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Toward a Mathematical Approach to Sound Waves for Enhancing Digestive Health

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Abstract: The growing interest in noninvasive health monitoring has motivated research into using digestive system sounds as diagnostic indicators. This study proposes the Mathematical Formula for Systematic Digestive Sounds (MFSDS), a method that converts abdominal audio signals into mathematical formulas for automated analysis. The approach integrates devices from the Internet of Things (IoT), signal processing, and artificial intelligence to address challenges such as acoustic complexity, environmental noise, and individual variability. Experimental evaluation with datasets of 25, 50, and 100 formulas achieved similarity rates between 50% and 67%, indicating potential for improvement. Although initial accuracy remains below clinical application thresholds, the results suggest that the integration of advanced AI techniques could improve precision and adaptability. The MFSDS framework offers a novel perspective for preventive healthcare and real-time gastrointestinal monitoring.

Keywords: stomach monitoring, mathematics in health, sound health, monitoring, stomach noise
Categories: H.3.1, H.3.2, H.3.3, H.3.7, H.5.1
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1 Introduction

As we move into the digital age, electronic devices have become integral to daily life, transforming communication, work, and healthcare. Artificial intelligence (AI) and big data have improved diagnostics, treatment planning, and efficiency in healthcare institutions [Al-Dmour et al. 2025]. Technological advances continue to drive innovative healthcare solutions [Yadav 2024]. Wearable technologies have become key tools for real-time health monitoring, with devices such as smartwatches, smartbands, blood pressure and glucose monitors, and portable ECGs enabling the collection of real-time health data. The Internet of Things (IoT) has further advanced healthcare by collecting time series data such as ECG signals, respiratory rates, and heart rates [Cao et al. 2023], which are analyzed by healthcare centers using machine learning techniques such as Long Short-Term Memory (LSTM) networks.

The Mathematical Formula for Systematic Digestive Sounds (MFSDS) offers a novel, noninvasive approach to monitoring intestinal health. Using advances in peripheral devices and the Internet of Things (IoT), it automates digestive sound analysis. Improvements in vibration and audio capture have improved diagnostic accuracy and treatment in healthcare. Although traditional auscultation with stethoscopes remains common due to its simplicity, modern tools like audiometry, echocardiograms, and ultrasound provide more precise diagnostics. These technologies enable a detailed analysis of digestive system sounds, helping to detect conditions such as severe hunger [Maria and Jeyaseelan 2021]. Early detection of the presence of food in abdominal sounds is crucial for optimizing devices such as artificial pancreases [Kumar et al. 2019]. In this context, emerging tools for digestive sound analysis extend these innovations, opening new possibilities for monitoring gastrointestinal health.

This study examines digestive sound analysis as a technological approach to persistent gastrointestinal challenges. Digestive disorders affect hundreds of millions globally and are linked to malnutrition, diabetes, and chronic conditions [Marathe et al. 2024], underscoring the importance of noninvasive monitoring for early detection and prevention. Unlike earlier research, which focused mainly on classification accuracy [Güvenç et al. 2024], this work introduces a mathematical modeling framework that translates digestive sounds into structured formulas, improving explainability and facilitating integration of artificial intelligence into biomedical workflows. Advances such as audiovisual analysis for abdominal sound mapping [Dimoulas 2016], intrinsic mode function–fractal dimension filtering for distinguishing normal and abnormal sounds [Grizzi et al. 2023], and IoT-based devices (I-DAQ, Raspberry Pi, ESP32) achieving 84.3% accuracy in gastrointestinal analysis [Güvenç et al. 2024] demonstrate the growing potential of this field. Building on these innovations, the present study emphasizes mathematical modeling as a means to derive new indicators of microbial metabolic activity, enabling sensitive monitoring of anaerobic digestion (AD) processes [Nie et al. 2023]. Nevertheless, challenges such as sound complexity, subjectivity, technological limits, and individual variability continue to hinder progress.

This study seeks to explore how the conversion of these sounds into mathematical formulas can reveal new patterns, potentially advancing medicine and healthcare. However, capturing and analyzing these sounds is difficult, mainly due to the need for devices to adapt to the dynamic structure of the abdomen and maintain consistent skin contact during respiration [Lee et al. 2021]. Environmental noise is a major challenge in digestive sound analysis, as external sounds such as speech and door noise can impair meal detection, requiring testing under noisy conditions and noise cancellation techniques [Kumar et al. 2019]. Furthermore, the non-linear and poorly understood properties of abdominal sound propagation affect noise levels and quality [Dimoulas 2016]. Limited datasets further hinder analysis, emphasizing the need for larger samples before clinical use [Kumar et al. 2019]. These challenges highlight the importance of interdisciplinary efforts to improve the reliability of stomach sound analysis in healthcare.

The fundamental research question that guides this study is the following:

How can a mathematical formula representing the states of the digestive system be used to derive indicators of its functionality and evaluate human health?

To address this research question, the study explores the use of mathematical representations of digestive sound analysis states and translates them into possible practical tools and insights, resulting in the following scientific contributions:

- Integration of AI and Mathematical Tools: The MFSDS Algorithm integrates artificial intelligence with mathematical tools like Euler's formulas and the Discrete Fourier Transform to analyze intestinal sounds. Initially using 100 formulas, it achieved an accuracy of 70%, while smaller sets yielded a lower precision (50% with 25 formulas and 60% with 50). Future developments plan to use regressive artificial language processing to automate formula generation, enhance real-time digestive health monitoring, and transform diagnostic capabilities in healthcare.

- Innovative Preventive Healthcare Approaches: The hypothesis suggests that the conversion of wave sounds into mathematical formulas can lead to innovative health solutions, especially in preventive care and personalized medicine. Automated algorithms can transform early detection by enabling real-time identification of health risks, promoting proactive healthcare, and helping to reduce chronic and acute digestive disorders.

- Technological and Occupational Health Contributions: This study conceptually contributes to the development of innovative products and devices by automating digestive sound analysis through mathematical algorithms for pattern recognition. These technologies enable real-time monitoring and early detection of gastrointestinal issues, assisting healthcare professionals by efficiently handling large volumes of data for more personalized care. Research also supports occupational health by analyzing digestive sounds to assess employee health. Offered as an open-source solution, it encourages wider adoption and further research. Integrating mathematical models into this field promotes biotechnological innovation and improves healthcare efficiency. The application is available at github.com/kevinlimak10/MFSDS, the corresponding dataset can be accessed at kaggle.com/datasets/kevinlima/mathematical-formula-systematic-digestive-sounds.

2 Related Work

To establish the theoretical foundation of this study, it is essential to outline the physical and biological principles that underlie the analysis of digestive sound signals. Sound waves, defined by frequency and amplitude, are governed by physical laws and continue to be studied in physics. The digestive system, in contrast, functions through complex biochemical processes. At their intersection, bioacoustic signals offer valuable insight into gastrointestinal health and internal physiology. Sound waves are disturbances traveling through matter, created by vibrations that produce compressions and rarefactions. Frequency determines pitch, and amplitude defines volume. Sound, as a form of energy, is transmitted through waves [Goldsmith 2015]. Wave behavior can be described through particle motion or field changes, with acoustic complexity that involves bass, treble, and midtones. Wave propagation is generally modeled using a partial differential equation common to many physical systems [Freegarde 2012].

