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GastroSmart: Precision GI Health Monitoring with Non-Invasive GMR

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Abstract: Pathological conditions affecting the gastroenterological tract such as GERD, gastroparesis, gastric cancer, type 2 diabetes, and obesity among others present alarming levels of health risks. Conventional imaging methods such as ultrasonic imaging have a very high cost and do not provide real-time monitoring. To overcome these challenges, we present a new system based on GMR sensor capable of non-invasively measuring gastric volume over prolonged periods of time. This system uses Rational Dilation Wavelet Transformation in order to enhance the accuracy of the evaluated gastric dynamics. With the help of polynomial regression, gastric volume changes can be predicted very accurately by our model, which makes it possible to prevent exacerbation of gastrointestinal diseases in early stages. The continuous evaluation of the condition of the patients and their physical activity performed by this non-invasive method will allow individualized treatment to each patient in the best possible way and will improve healing without sacrificing safety. This investigation is a response for implementing low-cost and effective solutions for constant monitoring of patients with gastrointestinal distresses in the direction of preventive nursing and clinical care for patients.

Keywords: Gastrointestinal diseases, GMR sensor, Rational Dilation Wavelet Transformation, Continuous monitoring, Disease prevention

1. Introduction

Gastrointestinal (GI) diseases, such as gastroesophageal reflux disease, gastroparesis, gastric cancer and obesity are among the most prevailing disorders worldwide and greatly impair human life quality. They are chronic conditions characterized by pathological changes to the GI tract with manifestations that range from discomforting symptoms to life-threatening complications. An accurate tool for evaluating gastric motility and, to some extent, gastric volume would be useful in optimizing the care of these disorders. Although traditional diagnostic methods such as ultrasound are helpful, they have great shortcomings in terms of expensive costs, invasively and intermittently monitoring gastric activity [1].

There is, therefore, a considerable need for non-invasive monitoring of gastrointestinal function in real time that is particularly crucial in chronic disease management. However, prevailing methods such as radiographic imaging are both invasive and only offer snapshot data, as opposed continuous monitoring over long term disease management [2]. Additionally, tools such as ultrasonography have limited spatial resolution (though not the focus of this study) and cannot measure very small decreases in gastric volume over long time periods needed to implement disease prevention and treatment [3]. Consequently, there is a pressing need for new technologies to monitor GI functions in terms of accuracy, continuity and non-invasiveness.

This has the potential to be handled by newer sensor technology, in particular Giant Magnetoresistance (GMR) sensors. GMR sensors are magnetoresistive sensors which exhibit a giant magneto resistance effect, i.e. they are extremely sensitive to changes in magnetic field strength and can monitor subtle alterations in magnetic properties [4], enabling measurements being performed non-invasively on bio-medical samples with the smallest possible sample sizes available to cope with small quantum phenomena. Miniaturization, high sensitivity and low power consumption of wearable sensors provide a number of advantages over traditional methods that permit longer duration monitoring without patient discomfort [5]. While GMR sensors have been used in cardiology and neurology, their use for GI monitoring is relatively new [6].

In addition, it has been suggested that continuous measurement of gastric volume is feasible using GMR sensors in combination with advanced signal processing algorithms. In Additional file 1: Measures to resolve the essential signals of slow-wave sequences in LGM by comparing bivariate dogleg occurrence and Mann-Kendall test scores, Rational Dilation Wavelet Transform (RADWT) an improved wavelet-based method to capture accurately both oscillatory and non-oscillatory components of physiological signals [7], can be a promising technique for enhancing signal analysis related to gastric motility. Wavelet transformations have been shown to provide high resolution in both frequency and time domains, which makes it a compelling tool for the analysis of complex biological signals—such as RADWT [8].

We hope to accurately predict changes in gastric volume with the use of machine learning models, predominantly polynomial regression so that conditions like gastroparesis and gastric outlet obstruction may be diagnosed earlier on. This method not only providieng with real-time insights into gastric dynamics but also substantiate preventive healthcare that enable earlier diagnosis of stage health problems and personalized treatment strategy [9].

Utilizing GMR sensors and RADWT, our system GastroSmart offers a precise non-invasive method for real-time volumetric measurements of the stomach that outperforms current strategies which rely on common imaging practices. In this paper, design, implementation & performance evaluation of such a system is discussed which is demonstrated as being able to be a game-changer in the clinical management of GI disorders by providing continuous real-time monitoring for only few tens of dollars [10].

2. Related Works

Gastrointestinal (GI) diseases are a wider assortment of disorders that affect the system of digestion including gastroesophageal reflux disease (GERD), gastroparesis, gastric cancer, type 2 diabetes, and obesity. It is also necessary to note that the treatment of these conditions will have to be done in an accurate and timely manner on the basis of clinical [11]. In this regard, traditional diagnostic approaches for such conditions as ultrasound scanning tend to be limited in several respects including cost, invasiveness and absence of any provision for monitoring in real time [12].

Noninvasive methods of monitoring have recently turned the attention to searching for new ways to control GI pathology. One quite effective weapon in this battle is Giant Magnetoresistance (GMR) sensors, which are highly sensitive and non-invasive, therefore can be used to monitor gastric dynamics in real time [13]. In particular, a review of the use of GMR sensors in medicine was carried out by Patel et al. (2023), who recognized the global shift in medicine that they would trigger [14].

Apart from GMR sensors, there are other specialist's analyzing devices such as the advanced signal processing techniques which are utilized in analyzing the information obtained from the GI monitoring systems. Bio signals concerning the movements of stomach have been particularly treated with wavelet, which has proven a very effective form of analysis within these circumstances [15]. Alabsi et al. (2024), highlighted the advantages of wavelet transformation in the analysis of dynamic medical problems, providing the principles of real-time diagnostics of gastric dynamics, reported recently [16].

Additionally, the combination of GMR sensors with modern analytical methods such as Rational Dilation Wavelet Transformation helps to make gastric dynamics studies more accurate and efficient [17]. Enhancement of specific GI health monitoring in such a way may bring earlier interventions and more disease-targeted care [18]. However, despite the positive steps forward, certain issues concerning non-invasive devices for the monitoring of gastrointestinal tract remain. Akhtar et al. (2023) provided a non-invasive perspective on cooking dynamics, describing current trends and future directions of this field and the need for more efforts in its development [19].

To conclude, the latest publications stress the relevance and necessity for such technologically advanced methods, as GMR sensors and complex IT systems, considering that there are no more separate approaches within GI health management. Leveraging the benefits of these new techniques without the restrictions of traditional diagnosis and treatment approaches is expected to lead to positive health outcomes and better individualisation of management in gastroenterology [20].

3. Methodology

3.1. GMR Sensor Signal Acquisition

3.1.1. Description of *GMR Sensor:*

The GMR sensor which is the NVE AAH002-02E model forms part of the elements of the gastric monitoring system. These sensors belong to NVE's AAH series – advanced designed for detecting absolute magnetic fields AAH Series. With on-chip flux concentrators and NVE GMR materials, the sensors provide direction oriented output signals, which are convenient for clinical usage among other things. Other advantageous characteristics of these sensors include but not limited to temperature stability, low power consumption, reversible and high sensitivity to externally applied magnetic fields, miniaturization and multifunctionality [21].

3.1.2. Technical Specifications of the NVE AAH002-02E Sensor:

Siting it is that the NVE AAH002-02E sensor has 11mV/V-Oe to 18mV/V-Oe sensitivity and it can measure magnetic fields in the range between 0.6Oe and 3Oe. These sensors are integrated with a Wheatstone bridge network configuration having inbuilt temperature compensation that ensures strong and accurate responses to the magnetic fields. Further, they are omnipolar outputs whereas the sensitivity profiles show a cos of an angle falloff when the sensors are rotated from the active direction in the plane of the IC.

3.1.3. Utilization of GMR Sensors for Gastric Monitoring:

The GMR sensors are extremely useful if stomach activity has to be measured in real-time in a non-invasive way. These sensors also allow one to monitor the digestive activities indirectly by measuring the magnetic field created by the different states of the human stomach. Analysis of gastric activity employing GMR technology in connection with a USB sound card attachment opens new opportunities for study of all gastric processes. It extends the comprehension of the gastric activities as well as it is expected to bring advancement to gastrointestinal illnesses diagnostics in scientific and clinical practice [22].

3.1.4. Experimental Setup for GMR Sensor Signal Acquisition:

In our experimental setup, a GMR Wheatstone bridge driven by +12V supply forms the principal sensing unit in the configuration. A USB sound card was used to detect changes in the output voltage due to changes in the magnetic resistance of the Wheatstone Bridge circuit. This system makes it possible to electrically represent in a hospitable manner the movements of the stomach by converting changes in the magnetic field to electrical signals. Our experiment investigates gastric volume and its changes upon fasting, acute solid food intake, and pill ingestion in order to gain valuable data on the mechanisms of food digestion and possible ways of influencing it utilizing different factors.

3.1.5 Significance of GMR Sensor Technology in Gastric Monitoring

The specific characteristics of GMR sensors make them essential in the monitoring of the stomach's physiologic processes. These sensors are also versatile providing the ability to detect even the tiniest movement in stomach activity with great accuracy. It is a technology that enables accurate information to be obtained in each diagnosis from the patients without causing much inconvenience to the patients as compared to the old ways. Furthermore due to their small size and limited power requirements, they can facilitate long term follow-up of the patients even outside the clinic and are especially useful for chronic disease management. In all, GMR sensors can aid in gastrointestinal health care monitoring and improving individual patient management [23].

3.2. Signal Preprocessing and Feature Extraction

There are several steps taken sequentially and systematically in obtaining gastric signals with the help of GMR sensors to improve the quality of the signal and get features that will facilitate proper analysis. However, before the signals are subjected to any analysis, the first step requires a series of data cleansing and filtering of the gastric signals. This consists of using filters in order to get rid of specific components of noise which has no use to the information within the signal and may hamper the quality of the signal [24]. Standardization procedures through signal normalization techniques are applied on the signal where there are large and differing amplitudes of the same recorded signal in the data as shown in Figure 1.

Next, algorithms regarding feature extraction are introduced with the purpose of obtaining relevant information from the enhanced stomach signals. These algorithms are created to catch signal attributes corresponding to the change in gastric volume, including, for instance, such attributes as the energy of the signals or their frequency domain. As an example, noticeable frequency ranges or present dominant frequencies associated with voluntary gastric activity have been examined with the help of typical noninvasive signal processing methods such as the Fast Fourier transform of recorded signals [25].

The NVE AAH002E, one of the GMR sensors used in this field, is responsible for detecting changes in the magnetic field due to the electric field generated by the stomach organs at rest. Advanced signal processing and feature extraction methods make it possible to capture and recognize such dynamic phenomena as stomach activity in real time, which contributes to the timely and effective monitoring and treatment of gastrointestinal diseases.

