure 3 (a) and (b) show a typical EGG signal acquired from normal individuals under pre-prandial and post-prandial conditions. It is observed that the x-axis shows the amplitude of the acquired EGG signal in volts and y-axis shows the sample data points acquired in different point of time. Also, it is seen in the figure 3, that the typical EGG signal acquired from normal individuals under pre-prandial and post-prandial conditions have no significant variation by visual examination except change in amplitude of both the EGG signals.



(a) **(b)**

Figure 3. Typical EGG signal acquired under **(a)** pre-prandial conditions; **(b)** post-prandial conditions.

The study is conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Ethics Committee of Gleneagles Global Health City, Chennai, India. (Reference number: **BMHR/2023/0055**). For this proposed study, the total of 200 EGG signals are acquired under pre-prandial and post-prandial conditions from normal individuals with their proper consent.

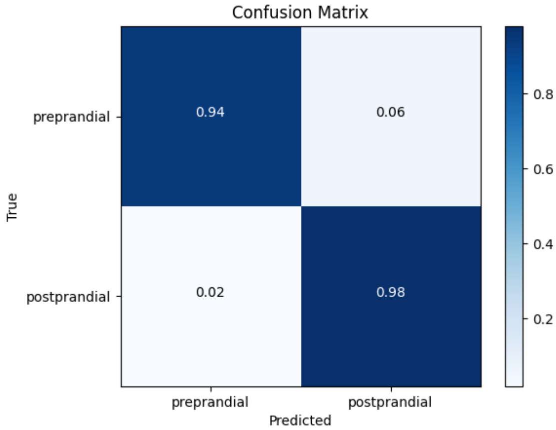


Figure 4. Confusion matrix for pre-prandial and post-prandial condition.

The EGG signals are analyzed using FFT and it is observed that there are no significant changes in frequency of the acquired pre-prandial and post-prandial EGG signals. Moreover, the 80 pre-prandial EGG signals and 80 post-prandial EGG signals are given to the proposed LSTM deep learning model for training process. Also, the 20 pre-prandial EGG signals and 20 post-prandial EGG signals are given to the proposed LSTM deep learning model for testing the model. The confusion matrix generated after the testing process is shown in the figure 4. Figure 4 shows the confusion matrix of binary class namely pre-prandial and post-prandial generated by the proposed LSTM deep learning model. Also, it is observed that the parametric values such as True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) are given appropriately in terms of true values versus predicted values. By using the above discussed parametric values, the four different performance metrics are calculated and the four different performance metrics such as accuracy, F1_Score, precision and recall of the proposed LSTM deep learning model is presented in the table 1.

Table 1. Performance metrics of LSTM deep learning model.

Performance Metrics	Percentage (%)
Accuracy	96
Precision	94.2
Recall	98
F1_Score	96

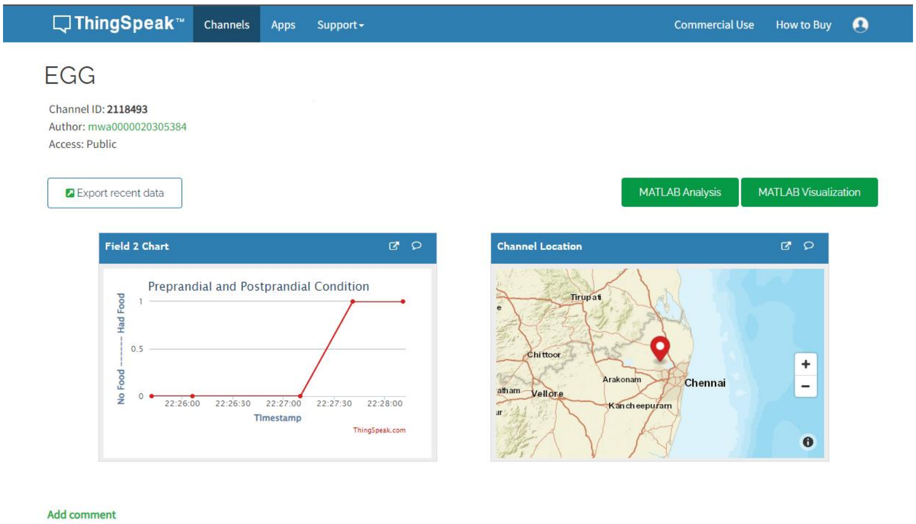


Figure 5. ThingSpeak User account for monitoring of pre-prandial and post-prandial conditions.

From the table 1, it is evident that the accuracy of the proposed LSTM model is 96% and the recall of the proposed LSTM deep learning model is 98%. Further, the precision and F1_Score of the proposed LSTM deep learning model is 94.2% and 96% respectively. Also, it is evident that the proposed LSTM deep learning model is capable of identifying the individual's food habits. Figure 5 shows the ThingSpeak user account for monitoring of pre-prandial and post-prandial conditions. Further, the food habits can be monitored by self or other person especially doctor personal by giving proper access. It is shown that the location of the person can also be visualized in the user page. The predicted output of the proposed LSTM deep learning model is logged to the field 2 Chart of the user account using API key. Furthermore, Also, it is seen that the field 2 Chart, the individuals food habits are logged with respect to date and time. From the literature, it is evident that the skipping/late consumption of food lead to various digestive abnormalities, however, it is evident that the proposed Internet of Things based smart digestive health monitoring device is highly efficient of identifying the individual's food habits/consumption results in maintaining healthy life since digestion plays vital role in every human's life.

5. Conclusion

In general, the acid produced by the stomach can sometimes leak into the esophagus because of improper closure of the cardiac sphincter, causing a burning sensation in the esophagus with symptoms such as regurgitations, belching and coughing. The main cause of this disease is basically linked to the patient's lifestyle and eating habits. In this work, a wearable device was designed and developed to monitor the food intake habits of the normal individuals to maintain healthy lifestyle. Further, the EGG signals were acquired from normal individuals for pre-prandial and post-prandial conditions and the LSTM deep learning model is utilized to identify the food intake habits of the normal individuals. Results demonstrate that the proposed LSTM model is good at classifying pre-prandial and post-prandial conditions which exhibits accuracy of 96%. Also, the ThingSpeak Internet of Things cloud platform helps the normal individuals to monitor the food intake habits day wise in a remote manner anytime since the data is being logged regularly to the ThingSpeak Internet of Things user account. Since the proposed device is compact and can be integrated in usual cloth wear, the device shall be used to monitor the digestive habits namely pre-prandial and post-prandial conditions effectively which leads to healthy life.

Author Contributions: R.K.D., P.A., V.S., and E.C. conceptualized the idea for this manuscript. R.K.D. provided the resources. P.A. designed and developed the hardware for data acquisition. P.P.

and A.M. carried out the investigation and data curation of the acquired data. V.S. validated the data and results acquired. P.A. prepared the original draft. V.S., E.C., and M.P.S. reviewed and edited the original draft. E.C. and M.P.S. supervised the work, and R.K.D. administered the work. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Conflicts of Interest: The authors declare no conflict of interest.

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