The digestive system processes and absorbs nutrients through specialized organs such as the mouth, stomach, intestines, liver, and pancreas [Martinez and Hartenstein 2019].

Digestion begins in the mouth and continues through the gastrointestinal tract, with nutrient absorption occurring primarily in the small intestine. Despite its efficiency, the system is prone to disorders such as GORD and ulcers [Healthdirect Australia 2023]. Digestion is regulated by coordinated actions of the nervous, endocrine, and gastrointestinal systems, which integrate behavioral and hormonal signals [Johnson and Gerwin 2007]. Enzymes, including brush border enzymes, aid in nutrient breakdown and absorption, highlighting the system's complexity and interdependence. The human digestive system generates complex bioacoustic signals that are important for gastrointestinal health. Devices capturing these sounds need flexibility and skin conformity to accommodate abdominal motion [Lee et al. 2021]. Environmental noise, such as voice and door sounds, complicates analysis and requires robust noise cancellation [Kumar et al. 2019]. Accurate localization and mapping are essential and must be tested in real settings [Dimoulas 2016]. Despite the challenges in modeling abdominal sounds, they show potential for early food detection in realistic noisy conditions [Kumar et al. 2019].

Building on these theoretical considerations, it was necessary to conduct a systematic review of the literature to identify existing studies that address the relationship between digestive processes, sound analysis, and health monitoring. The research used multiple academic search engines to identify relevant articles. The portals used were PubMed, Elsevier, IEEE, ScienceDirect, Scielo, and Google Scholar. The following search string was applied during the literature review:

> ("sound" OR "audio") AND ("digestive" OR "health" OR "gastrointestinal" OR "meal detection") AND ("microsensors" OR "wearable bioelectronics" OR "monitoring")

In the past two years, more than 300 articles have been published, with two focusing on gastrointestinal monitoring and digestive health [Yadav 2024, Güvenç et al. 2024]. Upon expansion to five years, about 1,500 articles were found, including around 150 related to digestive topics [Cao et al. 2023, Grizzi et al. 2023]. A 10-year search yielded nearly 2,300 results, highlighting the growing interest in research in this field. The research methodology, shown in Figure 1, has three parts. The Base section covers the digestive system, sound waves, and AI research, providing foundational knowledge and initial research steps. The Supporting Information section addresses healthcare monitoring challenges and models to tackle them. The Specification section focuses on specific methods for monitoring digestive sounds, used to model, compare, and validate results, with a narrower scope than the previous sections.

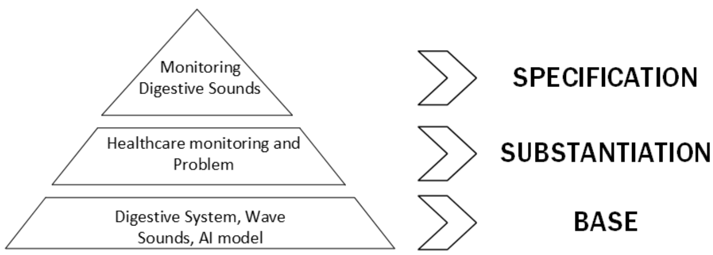

Figure 1: Related work selection stage

2.1 Selected Works

The works selected and described below represent important contributions to the field of abdominal sound analysis and health monitoring. The studies are briefly summarized to highlight their objectives, methodology, and significant findings.

Choi et al. [Choi et al. 2024] developed a novel noninvasive sensor for real-time monitoring of human sound and movement signals. The sensor demonstrates high piezoelectric performance and biocompatibility, which allows it to operate as a self-powered device without the need for external batteries. Morphological and biocompatibility tests confirm its safety and potential for practical health monitoring applications.

Güvenç et al. [Güvenç et al. 2024] focused on the analysis of intestinal sound (bowel sounds (BS)) using a discriminative Common Vector Analysis (CVA) approach. The CVA is a statistical classification method that reduces high-dimensional data to a lower-dimensional subspace, emphasizing differences between classes by computing a representative 'common vector' for each class, which enables accurate extraction of distinctive acoustic patterns from complex bowel sounds. Their methodology improves the accuracy of BS detection, achieving an 84.3% recognition rate, and covers signal acquisition, preprocessing, feature extraction, and classification, making it a reliable tool for abdominal sound classification.

Grizzi et al. [Grizzi et al. 2023] investigated the irregular patterns and self-similar patterns of the gastrointestinal system through fractal geometry. This study highlights the limitations of Euclidean geometry in describing complex digestive structures and emphasizes the value of fractal analysis to understand both physiological and pathological aspects of the GI tract.

Lee et al. [Lee et al. 2021] explored the use of digital stethoscopes for noninvasive monitoring of bowel sounds. The device accurately records bowel sounds during respiratory changes and demonstrates the potential of flexible electronics to monitor the bowel environment, although more work is needed on noise reduction and algorithm improvement.

Maria and Jeyaseelan [Maria and Jeyaseelan 2021] proposed the BWP-DHOA-RNN method to detect a hungry stomach using audio signals. The method is a deep learning architecture designed for sequential data, capable of capturing temporal dependencies within the signals. Applied to bowel sound analysis, RNNs learn dynamic patterns over time, allowing automated detection of physiological states, such as hunger, and providing a robust framework for noninvasive monitoring of digestive health. This approach outperforms existing techniques, achieving a high precision of 93.75% in automated hunger detection.

Kumar et al. [Kumar et al. 2019] presented a pilot study on the detection of food through abdominal sounds, reporting detection accuracies of 75% for one subject and 50% for another. However, the study noted delays in response times, emphasizing the need for improved detection accuracy and real-time responsiveness.

Although recent contributions have advanced abdominal sound analysis. Sensor-based approaches ([Choi et al. 2024] and [Lee et al. 2021]) demonstrate feasibility, but are vulnerable to noise and inconsistent signal quality. Structural models [Grizzi et al. 2023] reflect gastrointestinal complexity but do not yet yield clinically actionable metrics. Early computational work [Kumar et al. 2019] suffered from low accuracy and slow response. Later machine learning frameworks ([Güvenç et al. 2024] and [Maria and Jeyaseelan 2021]) improved performance, but their opaque architectures limit clinical trust. These shortcomings in robustness, timeliness, and interpretability underscore the need for explainable methods.

2.2 Comparison of Selected Works

Table 1 summarizes the key results of the selected studies, highlighting their precision and main contributions. The studies vary in their main focus and reported accuracies. Maria and Jeyaseelan [Maria and Jeyaseelan 2021] achieved the highest accuracy (93.75%) for the detection of hungry stomachs using audio signals, indicating significant progress in this niche. Güvenç et al. [Güvenç et al. 2024] reported 84.3% accuracy in bowel sound detection by applying advanced vector analysis techniques, improving classification performance.

Authors (Year)	Accuracy	Results
[Choi et al. 2024]	-	Real-Time Monitoring and sensor have high sensitivity.
[Güvenç et al. 2024]	84.3 %	Vector analysis enhances bowel sound detection.
[Grizzi et al. 2023]	-	Potential application in biomedical fields.
[Lee et al. 2021]	-	Accurately collects bowel sounds from the abdomen.
[Maria and Jeyaseelan 2021]	93.75 %	Great performance in hungry stomach detection.
[Kumar et al. 2019]	75 %	High detection accuracy rate at meal detection.