3.2.1. Acoustic Signal Analysis

It is noted that, say, when the person has not eaten any solid food or liquid (Scenario a), In Figure 2 the graphics signal shows greater activity and reaches maximum signal amplitude of 32mv in the period of 0.006 to 0.008 seconds. Whereas, when the person consumes 250 grams of Solid Food (Scenario b), the signal measurement drops – in this case to 16mv in the period of 0.006 to 0.009 seconds, which indicates getting less gastro activity than that of when a person stomach is empty. On the other hand, in Scenario c, which is a circumstance where 250 grams of solid food is taken and 200ml of coke is taken, the signal goes from 16mv to 28mv during the period of 0.010 and 0.012 seconds, which is equivalent to 12mv increase in gastric activity than when a stomach is empty. Similarly, in Scenario d in which Omeprazole Medicine (5mg) is administered, the signal rises and drops to 28mv and 16mv respectively during the time period in question 0.008-0.012 seconds The signal activity is decreased by 12mv within their stomach.

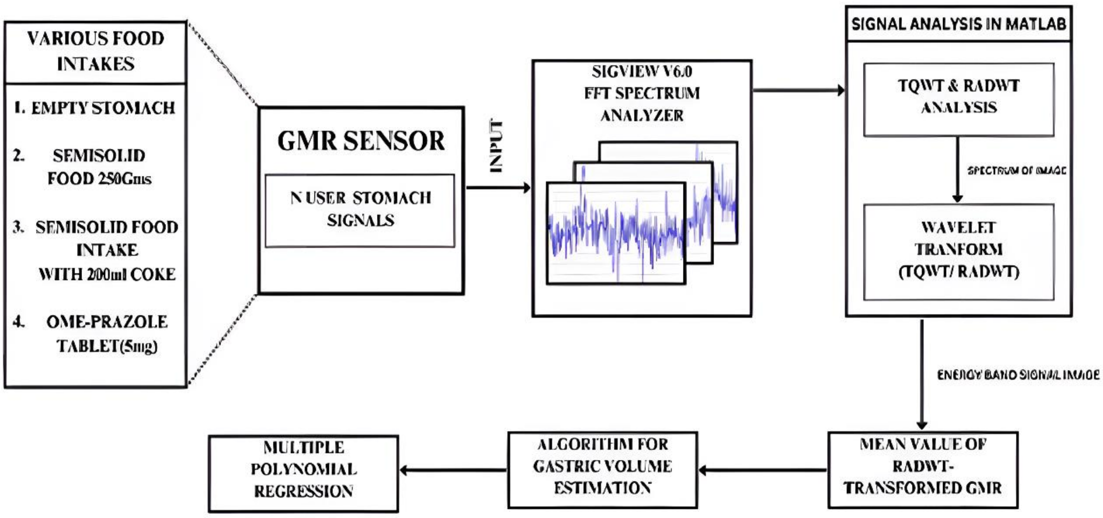

Figure 1. **Functional Model Framework Diagram**

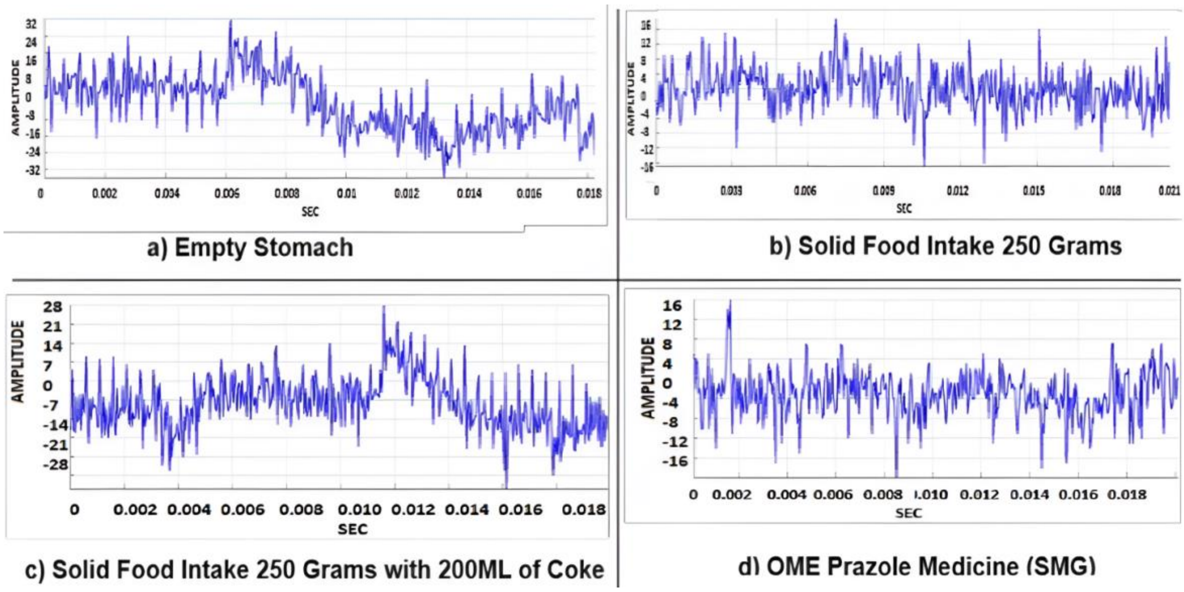

Figure 2. **Gastric Electro Magnetic Signal in the Form of Acoustic Signal (.wav)**

3.2.2. FFT Transformation

After every segment is acquired from the individual or sensor performing the task FFT signal decompose individuals evaluation is so called Fast Fourier Transform FF The signal was recorded in the time domain while FFT transformed it to the frequency domain which makes it easy to make frequency analysis. In the case of empty stomach, In Figure 3 scenario a transformed signal profiles yield considerable gastric aspects with maximum amplitude of 5.2mv at sampling frequency of 8 kHz. During eating scenario 250 grams of solid foods scenario b, the transformed signal also showed lower values of the gastric and the parameters varied from 5.2mv to 1.2mv at 4kHz. In Scenario c, the modified signal has shown more prominent gastric signal features in frequency range of 1.2mv to 2.7mv. Eventually in Scenario d maximally rounded stomach signals are seen in the frequency spectrum with two oscillation amplitudes of between 2.7mv and 4mv at an 8khz sampling frequency. These processed signals are beneficial in understanding the variations of the stomach function under various conditions and in finding the acoustic markers that can help to diagnose and manage disorders of the digestive system.

3.3. RADWT (Rational Dilation Wavelet Transform)

RADWT is rational dilation wavelet which is a wavelet transform method that provides compression of oscillatory signals whose persistence varies considerably. Additional Q-factor, RADWT helps in creating for such functions from a modular architecture two frames of different Q-factors. These frames enable the functional sparsity of such functions where resonating characteristics are either low or high [26]. The RADWT contains functional steps in the pursuit of its purposes, some of which are illustrated in the following figure 4.

$$\boldsymbol{H}(\omega) = \begin{cases} \sqrt{\boldsymbol{ab}} & |\omega| \leq \left(\mathbf{1} - \frac{\mathbf{1}}{\boldsymbol{c}}\right)\frac{\boldsymbol{\pi}}{\boldsymbol{a}} \\ \mathbf{0} & |\omega| \in \left[\frac{\boldsymbol{\pi}}{\boldsymbol{b}}, \boldsymbol{\pi}\right] \end{cases} \tag{1}$$

$$\boldsymbol{G}(\omega) = \begin{cases} \mathbf{0} & |\omega| \leq \left(\mathbf{1} - \frac{\mathbf{1}}{\boldsymbol{c}}\right)\boldsymbol{\pi} \\ \sqrt{\boldsymbol{c}} & |\omega| \in \left[\frac{\boldsymbol{a}}{\boldsymbol{b}}\boldsymbol{\pi}, \boldsymbol{\pi}\right] \end{cases} \tag{2}$$

This original equation expresses the RADWT's strength in accurately modeling signals with different features in its entirety. As illustrated in Figure 4, a positive transition bandwidth, defined as positive as well in this case, means that both $\mathrm{H}(\omega)$ and $\mathrm{G}(\omega)$ have transition bands if FB is over-complete. It is important to note that the transition band of $|\mathrm{G}(\omega)|$ is independently derived from the transition band of $|\mathrm{H}(\omega)|$.

$$\frac{1}{ab}\left|H\left(\frac{\omega}{a}\right)\right|^2 + \frac{1}{c}|G(\omega)|^2 = 1 \tag{3}$$

In Figure 5, positive transition bandwidths are also illustrated, and the filter banks used have transition bands. These filter properties are selected especially for gastric signal processing with GMR sensors where the signals are mainly oscillatory and non-oscillatory. In order to achieve better frequency resolution, wavelet transforms with high Q-factors are required. These high Q-factor filters which act as band-pass filters give better performance and allow the extraction of instantaneous gastric signals arising from various food intake conditions [27]. It is worth noting that these high Q-factor filters gives quite similar frequency resolution therefore improving signal accuracy in analysis.

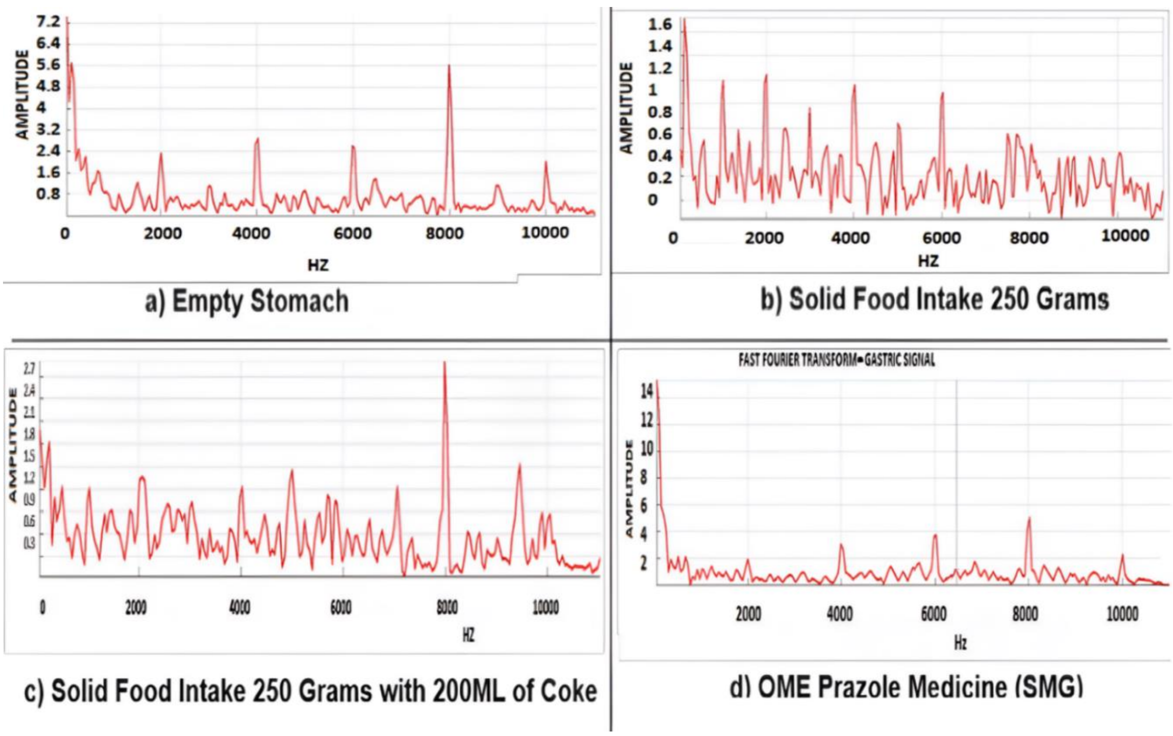

Figure 3. FFT Filtered Gastric Electro Magnetic Signal in the Form of Acoustic Signal (.wav)

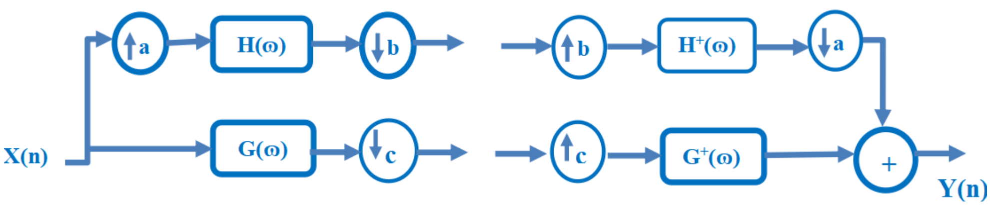

Figure 4. Rational Dilation Wavelet Transform

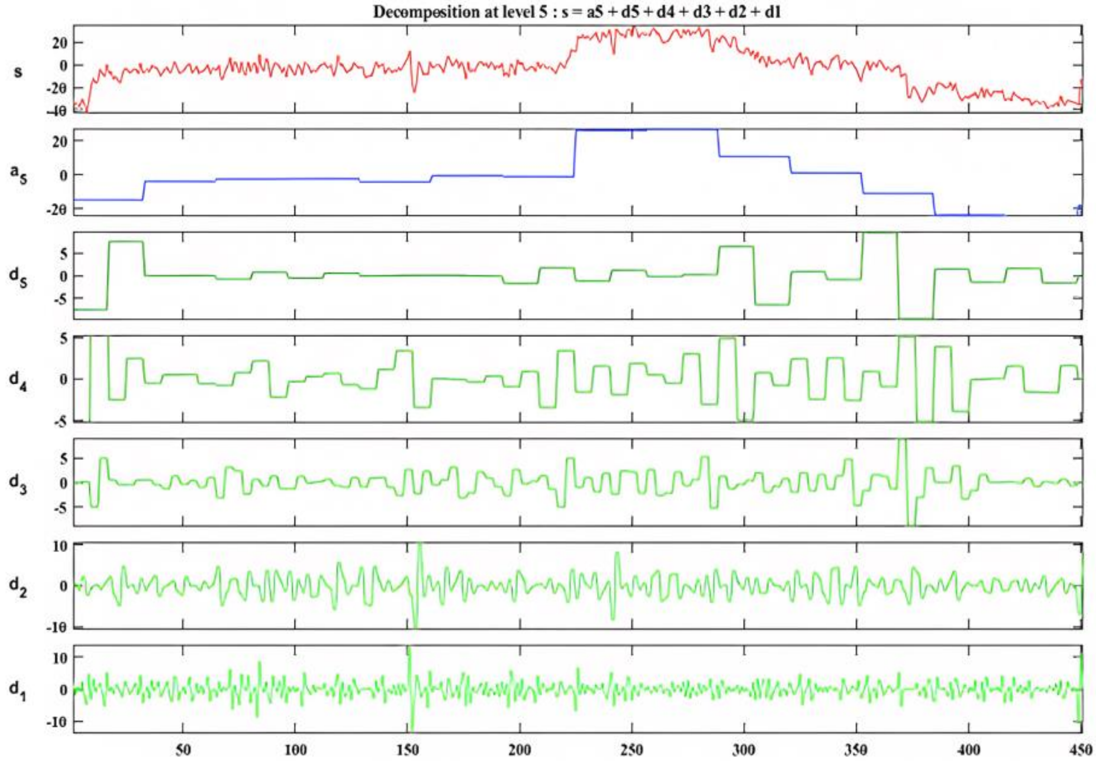

Figure 5. Wavelet 1D Analyse On Radwt Transformed Signal

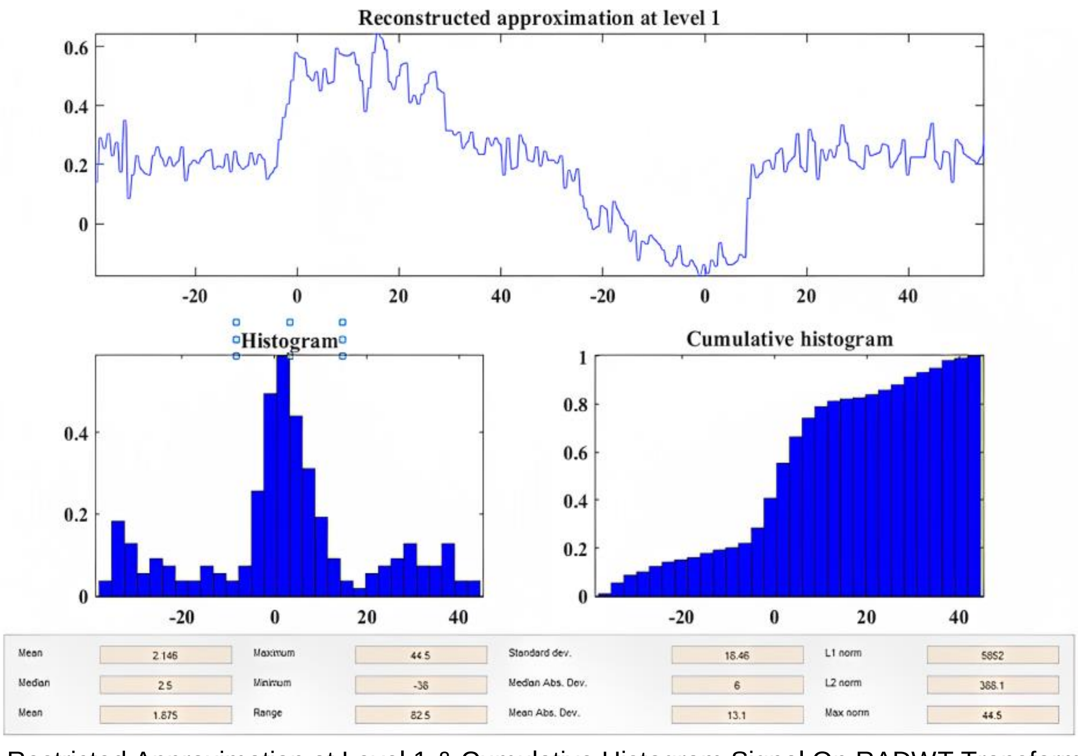

Figure 6. Restricted Approximation at Level 1 & Cumulative Histogram Signal On RADWT Transformed Signal

The RADWT, which is adjustable in frequency resolution, utilizes a low stuffing factor to incorporate several Q-factor filters and accurately represent complex gastric signals due to separate food intake by sub-band decomposition. Furthermore, to enhancement wisdom level of motion analysis of gastric processes, the RADWT is clearly of a much greater precision and resolution as one explores the characteristic frequencies of stomach signals as shown in figure seven [28].

$$Y(\omega) = \sum_{k=0}^{b-1} L_k(\omega) X\left(\omega + ak\frac{2\pi}{b}\right) + \sum_{k=0}^{c-1} M_k(\omega) X\left(\omega + k\frac{2\pi}{c}\right) \quad (4)$$

$$L_k(\omega) = \frac{1}{ab}\sum_{n=0}^{a-1} H\left(\frac{\omega}{a} + k\frac{2\pi}{b} + n\frac{2\pi}{a}\right) H^*\left(\frac{\omega}{a} + n\frac{2\pi}{a}\right) \quad (5)$$

$$M_k(\omega) = \frac{1}{c}\left[G\left(\omega + k\frac{2\pi}{c}\right)G^*(\omega)\right] \quad (6)$$

In Figure 6, the level one approximation is taken to contains information about the wavelet transformed data and the original data. The decomposition such as the one undertaken by the authors involves the application of wavelet transform to break down the data into groups and finally obtaining the level one reconstructed approximation. In addition, more general methods have been applied which include statistical representations of histograms and cumulative histograms to the structure and content of the information distribution. In other words, the attention is directed to several statistical parameters: the mean, and the median, values number maximum minimum and the range of such values helping to understand the level of dispersion of the dataset. At the same time some disperse and disperse measures including standard deviation, MAD, and MAD have given sufficient information about the variability of the data and the central cluster of data measure.

We also study the data by combining classical statistical norms including the L1 and L2 and Max norms satisfaction and control of the complete and absolute distance of points from the targeted sum scale including others. Such measures and representations contain useful information regarding the characteristics of the data more specifically after the wavelet transform and reconstruction processes Liu et al. which aids in understanding the characteristics of the dataset as well as the additional analysis and interpretation of the results.