Table 1: Comparison of related work

In contrast, Kumar et al. [Kumar et al. 2019] demonstrated promising meal detection accuracy (75%) but noted delays that affected real-time response. Other works such as [Choi et al. 2024], [Grizzi et al. 2023], and [Lee et al. 2021] focus more on device development, fractal analysis, and signal collection, respectively, and do not provide direct accuracy metrics but contribute significantly to methodological and technological progress. Collectively, these studies highlight the trend toward improving noninvasive abdominal sound monitoring through advanced signal processing, novel sensor design, and computational modeling. They underscore the importance of accuracy, responsiveness, and robustness for future clinical and practical applications.

3 MFSDS Model

To address the research problem, the MFSDS framework was designed to transform abdominal audio signals into formal mathematical representations. Given a discrete signal x(t), spectral decomposition is obtained through the Discrete Fourier Transform (DFT):

$$X(\omega k)\triangle \sum_{n=0}^{N-1} x(tn)e^{-j^{\omega}k^{t}n}, k = 0, 1, 2, ..., N-1$$

where the complex exponential term, defined by Euler's identity $e^{j^{\omega}k^{t}n} = \cos(j^{\omega}k^{t}n) + j\,\sin(j^{\omega}k^{t}n)$, establishes a direct correspondence between digestive sound waves and their sinusoidal components. From this formulation, amplitude, frequency, and phase features are extracted and subsequently vectorized. The descriptors serve as input to two complementary analytical strategies. First, Random Forest classifiers are used to predict spectral parameters. Second, a convolutional neural network based on the VGG16 architecture is applied. This network employs three-by-three convolutional filters, max pooling layers, fully connected layers, and dropout regularization. The dataset is divided into training and testing subsets, and performance is assessed systematically using accuracy metrics. Together, these steps ensure that digestive sound signals are rigorously translated into mathematical representations, enhancing the interpretability and reproducibility of gastrointestinal monitoring.

3.1 Process Steps

The implementation procedure, illustrated in Figure 2, begins with an audio file that is preprocessed by decomposing it into channels and frames and then segmented into smaller chunks for efficient handling. The study employs the VGG16 architecture for feature extraction, selected for its balance of accuracy, simplicity, and interpretability when compared with more recent models such as ResNet and Inception. ResNet requires deeper residual connections and consequently higher computational resources, as described in [He et al. 2024], while Inception's multi-scale convolutions, although enhancing feature diversity, introduce architectural complexity and higher parameterization that can hinder real-time or embedded deployment. In contrast, the study of Zakaria et al. [Zakaria and Hassim 2024] relate, VGG16's uniform 3×3 convolutional filters enable hierarchical feature extraction without heavy hardware demands, which is critical in the MFSDS framework where interpretability and limited data availability are essential.

VGG16 has been extensively validated in biomedical contexts, as emphasized by Güvenç et al. [Güvenç et al. 2024], providing a robust and reliable baseline for digestive sound analysis and related applications. In this work, pre-trained ImageNet weights are employed to ensure robust performance while reducing the need for extensive retraining. In this implementation, the block5_pool layer of VGG16 is used to extract high-level features, capturing abstract patterns essential for comparison tasks. By removing the top classification layers, the model functions solely as a feature extractor, producing rich, high-dimensional vectors well-suited for similarity measurement. The similarity between extracted features is computed using cosine similarity, a widely used metric for comparing high-dimensional vectors. Audio segments are compared by similarity to a known dataset to evaluate precision, with precision metrics computed via aggregation and statistical methods. Intermediate results are temporarily stored in memory and later saved for analysis.

As illustrated in Figure 3, VGG models are widely used for image classification, Zakaria et al. [Zakaria and Hassim 2024] describe the VGG models are easy to understand, modify, and experiment with due to their series of small, uniform filters. A key innovation of VGG16 is the use of multiple small 3×3 filters to deepen the network, improving performance while maintaining a manageable number of parameters. The VGG16 architecture comprises 13 convolutional layers, five pooling layers, and three fully connected layers, allowing it to capture intricate features while keeping complexity tractable. Each layer can represent the level of gene expression at time t, as described by Vohradský [Vohradský 2001]. While fully connected layers are computationally intensive and may challenge front-end deployment, the relatively straightforward architecture of VGG16 reduces overall complexity, mitigates overfitting risks, and allows easier interpretation of key factors for clinical adoption. In this context, "computing" refers to resource consumption, whereas "process" denotes the sequence of steps involved in implementing the model. At the same time, VGG16 can face training challenges such as

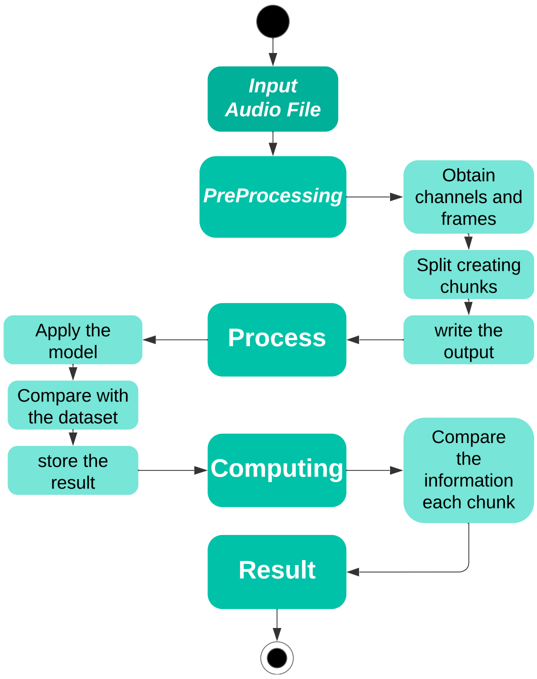

Figure 2: General activity diagram

vanishing gradients and slow convergence. Although alternative architectures such as ResNet or Inception may offer benefits in computational efficiency or deeper feature representation, VGG16 remains a robust choice due to its balance of simplicity, strong performance, and extensive validation in complex medical datasets, as emphasized by Hcini et al. [Hcini et al. 2022].

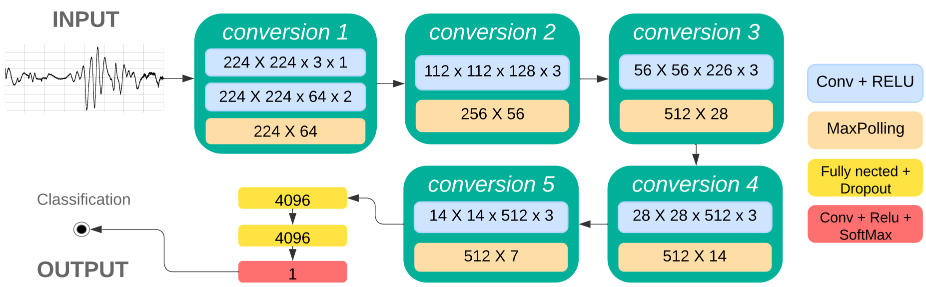

Figure 3: Model activity diagram

3.2 Responsibilities and Roles

This model is organized into six distinct classes, each assigned a specific responsibility, as illustrated in Figure 4. The `Wave` class serves as the core component of the audio data processing pipeline. Initiates the process by encapsulating functionalities for audio wave preprocessing, chunk creation, and sample normalization. The `pre_process()` method initializes the necessary attributes, invokes the `create_chunks()` method, and stores the results in memory for subsequent access. The `create_chunks()` method receives the audio wave as input, segments it into multiple parts, generates a list of audio segments, and converts these into instances of the `Plot` class. The `normalize_sample()` method is applied to reduce the noise in the audio signal, thus minimizing its impact on later processing stages. The `DFT` class encapsulates the implementation of the Discrete Fourier Transform (DFT). It maintains attributes for the signal, sampling rate, and frequency components required to apply the DFT. The `apply_dft()` method leverages these attributes to compute the DFT and returns the result as a `Plot` object. The `compute_dft()` method is responsible for performing the DFT computation on individual frames, transforming them from the time domain to the frequency domain.

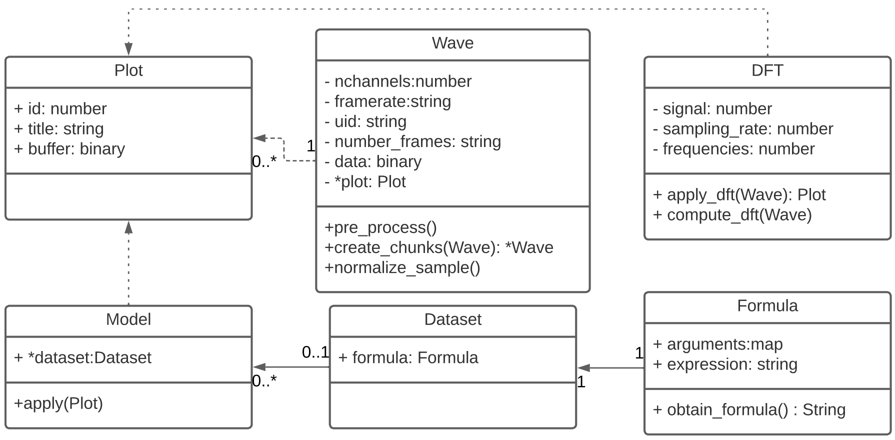

Figure 4: Class diagram

The `Plot` class represents a clean and computed image object used within the model. It serves as a visual representation of a waveform and contains metadata such as the original audio reference and a title, which aids in debugging. The `buffer` attribute stores the image data in binary format. The `Formula` class encapsulates a mathematical formula. It includes attributes such as `arguments`, stored as a map for dynamic value replacement, and `expression`, which holds the complete mathematical expression without substitutions. The `obtain_formula()` method uses the `arguments` map to dynamically replace variables in the expression. The `Dataset` class represents a collection of `Formula` objects and serves as the input reference for the `Model` class. The `Model` class is the central processing unit of the system. Its `apply()` method uses an algorithm based on the VGG (Visual Geometry Group) network to perform conversions. This method prepares and executes the comparison between `Plot` objects and predefined `Formula` instances. The algorithm assesses precision by measuring the similarity between waveform representations and mathematical formulas, ensuring accurate and reliable comparisons.

The `Neural` class serves as a pivotal component within the audio data processing framework, managing essential tasks related to dataset handling, neural model training, real-time data processing, classification and analysis. This class is responsible for organizing and maintaining the dataset used to train the neural network. It includes methods to load, structure, and ensure the dataset's readiness for model training. A key function of the `Neural` class is to train a sequential neural model using the stored dataset. Using machine learning libraries or frameworks, the training pipeline is coordinated by feeding the dataset into the model over multiple iterations, adjusting parameters, and optimizing performance. These processes enable the model to learn patterns effectively from the input data, preparing it for accurate classification and prediction tasks.

3.3 Error Analysis

The paragraph explains the importance of waveforms like sine, square, and sawtooth in sound synthesis because of their unique harmonic traits. According to Freeman [Freeman 2023], the sine wave is the simplest, producing a pure tone with only the fundamental frequency. The square wave has odd harmonics with decreasing amplitudes, creating a sharp timbre, whereas the sawtooth wave includes both odd and even harmonics, producing a bright, choppy sound. These form the basis for seven types of waveforms. A dataset was generated using a Python script, using a 1-second duration, a 44.1 kHz sampling rate, and a 5 Hz base frequency with slight variations to mimic natural changes. The dataset includes seven waveform types: sine, square, triangular, sawtooth, white noise, pink noise, and rectangular. Each has distinct characteristics: sine waves are smooth and periodic; square and rectangular waves alternate levels but differ in duty cycle; triangular and sawtooth waves have linear transitions; white noise has random amplitudes with flat spectral density; and pink noise applies frequency-dependent scaling to white noise for a balanced spectrum.

To aid in visualization, ten variations of each waveform were plotted, emphasizing their unique features and harmonic structures. The waveforms were organized into separate directories, making the dataset well-structured and useful for sound synthesis research and analysis. To assess the precision of classification, a confusion matrix was created, as shown in Figure 5. The results show high accuracy across most waveforms, with Pink Noise, Rectangular, Square, and White Noise each reaching 99 correct classifications. The sine and Sawtooth waves also performed strongly, with 95 and 96 correct predictions, respectively. Some misclassifications occurred: the Sine Wave had four errors, the Sawtooth Wave three, and the Triangular Wave faced the most challenges with 20 misclassifications. This likely results from overlapping harmonic content causing confusion with Sawtooth or Sine waves, emphasizing the difficulty of distinguishing waveforms with similar spectra and the need for advanced feature extraction in signal processing.

3.4 Aspects of Implementation

For this, we use the equations of modulation of waveforms [Carcione 2009]. The wave function equation for a sinusoidal wave is expressed as:

$$x(t) = A\sin(\omega t + \phi) \tag{1}$$

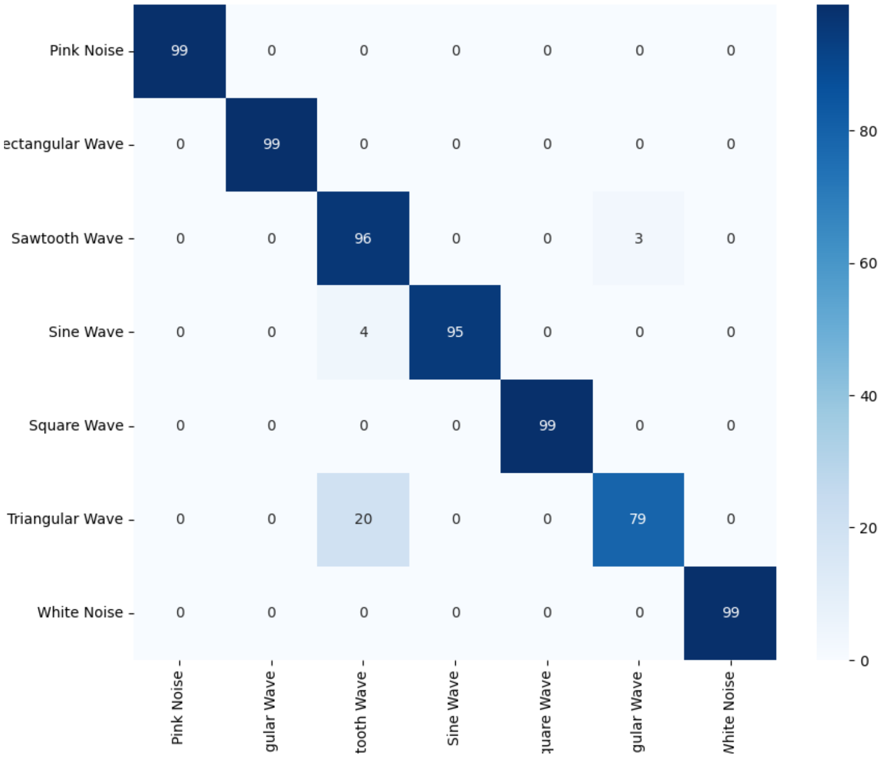

Figure 5: Confusion Matrix

This equation encompasses several parameters, where A represents the peak amplitude, which is non-negative and denotes the maximum value of the wave. The term ω is the radian frequency, measured in radians per second, indicating the rate of oscillation. The variable t stands for time, the independent real variable measured in seconds, and ϕ is the initial phase in radians, determining the starting angle at $t = 0$. In audio applications, these parameters have specific interpretations and typical values. The peak amplitude A is often simply referred to as the ”amplitude”. For instance, the statement “the amplitude of the tone was measured to be 5 Pascals” describes the peak value of the wave's oscillation. The radian frequency ω is given by formula $\omega = 2\pi f$, where f represents the frequency in hertz (Hz), which measures the number of cycles per second. The instantaneous phase $(\omega t + \phi)$ is the phase of the wave at any given time t. Due to the periodic nature of the sine function, which repeats every 2π radian, the initial phase ϕ can be considered within any 2π interval [Smith 2007].

Where $y(x,t)$ represents the wave sprain at position x and time t. The parameter A, it is the amplitude, determines the wave's maximum displacement from its equilibrium position, indicating the peak value of the wave's oscillation and reflecting the wave's energy and intensity. The λ stands for the wavelength of the wave, representing the spatial length between two consecutive identical points on the wave. v denotes the velocity of the wave, indicating the speed at which the wave propagates. 2π is a constant that converts radians to cycles within the sine function. $x - vt$ is the combination of position x and time t, signifying how far the wave has traveled from its initial position. This equation allows us to describe how a sinusoidal wave changes its shape and position over time and space. This function describes the behavior of sinusoidal waves in a specific medium and helps in modeling and understanding wave behavior, such as the propagation, amplitude, wavelength, and frequency of waves.

The linear wave equation relates the spatial and temporal derivatives of the displacement $y(x,t)$ and is given by:

$$\frac{\partial^2 y(x,t)}{\partial x^2} = \frac{1}{v^2} \cdot \frac{\partial^2 y(x,t)}{\partial t^2}$$

This equation demonstrates the relationship between the second spatial derivative of displacement with respect to position x and the second temporal derivative of displacement with respect to time t. The parameter v represents the speed of the wave, indicating how fast the wave propagates through a medium. The equation states that the rate of change of displacement with respect to space is related to the rate of change of displacement with respect to time through the square of the wave speed. This equation establishes the connection between the spatial and temporal derivatives of a wave's displacement and is used to study wave phenomena, predict wave behavior, and derive mathematical models in fields such as acoustics, optics, electromagnetism, and quantum mechanics. The velocity is essential for determining how fast a wave propagates through a given medium, helping predict the speed of sound, light, or other types of waves in various materials. With this equation, it is also possible to calculate the velocity of a wave using its wavelength and frequency.

$$v = \lambda \cdot f$$

Where v represents the velocity of the wave, λ denotes the wavelength of the wave, depicting the spatial extent between two successive identical points, and f stands for the frequency of the wave, indicating the number of cycles or oscillations per unit time. This equation shows that a wave's velocity is the result of multiplying its wavelength by its frequency. It helps in understanding the concept of interference in wave systems. The Equation of Superposition is used to demonstrate how individual waves combine to form a resultant wave. Superposition is crucial for comprehending phenomena such as constructive and destructive interference in wave optics, acoustics, and signal processing. The equation representing the superposition of two waves is as follows:

$$y(t) = 2A \cos\left(\frac{\omega_2 - \omega_1}{2} t\right) \cos\left(\frac{\omega_2 + \omega_1}{2} t\right)$$

This equation describes how two sinusoidal waves with slightly different frequencies combine to form a new wave with distinct characteristics. Each term in the equation plays a specific role in shaping the resultant wave. In this context, A represents the amplitude of the individual waves; for simplicity, it is assumed that both waves have the same amplitude. The symbols ω_1 and ω_2 denote the angular frequencies of the first and second waves, respectively, while t is the time variable. The equation is derived from the superposition principle, which asserts that the combined wave is the sum of the individual ones. When two waves with slightly different frequencies are superimposed, they produce a time-varying pattern known as the beat phenomenon [Aguilar et al. 2012].

3.4.1 DFT - Discrete Fourier Transform

The Discrete Fourier Transform (DFT) defines the transformation of a discrete time signal $x[n]$ into its frequency domain representation $X(\omega_k)$. This transformation is achieved by adding the values of the signal multiplied by complex exponentials at discrete intervals. The Inverse Discrete Fourier Transform (IDFT) reverses this process, converting the frequency domain representation back into the original time-domain signal. The formula of DFT may be defined by

$$X(\omega k) \triangle \sum_{n=0}^{N-1} x(tn) e^{-j^{\omega} k^{t} n}, k = 0, 1, 2, ..., N-1$$

and the IDFT are defined by

$$x(tn) = \frac{1}{N} \sum_{k=0}^{N-1} X(\omega k) e^{j^{\omega} k^{t} n}, n = 0, 1, 2, ..., N-1$$

In the DFT equations: - $X(\omega k)$ represents the spectrum of signal x at a specific radian frequency ωk. - $x(tn)$ signifies the amplitude of the input signal in discrete time instances tn. - N denotes the number of samples in both the time and frequency domains. - T represents the sampling period (in seconds), with fs being the sampling rate in Hertz. - n and k denote sample numbers and frequency sample indices, respectively.

These equations illustrate the relationship between the signal in the time domain and its frequency representation, which allows the analysis and manipulation of signals in the frequency domain using discrete samples [Smith 2007]. The Discrete Fourier Transform (DFT) and its inverse counterpart (IDFT) play crucial roles in signal processing applications. When the DFT equation is expressed in a more concise form by setting the sampling period to 1, it simplifies the mathematical representation but reduces the physical interpretability compared to the original formulation. To comprehend and manipulate DFT equations, it is essential to understand complex numbers, imaginary exponents involving symbols such as j and e, and their occurrence within exponentials. These concepts lead to Euler's identity, a fundamental equation that expresses complex sinusoidal functions in terms of cosines and sines [Dai 2015]. Throughout the 20th and 21st centuries, Euler's formula has received significant attention across various fields, including theoretical kinematics, robotics, geometric algebra, and multibody dynamics. Mathematicians and researchers have continued to explore and extend its applications, leading to advancements in rotation tensors, quaternion representations, motion planning, mechanics, computer graphics, and beyond.