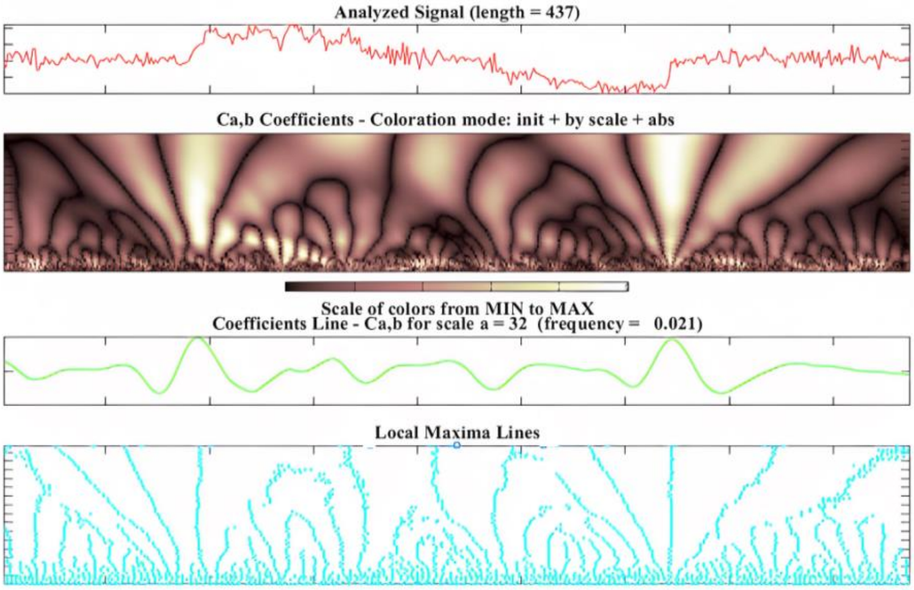

Figure 7. Characteristics of Analysed Signal in Collaboration Mode

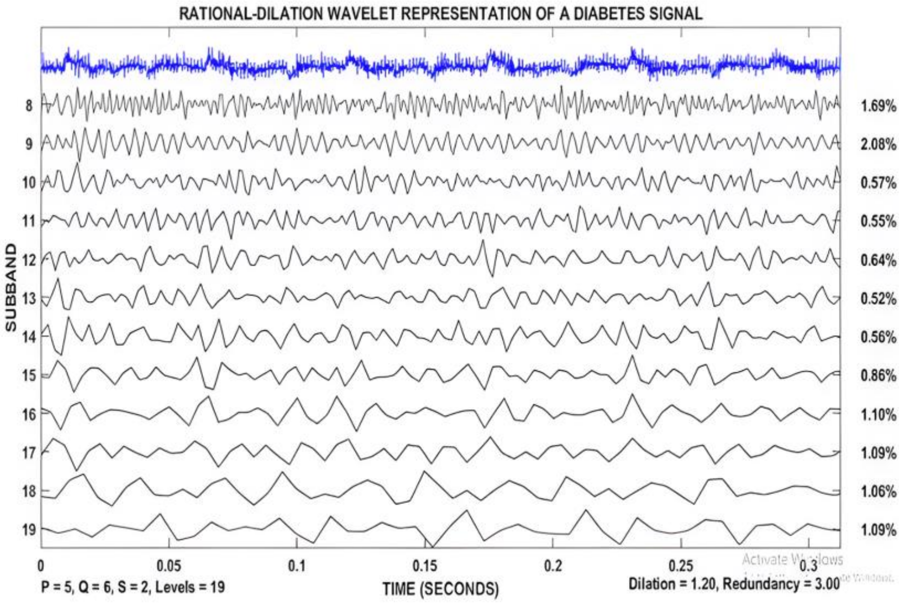

Figure 8. Rational Dilation Representation of Diabetes Signal

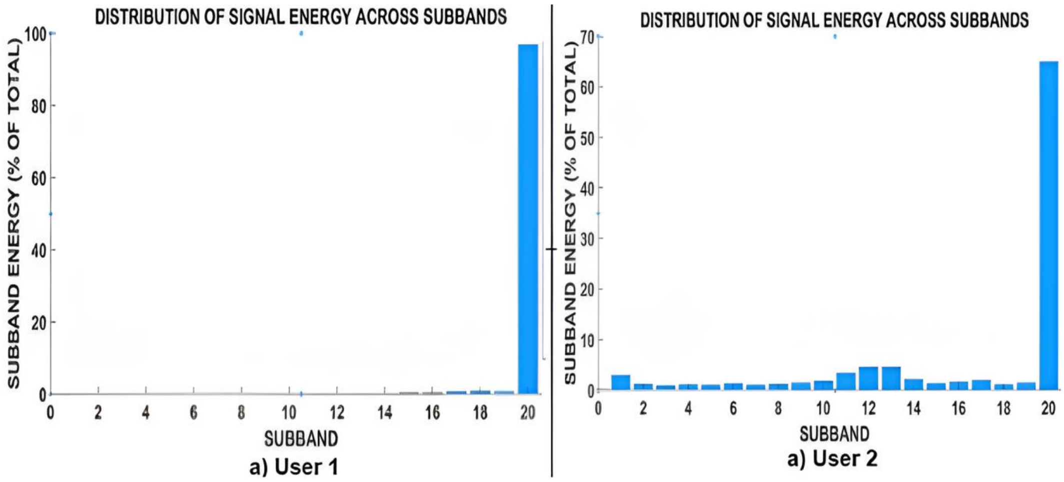

Figure 9. Empty Stomach for User 1 and User 2

In Figure 7, the characteristics of the analyzed signal are shown in collaboration mode, this time along it axed borders. The signal length is made up of 437 data points and is presented using the "int + by cream + abs" magnification mode. As above, this mode colours the coefficients according to the intensity and scales them ranging from there lowest to there highest extent. Lines with the coefficient named "ca" represent the Approximation Coefficient AC of scale "a=32" or of frequency 0.021 and Line "cb" the detail coefficients. In addition, local maximum lines identify salient points or extreme present in the signal’s frequency domain This analysis made possible by the RADWT gives a closer view on the diabetic signals as it allows for the segregation of signals into subbands in time. Through steps such as subband decomposition, temporal representation, and sparse representation, RADWT helps in observing the patterns and the dynamics of the signal over time and in particular, the frequency characteristics of the signals and the evolution of those signals over time shown in Figure 8.

4. Results and Discussion

In this section, we describe the procedure along the lines of slope (m) and intercept (b) calculations of GMR signals as they pertain to the estimation of gastric volume. Employing individual processes laid down in the instructions, we proceed to analyze GMR signals of User 1 and User 2 against different physiological conditions and food intakes. We intend to determine how GMR signals correlate to gastric volume in this manner, in order to develop cheaper and easy methods of measuring gastrointestinal motility in a non-invasive manner.

The subsequent tables include relatively numerous GMR mean values, derived signals, volume estimations under the predefined conditions of each experiment. Also, either GMR-based and ultrasonic based techniques on measuring gastric volume could be informative about the fields of application and the accuracy of those measurements [29]. The method of polynomial regression will be used as one of moderate stretching treatment to model the relationship between GMR signals and gastric volume assuming it to be nonlinear and thereby demonstrate potential uses of these measurements clinically.

On the other hand, particularly with reference to the results and discussion, we give consideration of the meaning of our results looking towards the use of GMR based gastric volume estimation in the diagnosis and treatment of disorders of the digestive system. In addition, polynomial regression analysis offers in-depth comprehension of the correlation between various measurement methods, thus directing the search in more effective ways & informing the choices made in practice. In this thorough analysis, we try to aid in the development of the noninvasive techniques of examination of the gastrointestinal tract and improving the patient outcomes.

4.1. Analysis of Gastric Acoustic Signals under Different Conditions Using Q-Factor Transform

In this part we focus on the expedition of gastric acoustic signals analysis investigating different physiological states and Q-Factor transform as a signal processing technique. The use of TF allows looking at the energy of the signal in several frequency bands and also gives acoustical information regarding the activity of the stomach.

4.1.1. Empty Stomach Scenario:

To begin with, we concern ourselves with recording the acoustic signals from voluntarily starving subjects. With the Q-Factor transform we analyze how energy of these signals is distributed in several subbands in terms of oscillatory & non-oscillatory components for gastric activity. The second order statistics of fasted individuals gives useful information on gastric functions as shown in Figure 9.

4.1.2. Solid Food Intake (250 Grams):

In Figure 10, the eating response was measured by recording acoustic signals after eating a 250-gram solid food meal. We seek to assess the effect of meal ingestion on the distribution of signal energy across several frequency subbands with the intention of clarifying the changes that occur in gastric activity and the corresponding acoustic response. This research help a deeper inclination of the physiological effect to solid food consumption.

4.1.3. Solid Food Intake (250 Grams) with 200ml Coke:

Now we examine combined influence of solid food + Coke on gastric activity looking back at C3 (the solid food and Coke dislike, hence we prefer microwaveable food instead of fast food which required chewing which people tend to eat in a hurry) scene. Since both solid food & coke were consumed successively, we figured it is wise to see how those together impact tummy as shown in Figure 11. Q-Factor transform is also employed to examine where energy within the signal that we record is grouped, in order to look for any new sounds that would be observed when the subjects eat & drink at the same time.

4.1.4. Omeprazole Capsule (5mg) Intake:

Lastly, in this paper by mean of related studies we investigate also a possibility of effecting medication on gastric activity and for this purpose, participants of clinical research were asked to take Omeprazole capsules 5 mg each. In Figure 12, After recording signals post medication, the distribution of subband energy of the signals is utilized to look for new dynamics inside the stomach that are the result of certain medications. This research seeks to relevant issues how medications may change the stomach sounds patterns over the range of the utility of acoustic methods for non-invasive examinations of the human digestive system.