The Euler Identity, like $e^{j^{\omega} k^{t} n} = \cos(j^{\omega} k^{t} n) + j \sin(j^{\omega} k^{t} n)$, elucidates how complex sinusoids can be defined and provides insights into sinusoidal behavior, especially with respect to audio signals. The sum of the elements within the DFT definition represents the inner product of signals x and *sk*, denoting the computation of their similarity or correlation. This leads to expressing the DFT using inner-product notation, $X(k) = x, sk$, where *sk* is a sampled complex sinusoid at a normalized radian frequency $\omega k = 2\pi k/N$. Furthermore, standing the inverse DFT involves understanding it as a weighted sum of projections of the signal onto a set of basis sinusoids *sk*. The IDFT equation, $x(tn) = \frac{1}{N} \sum_{k=0}^{N-1} X(\omega k) e^{j^{\omega} k^{t} n}$, signifies the reconstruction of the signal from its spectral components.

3.4.2 Application Logic

The process begins by loading the audio dataset or accessing audio files to initiate subsequent processing steps. To ensure data consistency and enhance the accuracy of the analysis, pre-processing techniques are applied. These techniques may include normalization, noise reduction, and segmentation, which prepare the audio signals for more effective feature extraction and classification. This involves normalizing each audio sample within the range of -1 to 1, thereby enhancing signal quality and potentially leveraging parallel processing techniques for improved efficiency. After preprocessing, the Discrete Fourier Transform (DFT) is applied. This mathematical operation converts preprocessed audio signals from the time domain to the frequency domain. The audio signals are divided into frames, and the frequency components are computed using DFT or Fast Fourier Transform (FFT) algorithms for each frame, as illustrated in Algorithm 1. In the frequency domain, the spectrum is analyzed to identify significant features. This includes detecting peaks or distinctive patterns and extracting essential information such as amplitude, frequency, and phase characteristics. These extracted features are critical for understanding the underlying structure and content of the audio data.

Algorithm 1 DFT-Based Sound Compression Algorithm

INPUT: AudioSignal
OUTPUT: CompressedSignal
function DFTCompress(AudioSignal)
    $N \leftarrow length(AudioSignal)$
    # Apply Discrete Fourier Transform
    $Transform \leftarrow DFT(AudioSignal)$
    # Determine cutoff for compression
    $Threshold \leftarrow ComputeThreshold(Transform)$
    for all $i \in Transform$ **do**
        if $|Transform[i]| < Threshold$ **then**
            # Discard low-energy components
            $Transform[i] \leftarrow 0$
        end if
    end for
    # Apply Inverse DFT to reconstruct signal
    $CompressedSignal \leftarrow IDFT(Transform)$
    return $CompressedSignal$
end function

The MFSDS algorithm processes an audio dataset by performing a series of steps to transform and analyze the audio data, as shown in Algorithm 2. First, it reads an audio file and generates a waveform representation of the audio. The waveform is then normalized and preprocessed to ensure that the data are prepared for further analysis. Subsequently, the audio is divided into smaller chunks, and a Discrete Fourier Transform (DFT) is applied to each chunk, converting the signal from the time domain to the frequency domain. This frequency domain representation is then processed using a model that probably performs a transformation or feature extraction. The outcome is a set of processed audio waveforms that are returned as the final output. This algorithm integrates audio preprocessing, frequency analysis, and machine learning techniques to produce a refined set of audio features.

The VGG16 architecture is employed in this set-up as a pre-trained feature extractor for both image classification and comparison tasks. Initially, VGG16 is loaded without its

Algorithm 2 MFSDS Algorithm

```
INPUT: AudioDataset
OUTPUT: Processed waves
function ProcessAudio(AudioDataset)
    audio_file ← read_file()
    wave ← Wave(audio_file)
    wave.normalize_sample()
    wave.pre_process()
    waves ← wave.create_chunks()
    for all i ∈ waves do
        plotDft ← Dft.applyDft(wave)
        processed_waves[i] = model.apply(plotDft)
    end for
    return processed_waves
end function
```

fully connected layers (by setting *include_top=False*), enabling the model to use only the convolutional layers, which capture essential features such as edges, textures and object components. These convolutional layers, pre-trained on ImageNet, are frozen to prevent updates during training, thereby concentrating the learning on the newly added layers tailored for the specific classification task. The model is then extended with additional fully connected layers, followed by a softmax output layer for multi-class classification. It is trained on the custom dataset using the Adam optimizer and categorical cross-entropy loss. During training, the model processes images using the VGG16 base for feature extraction, training only the newly added layers for the target task. This process, known as transfer learning, leverages the features learned by VGG16 on ImageNet to adapt to the custom dataset, improving performance even with limited data. After training, the model can be saved for future predictions or further analysis.

For image comparison, VGG16 is again used as a feature extractor. Two images are processed to extract features from the last pooling layer (*block5_pool*), and the resulting feature vectors are compared using cosine similarity. Cosine similarity measures the angle between the vectors, providing an indication of how similar the two images are. This approach highlights the versatility of VGG16 in both classification and similarity assessment tasks, utilizing its pre-trained feature representations effectively. The extracted features from the frequency spectrum analysis are then saved in a database for future reference or analysis. This step enables the preservation and easy retrieval of crucial information obtained from the audio signals. Finally, the extracted features are fed into a Neural Sequence Model. This model leverages the sequence of extracted features as input for tasks like classification, generation, or other sequence-based operations. The neural sequence model processes this information to perform tasks such as identifying speech patterns, recognizing audio categories, or even generating new audio sequences based on learned patterns.

4 Evaluation Methodology

This study follows a structured qualitative research methodology [Kothari 2004], focusing on sound waves and their role in health diagnostics. The purpose of this project is to explore and interpret the meanings and applications of these waves, particularly in the digestive system, by converting them into mathematical formulas to uncover medical insight. The research is exploratory, using bibliographic methods [Gerhardt and Silveira 2009] to review relevant literature. It is organized into seven phases and three interconnected methodological blocks, Rupture, Construction, and Finding, as shown in Figure 6, reflecting the dynamic and iterative nature of the investigation.

4.1 Rupture

The research follows three phases: recapture, construction, and finding. The recapture phase aims to understand the context and break away from prior knowledge to explore new areas. In the construction phase, a problem is identified, and an analytical model is developed. The finding phase focuses on finding relevant data, analyzing it, and drawing conclusions. The study begins by formulating the key question: "What is the mathematical formula that describes the states of the digestive system?" This question guides the research, followed by a bibliographic review to understand current knowledge and identify relevant studies.