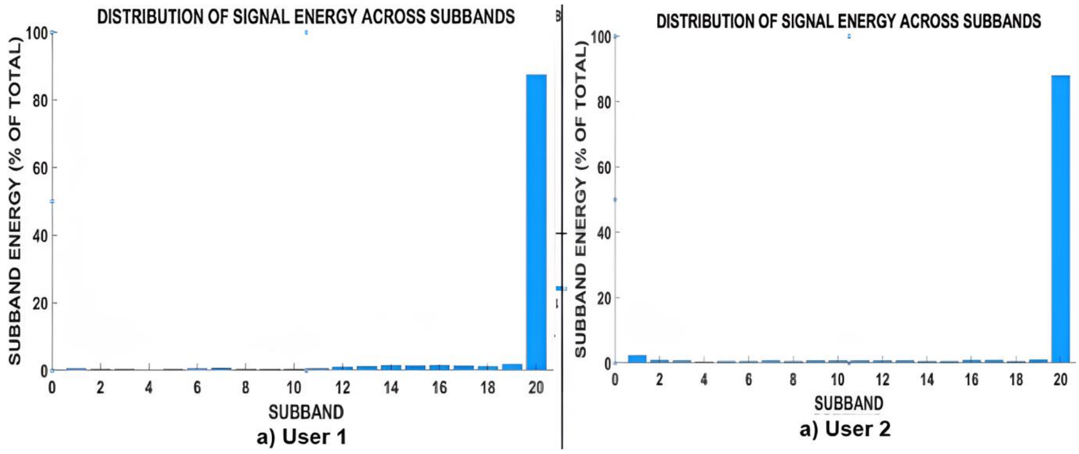

Figure 10. Solid Food Intake (250 Grams) for User 1 and User 2

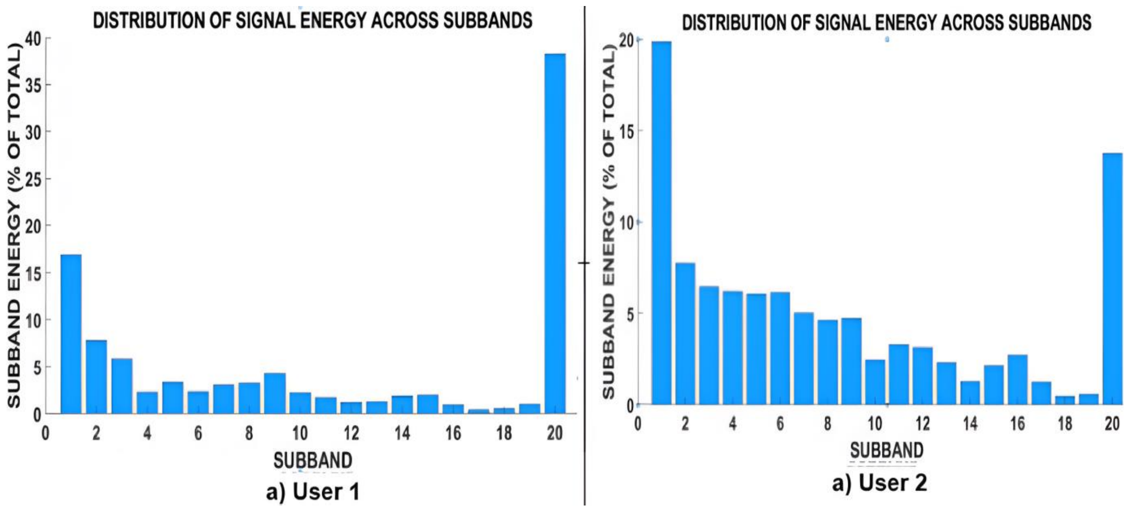

Figure 11. Solid Food Intake (250 Grams) with Coke (200ml) for User 1 and User 2

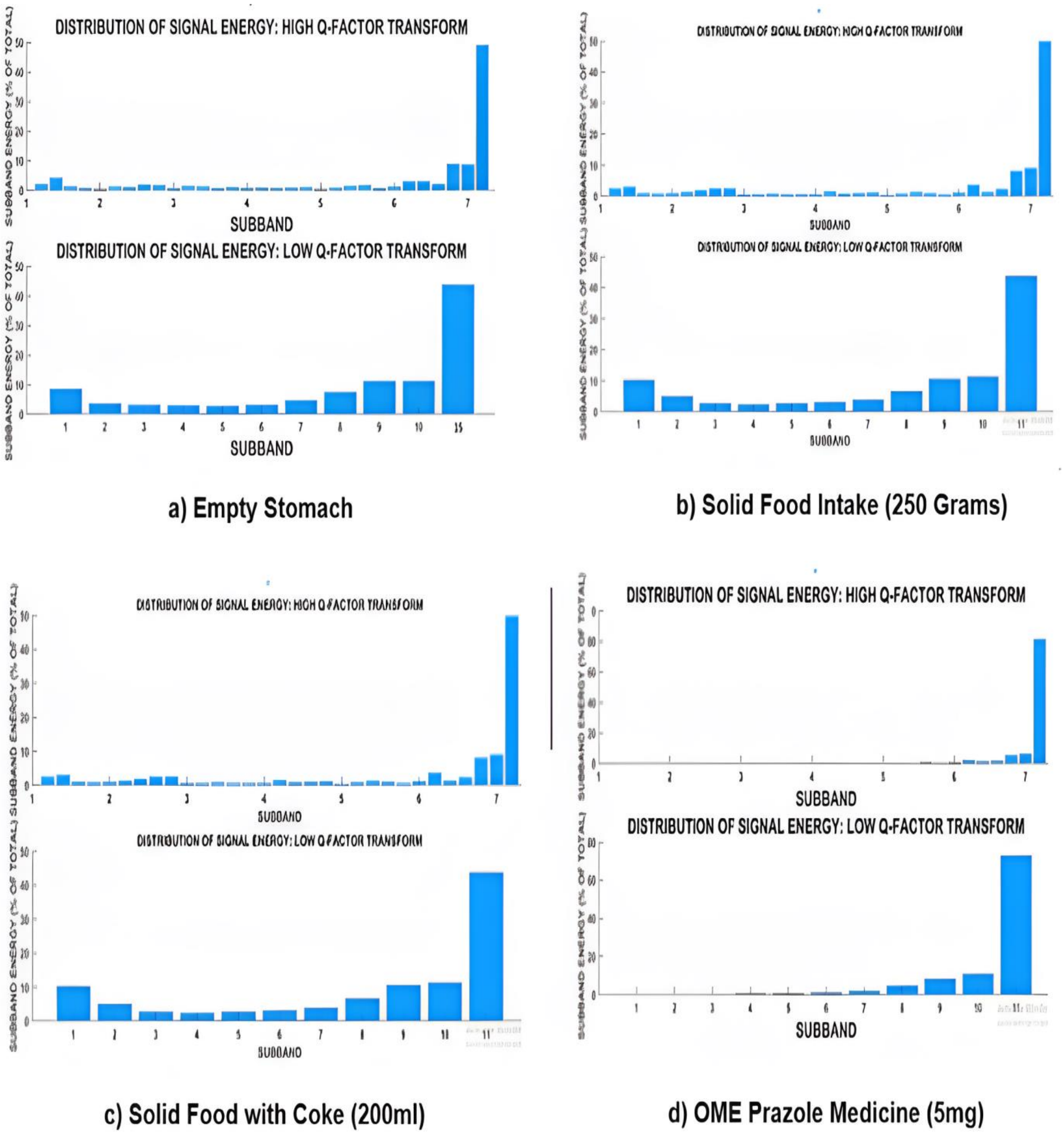

Figure 12. Distribution Signal Energy Q-Factor Transform

With the aim of leveraging the Q-Factor transform technique for more in-depth examination of the recorded signals in really different conditions to be able to bring new understanding regarding gastric functions and systemic relations with acoustic biomarkers. Associations between laden with acoustic parameters disease processes and different levels of interventions present a significant clinical potential for treatment and preventive means of gastrointestinal disease. This analysis of the complex and changing gastric activity contributes to the development of non-invasive approaches for the assessment of the gastrointestinal system and the improvement of individual-oriented medical treatment.

4.2. Calculation of Mean

For the calculation of the gastric volume, the linear regression model was applied using the slope m, GMR signal and intercept (b) values obtained from the tabulated column. One such example is that of the model which predicted a value of gastric volume GV approximately equal to 42.13 ml when slope of 4.467334 and GMR signal of 5.39 and intercept of -18.064481 are set. The estimated GV was also around 63.7 ml with the slope of 5.08, GMR signal of 7.92 and intercept of -23.46, In another case where for sink volume sacrifice this alternate volume was programmed with slope of 11.695, GMR signal of 9.26 and intercept (b) of -62.13795 the septic indicator projection GV around 170.48 ml. Finally, with a slope of 2.8554585, GMR signal of 5.84, and intercept of –6.234341 the GV calculated was 22.90 ml. Such calculations illustrate how GMR signals are used with linear regression analysis in obtaining gastric volumes providing good understanding of the gastric-related phenomena depicted in Table 1.

Table 1. Calculation of Mean - Empty Stomach - USER 1 (Age 44)

Name of the signals	Ultrasonic Method Gastric Volume Measurement	GMR1	GMR2	GMR3	GMR4	GMR5	GMR6	GMR7	GMR8	GMR9	GMR10	GMR11	GMR12	GMR13	GMR14	GMR15	GMR16	GMR17	GMR18	GMR19	GMR20	Sum= ∑GMR(i)	GMR Signal	Dev = GMR signal-	Dev^2	GMR Based
S	2.2	1.8	1.3	1.9	1.6	1.5	0.4	1.46	1.5	1.75	1.5	1.4	1.84	1.7	1.5	1.6	1.7	1.75	1.68	1.3	31.15	60.3	3.02	-2.19	4.81	31.54
S		1.18	1.23	1.9	1.26	1.25	1.14	1.26	1.5	1.75	1.5	7.4	1.84	1.27	1.5	1.6	1.7	1.75	1.58	1.34	73.8	107.8	5.39	0.18	0.03	42.13
S		1.8	2.3	1.29	1.26	1.75	1.44	1.42	1.25	1.75	1.5	1.4	1.84	1.7	1.35	1.26	1.27	1.75	1.68	1.53	115.12	144.7	7.23	2.02	4.09	50.38
Mean																							.21	Σ	8.93	
Slope (m)= (Sum of Deviations / (3-1))= 4.467334														b= Mean -(m* Mean)= -(-18.06481)												

Table 2. Calculation of Mean - Empty Stomach - USER 2 (Age 70)

Name of the signals	Ultrasonic	GMR1	GMR2	GMR3	GMR4	GMR5	GMR6	GMR7	GMR8	GMR9	GMR10	GMR11	GMR12	GMR13	GMR14	GMR15	GMR16	GMR17	GMR18	GMR19	GMR20	Sum=	GMR Signal	Dev = GMR signal- Mean	Dev ^2	GMR Based
S		0.86	1.3	0.9	0.6	0.5	0.4	0.4	0.5	0.5	0.5	0.4	0.4	.7	0.5	0.6	0.7	0.7	0.6	0.3	37.8	49.2		1.23	1.52	30.6
S	52.1	0.74	0.82	0.96	0.84	0.98	0.92	0.88	0.94	0.72	0.86	0.98	0.94	.84	0.91	0.86	0.99	0.78	0.89	0.92	64.6	81.4		.38		39.60
S		0.72	0.82	0.76	0.85	0.94	0.94	0.83	0.96	0.89	0.98	0.88	0.94	.94	0.98	0.84	0.88	0.82	0.85	0.96	123.4	140.2	7.01	.32		56.01
																						Mean	3.69	Σ	11.1	
Slope (m)= (Sum of Deviations / (3-1))= 5.5801755														b= Mean -(m* Mean)= -(-16.90085)												

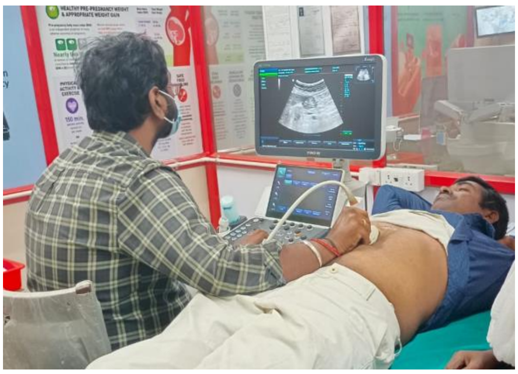

Figure 13. Gastric Volume of the Stomach Calculated using Ultrasonic Images for User 1

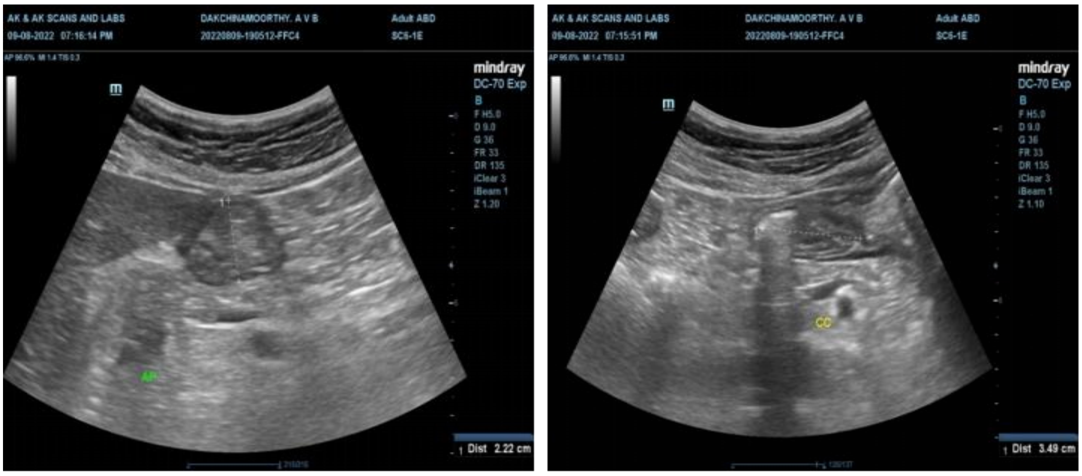

Figure 14. (Pre Coke) Solid Food 250 Grams Intake AP & CC Measurement

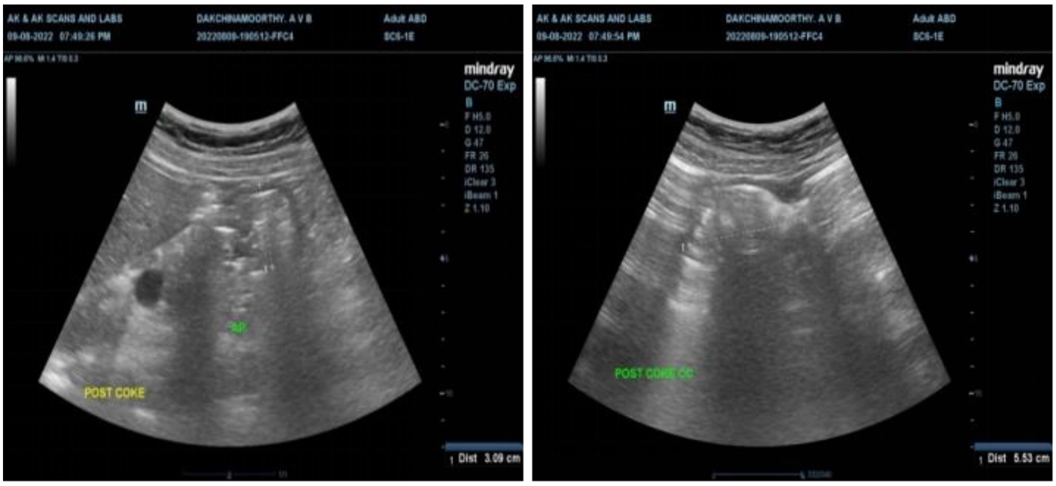

Figure 15. (Post Coke) Solid Food 250 Grams with Coke 200ml Intake AP & CC Measurement

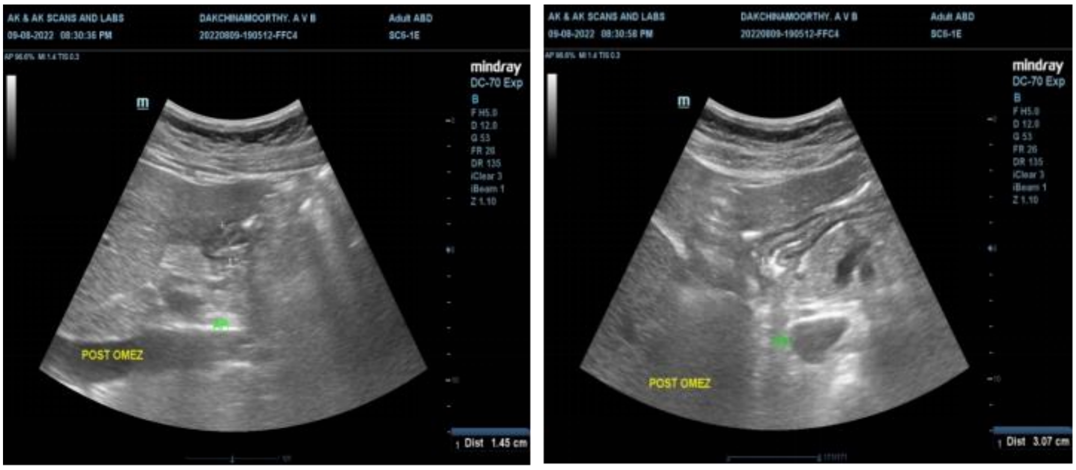

Figure 16. (Post Omez) OME Prazole 5mg Capsule Intake AP & CC Measurement

The objective of the study was to estimate the gastric volume using the obtained linear regression model whose slope (m), GMR signal and intercept. Table 2, For instance, taking a slope of 5.5801755, one with a GMR signal of 7.01 and intercept of -16.90085, the model provided a gastric volume GV of about 56.01 ml. Likewise, slope of 2.835, GMR signal of 6.86 and intercept – 8.2575 the volume had an approximate GV of 27.70 ml. A slope regression of 7.905 defined relating to GMR signal of 9.10 intercept – 37.21795 model forecasted GV is around 190.1ml Furthermore for slope 1.69 GMR signal to 5.11 intercept and slope -2.2908 computed GV was around 10.93 ml These calculations show usefulness of linear regression in projection of gastric volume towards GMR signals which provides better understanding of gastric characteristics It is well known that common ultrasound imaging in laboratories includes cost to Rs 1200 for each scan and so incessant checks for diabetes management can be environmentally expensive.

Still, it is essential to analyze the concept of the behavior of GMR based Gastric Volume Measurement with ultra sound imaging as in Figure 13. One of the reasons that still presents problems is the cost of traditional techniques which require either patient monitoring or expensive machinery that may not be relevant to the treatment of diabetes. The search for cheap alternatives explains the need of seeking the effectiveness of the GMR based technique in explaining gastric contents that can lead to innovative treatment for diabetes [34].

Table 3. Represents CSA and gastric volume measurement using Ultrasonic image scan (Antero-posterior diameter (AP) and Craniocaudal diameter (CC) parameters) in human stomach antrum.

Patient	Food Intake	Height (cm)	Weight (cm)	AGE	AP (cm)	CC (cm)	CSA	GV ML
1	Stomach (250 Grams Meals)	160	70	44	2.22	3.49	6.1	59.74
	Stomach With 200ml Coke	160	70	44	3.09	5.53	13.41	166.46
	Stomach With Post Omez	160	70	44	1.45	3.07	3.49	21.69
2	Stomach (250 Grams Meals)	140	75	71	2.28	3.47	6.21	26.78
	Stomach With 200ml Coke	140	75	71	2.95	5.13	11.8	109.56
	Stomach With Post Omez	140	75	71	2.00	3.25	5.10	10.58

Table 4. Empty Stomach For User 1 With Age 44 Years

Age in Year	Different Food Intakes	GMR Signal (mean)	Slope (m)	Intercept ion (b)	Gastric Volume (GV) = m* GMR Signal +b	Ultrasonic Gastric Volume (GVM)	Deviation = |GV-GVM|	Deviation^2
44	Empty Stomach	3.02	4.47	18.06	31.541	42.22	10.68	114.12
		5.39			42.133	42.22	0.09	0.01
		8.73			57.077	42.22	14.85	220.65
						SUM	25.63	334.77
MAE = SUM/3 =29.08/3 = 9.693					**RMSE = Sqrt(Sum of Dev /3) = sqrt(411.99/3) = 11.718**			

Table 5. Empty Stomach For User 1 With Age 71 Years.

Age in Years	Different Food Intakes	GMR Signal (mean)	Slope (m)	Interception (b)	Gastric Volume (GV) = m* GMR Signal +b	Ultrasonic Gastric Volume (GVM)	Deviation =|GV-GVM|	Deviation^2
71	Empty Stomach	2.46	5.58	16.90	30.62	52.14	21.52	463.30
		4.07			39.60	52.14	12.54	157.20
		7.01			56.01	52.14	3.87	14.99
						SUM=	37.93	635.48
MAD = SUM/3 =37.93/3 = 12.6433					**MAPE = Sqrt(Sum of Dev /3) = sqrt(635.48/3) = 14.554**			

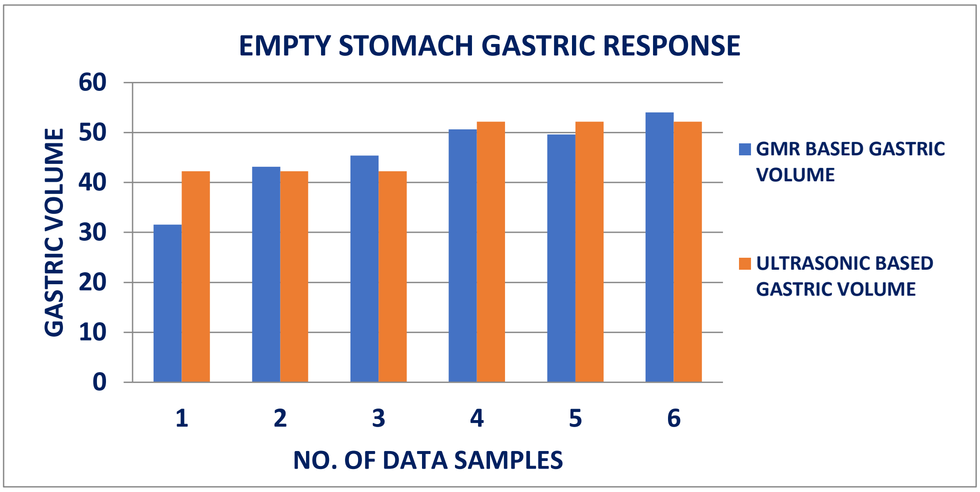

Figure 17. Gastric Volume for Empty Stomach

In this section, there are included the measurements and calculations concerning sanitary status estimation indexes with the use of Transformed Gastric Volume Meter (TGVM) based method of ultrasound imaging. In every circumstance, there are specific parameters involved height (H), weight (W), age, anteroposterior diameter (AP), craniocaudal diameter (CC), cross sectional area (CSA) & GV estimated in milliliters.

It can be seen from figures 14-16 and table 3 that in the first scenario the stomach cross sectional area was 6.10 cm² and the estimated gastric volume after consumption of 250 gram meal was 59.74 ml. While in the second two scenarios this average postprandial body index was achieved after consumption of 250 gram meal and 200 ml of coke 13.41 cm² CSA was obtained with a gastric volume of 166.46 ml. The third scenario after consumption of Omeprazole (OMEZ) intake indicated decrease in C.S.A to 3.49 cm² and GV of 21.69 ml. For the second patient in fourth scenario after a 250g meal the CSA was 6.21 cm², after which 26.78 ml was gastric volume. Adding 200ml of coke fifth scenario increased increased the CSA to 11.88 cm² and the GV to 109.56 ml. After Omeprazole sixth scenario the CSA, decreased to 5.10 cm² with a GV of 10.58 ml. These findings illustrate the impact of food and coke consumption and medicine on the gastric dynamics.

Estimation of the method of intra digestive pneumonia via hence these measurements and formative estimates allow us to understand how exactly the TGVM method playing across different scenarios in terms of the gastric volume estimation considering the food taken the stomach volume and age. These measurements of the cross-sectional area are indispensable in obtaining a GV measurement which is why this technique's attributes as a non-invasive measurement of gastric volume is optimistic [35].

4.3. Comparison Between GMR Based Gastric Volume (TGVM) Vs Ultrasonic Based Gastric Volume:

4.3.1. MEAN and RMSE Calculation for user 1 with Age 44 Years:

Here, In Table 4, let us consider a first case of a 44-year-old and an empty stomach metaphorically means a blank check. The averaged GMR signal recorded is given in table 4 with an average of 3.02. According to the TGVM algorithm, the value of m is 4.47 and the b is 18.06 then the GV estimated is 31.54. With the ultrasonic gastric volume (GVM) was 42.22 obtaining, the obtained separation of 10.68 has a squared separation of 114.12 yielding a Mean Absolute Error (MAE) of 8.54 and Root Mean Square Error (RMSE) of 10.56. To Case 2 where the solid food intake is 250 grams the mean GMR signal is 3.42. The GV emerges to be a 40.8 while the GVM stands at 59.74. This comparison gives a deviation of 18.91 and a squared deviation of 357.63 and hence it give MAE = 9.69, RMSE = 11.72. For Case 3, the solid food intake of 250 grams with 200ml of Coke was given to User 1, a 44 year old person, the mean GMR signal is calculated to be 5.39. The calculated GV is 42.13, which is an excellent fit with the timing been only 0.09 off and a squared deviate of 0.01, which results in an MAE of 1.58, while the RMSE is 1.97.