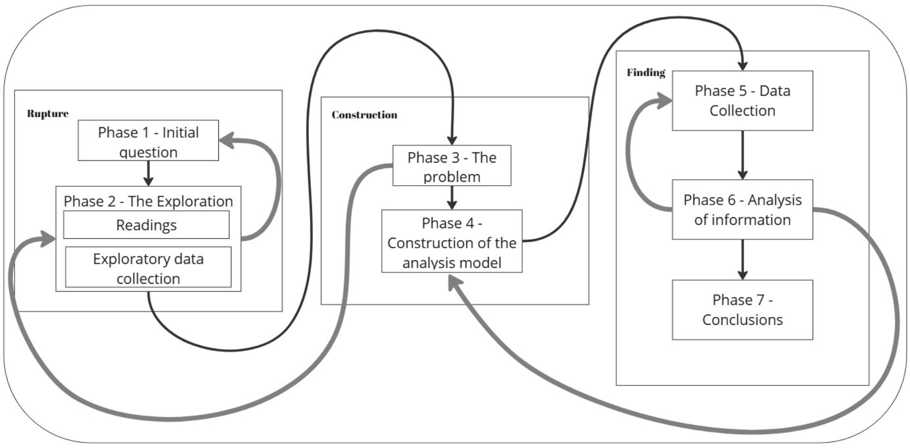

Figure 6: Research phases

4.2 Construction

With the knowledge base established, the third phase involves clearly identifying the problem to be addressed. This phase requires a detailed analysis of the literature reviewed during exploratory research, which results in a specific and measurable problem that is fundamental to the study. Next comes the construction of the analytical model, in which researchers define the methodologies and techniques to be used for data collection and analysis. This model serves as a detailed guide for the research process, ensuring consistency, rigor, and reliability of the results.

4.3 Finding

The subsequent phase is data acquisition, during which the researcher gathers pertinent information for the study. As depicted in Figure 7, this phase involves the collection of a more extensive and targeted dataset related to the digestive system, auditory characteristics, and monitoring methodologies. Data for this research were sourced from the dataset from Ficek et al. [Ficek et al. 2021], which contained 321,000 10 ms records each. These recordings captured intestinal sounds at night from 19 individuals using a specially designed contact microphone with acoustic and electromagnetic insulation. Data collection followed a strict protocol during sleep with fasting and minimal movement to isolate sounds from the complex motor complex of intestinal migration. While this dataset provides high-quality, noise-reduced samples, its demographic and situational scope is narrow, as it focuses only on a small adult group in nocturnal fasting conditions. Such constraints may bias the MFSDS model toward specific acoustic patterns and limit its generalizability across different age groups, genders, postprandial states, and pathological conditions. Noise was filtered out, frequencies limited to 0–1.5 kHz, and recordings were segmented into 2-second blocks, then further into 10-ms frames to ensure reliable analysis. The study progresses through three stages using sets of 25, 50, and 100 formulas to evaluate the model development. Each stage increases formula complexity, allowing comparison of results to track improvements or weaknesses. The first stage establishes a basic understanding, the second compares initial and intermediate results, and the final stage uses a larger set for a comprehensive analysis. This methodical approach aims to address the research question thoroughly.

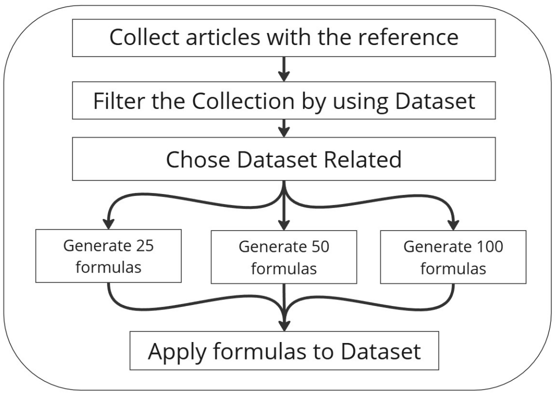

Figure 7: Phase - Data Collection

4.3.1 First Stage – Establishing a Baseline (Set with 25 formulas)

In this analysis, 25 formulas composed of basic trigonometric functions, such as sine ($\sin(x)$) and cosine ($\cos(x)$), are used. The variables x and y range from -10 to 10. These limits are imposed to avoid excessive amplitude and deviation from the evaluated values.

4.3.2 Second Stage – Intermediate Comparison (Set with 50 formulas)

In this stage, the set of 25 formulas described in the previous section is used, together with the formula

$$y(x,t) = A \cdot \sin(2\pi\lambda(x - vt))$$

using a range of values for x from -10 to 10, y from 100 to 200, and t equal to 100. This formula is described as a linear wave equation that relates the spatial and temporal derivatives.

4.3.3 Third Stage – Comprehensive Analysis (Set with 100 formulas)

Using the formulas described previously and incorporating the Discrete Fourier Transform, the values are processed as defined by the notation:

$$X(\omega k) \triangleq \sum_{n=0}^{N-1} x(tn)e^{-j\omega ktn}, \quad k = 0, 1, 2, \ldots, N-1$$

The values of n and k are randomly selected between 1 and 1000, T is set to 100, and N varies between 1 and 10. With the data in hand, the information is entered into the analysis phase. Here, the data are thoroughly examined, condensed, and processed. Statistical methods and analytical tools are often employed to identify patterns and trends, enabling the interpretation of results. Finally, based on the analysis conducted, the study's conclusions are drawn. This involves synthesizing the results and reflecting on how they address the initial research question. In addition, the conclusions may include discussions of the practical and theoretical implications of the findings, as well as suggestions for future research.

5 Results and Discussion

Using 25 epochs of random audio samples from the dataset with 25 formulas, the data in this set are imprecise, with values and similarity ranging between 50 and 60 percent, as shown in Table 2. The reliability of similarity percentages and data comparisons is a critical consideration, particularly when analyzing spectra. Delving deeper into this phase is essential to ensure robust conclusions. An important aspect to consider is the quality of the data itself. Factors such as noise, artifacts, or data pre-processing techniques can significantly influence the results.

In addition, statistical analysis plays a crucial role in assessing the significance of observed similarities or differences. Calculating confidence intervals, conducting hypothesis tests, or applying other statistical measures can provide insight into the reliability of the comparison. Visual inspection of the spectra is also valuable: direct examination of patterns or discrepancies can offer additional understanding beyond the sole reliance on similarity percentages. By incorporating these additional considerations into the analysis, a more complete understanding of the reliability of similarity comparisons can be achieved. This, in turn, enables more informed decision-making based on available data. The observed similarity percentages in this case are not reliable and, with the current dataset, it is not possible to make accurate comparisons or draw definitive conclusions. Moreover, potential biases in the dataset—stemming from its small size, limited demographic scope, and lack of variability across diverse populations—may further constrain

Formula	Recurrence	Median Similarity
sin(x)	8	0.54
tan(x)	6	0.53
1/x	5	0.58
eˆx	2	0.51
tan(xˆ3)	4	0.507

Note: Average Similarity is 0.536%

Table 2: Top 5 Recurrences Formulas with 25 epochs

the model's generalizability. As emphasized by Artzi et al. [Artzi et al. 2020], dataset composition directly impacts the fairness and reliability of predictive models in healthcare, where underrepresented groups may experience systematically reduced accuracy. To mitigate these concerns, future studies should prioritize the collection of digestive sound data across heterogeneous cohorts, including variations in age, sex, ethnicity, and health status. This diversity is essential to ensure that models trained within the MFSDS framework achieve robustness and equity when applied in real-world healthcare settings. As shown in Figure 8, the spectrum is not symmetrical and exhibits both gain and loss in amplitude over time.