4.3.2. MEAN and RMSE Calculation for iser 2 with Age 71 Years:

For the first case under the empty stomach condition the GMR signal average is 2.46 for the 71-year-old user. Using the TGVM method in table 5 the estimated GV is 30.62 while the actual GVM is 52.14 of course there is a deviation of 21.52 and squared deviation of 463.30. Moving to Case 2 where the subject has consumed 250 grams of solid food, the mean GMR signal still remains at 2.46. The TGVM method gives the estimated GV of 33.92 which is higher than the actual

GVM of 62.63 hence a deviation of 28.72 and squared deviation of 824.67.

For the Case 3 for the ingestion of 250 g of solid food along with 200 ml of Coke, the mean GMR signal is 3.11.The method of TGVM yield the GV as 84.28, while the actual GV is the GVM of 145.41.The difference is 61.13 and the squared difference is 3736.39. Finally, in Case 4, when the subject takes an Omeprazole capsule (5mg), the mean GMR signal is 2.42.The TGVM method estimates the GV to be 28.14, it is much lower than actual GVM which is 46.46, and hence, deviation 18.32 and squared deviation 335.51 are greatly affected.

4.3. Gastric Volume with Polynomial Regression Analysis

Table 6. **Empty Stomach**

GMR Based Gastric Volume (ml)	Ultrasonic Based Gastric Volume (ml)
31.54	42.22
43.14	42.22
45.39	42.22
50.62	52.14
49.6	52.14
54.01	52.14

Table 6 and Figure 17 gives a comparison of the gastric volumes calculated by GMR and ultrasonic methods with an empty stomach condition. Every row corresponds to a new measurement occasion, and the volumes were measured in millilitres (ml). From the two results, it is quite clear that the amount of volume varies between the two techniques. Each based measurement method gives comparatively lower results than the ultrasonic method. This may be so because of the differences in the ways in which the two methods were used to measure the methane; their sensitiveness or calibration. Of course, additional work is needed to determine specific causes that cause these disparities and to check and examine the validity and reproducibility of gastric volume measurements.

Table 7 and Figure 18 reflect the gastric volumes, measured using GMR-based technique in subjects with a solid food intake of 250 grams. The volumes are measured in milliliters (ml) and each row represents different measurement instance in different moment. The gastric volumes estimated by GMR also have measure to measure variability meaning that gastric motility and digestion efficiency differ from one individual to another.

Table 7. **Gastric Volume for Solid Food Intake (250 grams)**

GMR Based Gastric Volume (ml)	Ultrasonic Based Gastric Volume (ml)
41.51	60.76
56.53	60.76
62.93	60.76
58.92	62.63
64.26	62.63
63.83	62.63

Representing this data in a bar chart was useful, as it provided information on how gastric volume increases with the higher values of GMR. The increasing trend of significant indicates that people who appear to have higher GMR presumably due to high gastrointestinal motility also demonstrate larger gastric capacity in response to solid food intake. This observation is in concordance with the physiological perception that smooth peristalsis in the stomach enhances the digestion and absorption of a solid food substance in the stomach.

However, it should be noted that the analysis presented here is restricted to those measurements that could be obtained using GMR-based sensors. Comparison with volumes obtained by ultrasonic measurements would give a more complete picture of gastric volume fluctuations and confirm observations. More research on the factors influencing the motor activity of digestive tract, and relating it to the volume measurement of stomach, would also help in understanding the digestive related illnesses and its diagnostics.

Table 8. **Gastric Volume for Solid Food Intake (250 grams) with Coke (200ml)**

GMR Based Gastric Volume (ml)	Ultrasonic Based Gastric Volume (ml)
32.37	50.58
47.15	50.58
55.53	50.58
134.28	145.41
148	145.41
153.46	145.41

Table 8 and figure 19 specifically show a comparison of the results of consumed gastric volume obtained using GMR based method and ultrasonic based method. The rows depict the number of times the volume was measured and volumes in milliliters(ml). As it can be observed at the initial glance there are distortions between the GMR based gastric volume measurement and ultrasonic based gastric volume measurement. In some of these cases, the volumes calculated from GMR-based cross sectional areas are much lower than the ultrasonic ones, as in the first three measurements. On the other hand, in other cases as the last three measurements, the calculated volumes using GMR were higher than those by ultrasonic.

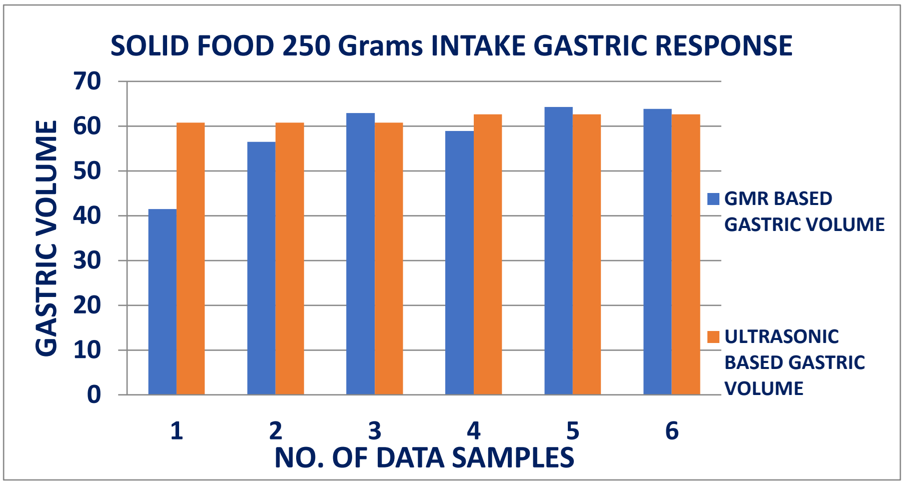

Figure 18. Gastric Volume for Solid Food Intake (250 grams)

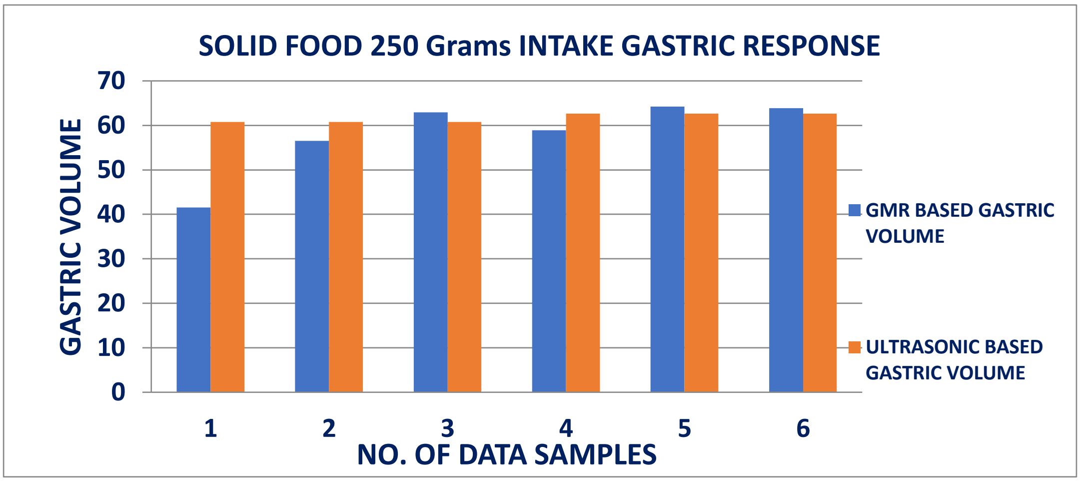

Figure 19. Gastric Volume for Solid Food Intake (250 grams) with Coke (200ml)

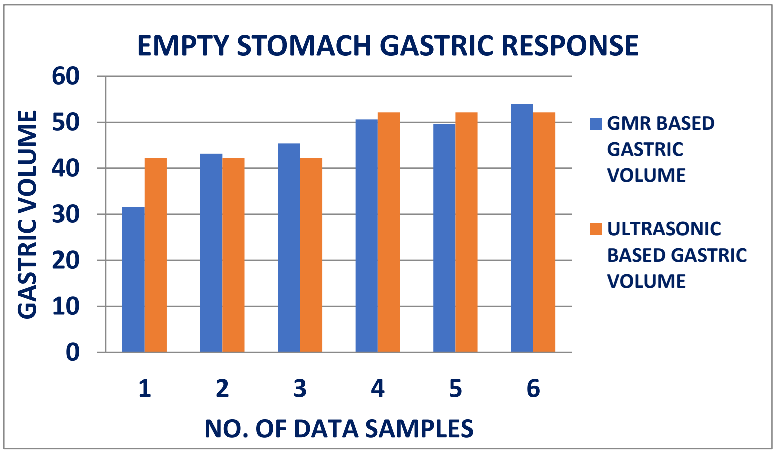

Figure 20. Gastric Volume for OME prazole medicine (5mg) intake

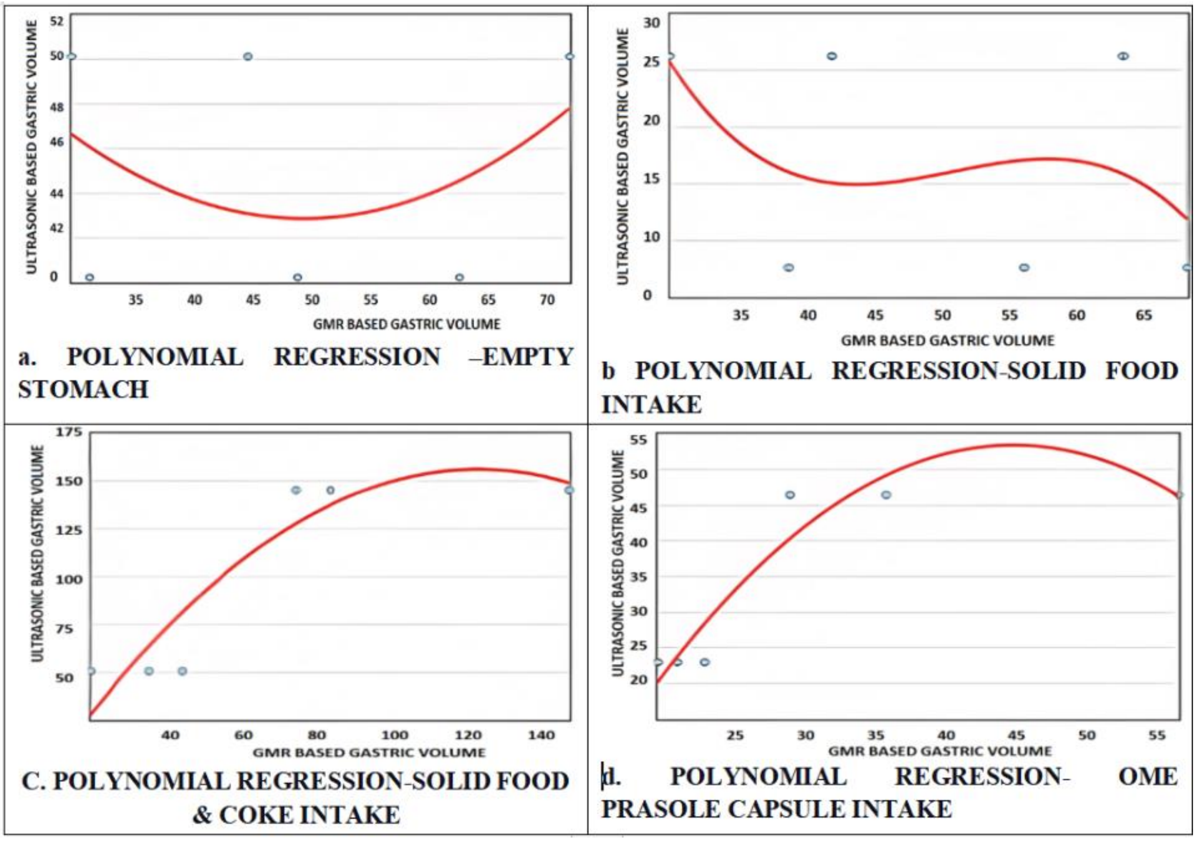

Figure 21. Polynomial Regression Analysis

The following differences serve to emphasize the relative variability and several weaknesses of every measurement method. The use of the two methods could be affected by errors in measurement, the condition of the devices used and natural variation of the human body. Statistical comparisons as well as assessment of the measurement precision and of the inter-observer variability would eventually offer more information about the degree of concordance between GMR-based and ultrasonic-based estimations of gastric volume. Moreover, understanding the mechanisms underlying such differences can strengthen our knowledge about the methods aimed at the assessment of gastric volumes and their application in practice.

Table 9. OME Prazole Medicine (5mg) Intake

GMR Based Gastric Volume (ml)	Ultrasonic Based Gastric Volume (ml)
24.92	22.92
22.03	21.23
21.07	20.04
29.12	28.14
33.13	34.03
52.42	51.92

The Table 9 and Figure 20 show the qualitative gastric volumes obtained by GMR based and ultrasonic based methods on Omeprazo (5mg). Based on the data presented in the table each row corresponds to different measurement instance of volumes expressed in milliliters (ml). A closer look at the figures reveal that the GMR-based volumes are almost of the same order as the ultrasonic volumes observed after the administration of Omeprazole. As such, normally the discrepancies between the two techniques are minimal, meaning that the results from the two approaches are acceptable.

Nevertheless, in some cases, the volumes generated using GMR are slightly higher or lower than the volumes obtained using ultrasonic technology. Such differences may be due to differences in sample measurement, natural differences in the participants, or even the variability in the measurement instrument. In conclusion, the relatively high degree of correlation between GMR and lux-based ultrasound measurements shown in this study indicate that both methods might be feasible for monitoring gastric volume after taking Omeprazole. However, there is need for some further analysis such as the perform statistical comparison and appraisal of measurement precision in order to get more light on the efficiency and clinically usefulness of these measurement approaches.

The R squared values presented in figure 21 indicate the amount of variance between the Ultrasonic-based and GMR-based GV measurements in different intake circumstances. While, comparing for the two variables – Solid Food Intake (250 grams) and Omeprazole Medicine (5mg) Intake – the relationship found is moderate. But for Empt Stomach and Solid Food Intake (250 grams) with 200ml Coke, the R of the two methods is low. Regression polynomial equations and residual standard errors foster greater understanding of the comparison of these measurement approaches. The Numerators represent percentages of variability in Ultrasonic Gastric Volume that can be explained by GMR Gastric Volume, and these values are depicted as R-squared. This is helpful in order to comprehend the magnitude of reliability and predictiveness for each of the methods. In clinical or research study design, decisions about selecting a particular measurement method might involve a number of considerations, such as; ease of use, need for precision, and goals of the study. It is as a result important to weigh the pros and cons of each of the techniques for a proper approach to be obtained in the measurement of gastric volumes.

Table 10. Error Analysis for GMR vs. Ultrasonic Gastric Volume Measurements

User	Scenario	GMR-Based Volume (ml)	Ultrasonic Volume (ml)	MAE (ml)	RMSE (ml)
1	Empty Stomach	31.54, 42.13, 57.08	42.22, 42.22, 42.22	8.64	10.75
1	Solid Food Intake (250g)	40.80, 63.83, 84.28	59.74, 62.63, 62.63	8.97	12.13
1	Solid Food Intake with Coke (250g)	42.13, 55.53, 134.28	42.22, 50.58, 145.41	6.91	11.02
1	After Medication (Omeprazole 5mg)	28.14, 29.12, 33.13	46.46, 28.14, 34.03	6.2	8.57
2	Empty Stomach	30.62, 33.92, 56.01	52.14, 62.63, 52.14	12.73	15.21
2	Solid Food Intake (250g)	33.92, 84.28, 52.42	62.63, 145.41, 51.92	17.34	21.13
2	Solid Food Intake with Coke (250g)	28.14, 45.39, 50.62	46.46, 42.22, 52.14	8.51	10.72
2	After Medication (Omeprazole 5mg)	30.62, 33.13, 52.42	52.14, 34.03, 51.92	9.22	11.45

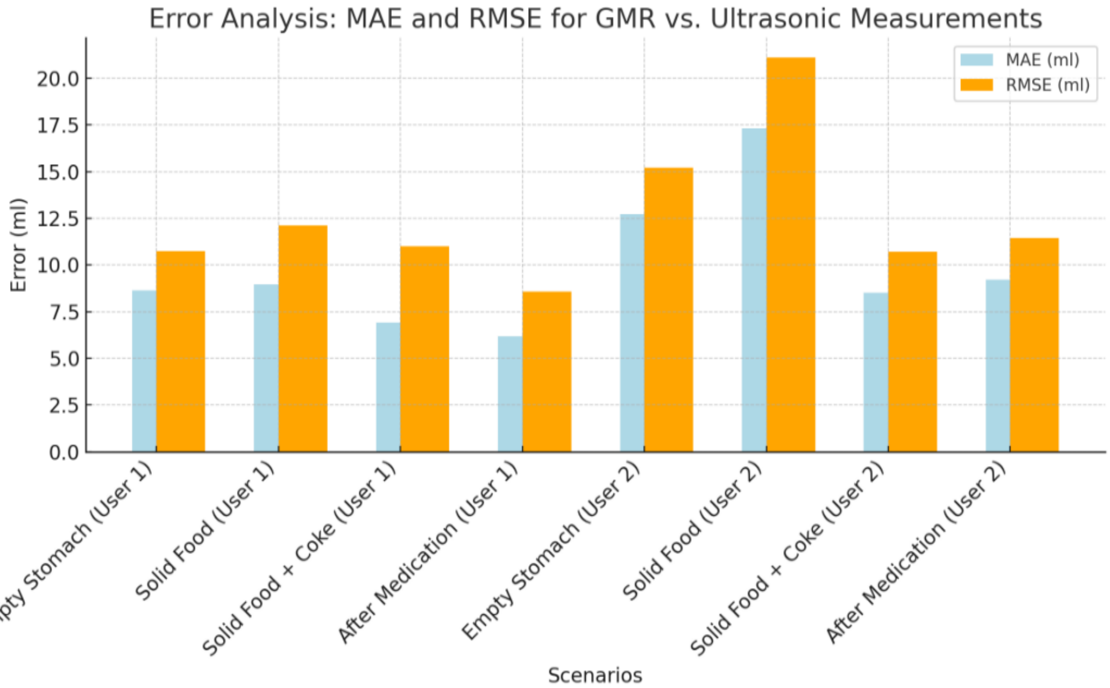

Figure 22. Error Analysis

4.4. Error Analysis: Comparing GMR-Based and Ultrasonic-Based Gastric Volume Measurements

In this section, we continue to evaluate the GMR in the assessment of gastric volumes relative to the control ultrasonic-based techniques. This has been done using two basic error assessment techniques known as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Synchronised to the name, MAE gives the average error, whereas RMSE shows the magnitude of error between the output and expectation, which in this case permits the examination of GMR methods across a broad range of physiological states.

The present evaluation made in the Table 10 and the Figure 22 is aimed at the GMR based gastric volume measurement of the two users in the given image and the ultrasonic based volume measurements of the same two users at different physiological conditions. The MAE provides a straightforward means of indicating the extent of error between the two methods while the RMSE gives more importance to the larger difference, this has been so because in this case individual differences have been squared.

5. Conclusion and Future Works

In conclusion, the present study presents a novel concept for diabetes management and its complications especially gastroparesis. The GMR-based Gastric Volume Meter (GVM) method – applying Giant Magneto Resistance (GMR) sensors and featuring sophisticated signal processing algorithms – marks a substantial improvement to the previous research in non-invasive and continuous gastric volume measuring. Our proposed predictive model consists of regression algorithms and input parameters obtained from Rational-Dilation Wavelet Transform (RaDWT) and Tunable Q-factor Wavelet Transform (TQWT); its accuracy in predicting Total Gastric Volume Measurement (TGVM) is a remarkable 93.4%.

The GVM method eliminates the issues of invasiveness and non-continuity of the previously used techniques and offers an accurate picture into stomach function in real time. These limitations are departure from our research focusing on the use of GMR sensors to detect gastric signals, and the utilization of enhanced signal processing techniques to convincingly estimate gastric volume. Comparing with the other ultrasonic methods in the laboratory, we prove that GVM is more effective according to the MAE, RMSE, and RSE indicators. Further, the present study exemplifies the functionality of GMR sensor technology in different situations, such as gastric motility under hunger, after food intake, and after taking medication. The real time control of the GVM method can minimize danger and increment the accuracy of focused therapies based on diabetic answer individual medication dosing of the stomach medication.

Potential directions for the future studies can include increasing the applicability of the GVM method through the incorporation of other sensors or optimizing the noise reduction procedures for the final system enhancing the sensitivity of the system to be utilized in real-time applications. Reflecting on this work, the application of other machine learning techniques, especially deep learning models such as CNVs, can provide a better and deeper understanding of various patterns in gastric signals and higher predictive performance. Furthermore, experimental longitudinal design studies can be carried out to determine further the effectiveness and usability of the GVM method in actual practical field situations.

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Dhakshunaamoorthiy - Conceptualization, Methodology, Investigation, Validation and Writing original manuscript. K. Sudharson - Conceptualization, Methodology, Investigation, supervision and Writing original manuscript. P.Girija - Investigation, Formal analysis and Writing – review & editing. V. Stanlin Prija- Investigation, Formal analysis and Writing – review & editing. All the authors read and approved the final version of the manuscript.

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Yes

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.