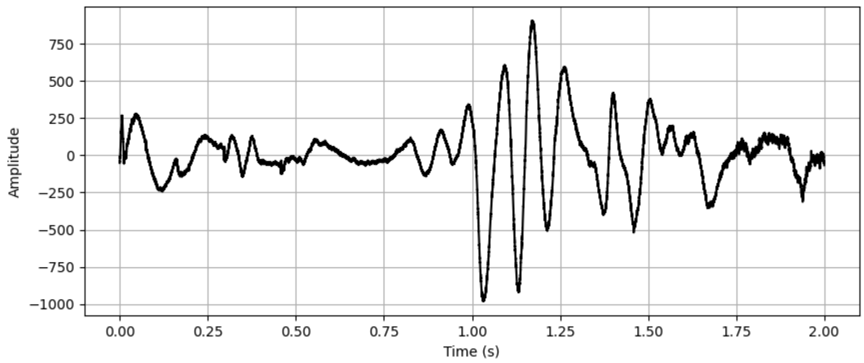

Figure 8: Spectrum wave

Analyzing the initial moment reveals an increase followed by a decrease in value, similar to what is illustrated in Figure 9. The image represents the mathematical function $f(x) = \frac{1}{x}$, known as the reciprocal function, in a two-dimensional Cartesian coordinate system. The curve approaches the y-axis as x approaches zero, illustrating a vertical asymptote at $x = 0$, indicating that the value of $f(x)$ increases indefinitely as x approaches zero. Furthermore, as x becomes increasingly positive or negative, the value of $f(x)$ approaches zero, indicating a horizontal asymptote along $y = 0$. This graph visually represents the behavior of functions near their asymptotes and how they tend toward infinity or essential concepts in calculus. This pattern is observed when a lower frequency with higher amplitude occurs, typically when the sound exits a resting state. In this context, x represents time and $f(x)$ corresponds to amplitude.

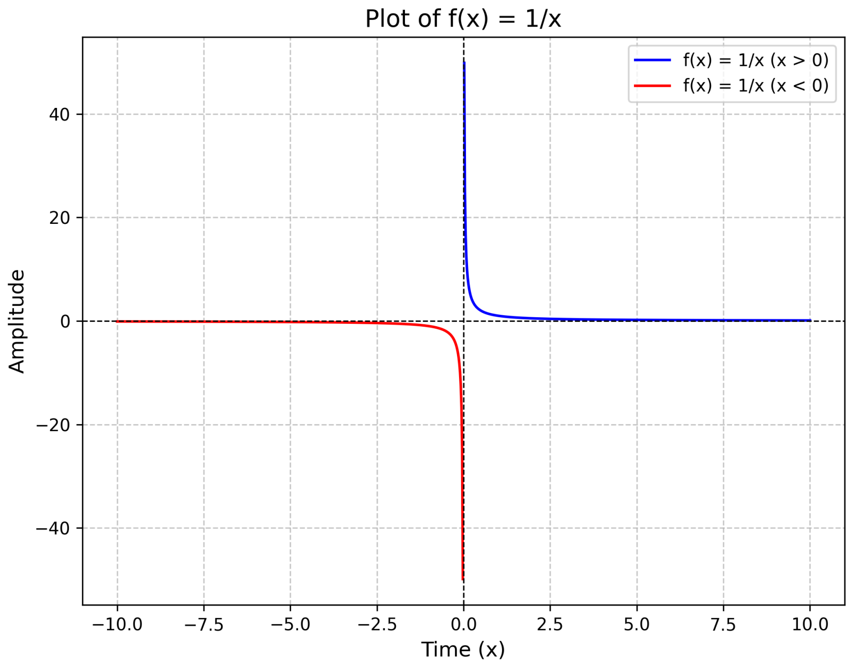

Figure 9: Cartesian graph of formula 1/x

Expanding the analysis to a set of 50 formulas, as shown in Table 3, the formulas were slightly modified to improve the precision of the results. In this extended set, we observed an increase in similarity between certain formulas, particularly those that involved Euler's formulas, with the similarity metric improving to approximately 60%. This represents a noticeable improvement compared to the previous set of 25 formulas, where similarity ranged between 50% and 60%. Despite this improvement, the variance in results remains substantial. This suggests that while there is a discernible improvement in pattern recognition with the larger set, the results are not yet sufficiently reliable for robust comparative analysis.

The application of 100 different formulas to process the epochs resulted in a 5% increase in similarity, with precision ranging from approximately 60% to 67%. The experimental results are presented in Table 4.

Adding more formulas led to a slight improvement, with the spectrum matching only occasionally. The project performed a complete process and collected the results accordingly. The algorithm returned the analysis of these 100 formulas by evaluating the time taken to process each quadrant and identifying the formulas with the highest recurrence during this period. As a result, the results are summarized in Table 5.

Processing 100 formulas allowed the algorithm to identify frequent formulas in audio segments, showing analytical potential but with low precision. The model improved as the number of formulas increased, indicating space for further enhancement. Analysis of healthy intestine data revealed that the MFSDS currently lacks sufficient accuracy for

Formula	Recurrence	Median Similarity
1 * exp(1j * (3.1 * x + π/4))	17	0.57
4.4 * exp(1j * (3 * x + π/0.3))	13	0.54
3.9 * exp(1j * (3 * x + π/1))	7	0.61
2.5 * exp(1j * (4 * x + π/1))	6	0.571
sin(x)	3	0.58

Note: Average Similarity is 0.56%

Table 3: Top 5 Recurrence Formulas with 50 epochs

Formula	Recurrence	Median Similarity
$1.9 \times \exp(1j \times (1.3 \times x + \pi/3))$	18	0.61
$1 \times \exp(1j \times (35 \times x + \pi/0.5))$	15	0.67
$3 \times \exp(1j \times (2 \times x + \pi \times 0.6))$	14	0.64
$2 \times \exp(1j \times (32 \times x + \pi/0.8))$	11	0.62
$100 \times \exp(1j \times (30 \times x + \pi/4))$	9	0.57

Note: Average Similarity is 0.63%

Table 4: Top 5 Recurrence Formulas with 100 Epochs

Time	Formula	Recurrence
0 at 100 ms	3 * exp(1j * (2 * x + π*0.6))	22
0 at 200 ms	1/x	17
0 at 300 ms	3 * exp(1j * (2 * x + π*0.6))	31
0 at 400 ms	100 * exp(1j * (30 * x + π/4))	22
0 at 500 ms	3 * 2 * exp(1j * (32 * x + π/0.8))	19
0 at 600 ms	1.9 * exp(1j * (1.3 * x + π/3))	17
0 at 700 ms	1 * exp(1j * (3.1 * x + π/4))	18
0 at 800 ms	2.5 * exp(1j * (4 * x + π/1))	23
0 at 900 ms	sin(x)	20

Table 5: Results - Time against Formula

bowel sound monitoring. Improving precision and incorporating regression-based AI could enable dynamic formula generation, enhancing accuracy with more data exposure. The study shares commonalities with existing research efforts; however, the examination of mathematical formulas applied in medical contexts represents a significant advancement. This research contributes to health monitoring methodologies by introducing novel technological and methodological approaches. As shown in Table 6, the studies by Choi et al. [Choi et al. 2024] and Maria and Jeyaseelan [Maria and Jeyaseelan 2021] highlight the importance of sensor development and algorithmic precision, which complement the practical applications in noninvasive monitoring discussed by Lee and Kumar. Furthermore, the exploration of deeper physiological insights by Grizzi et al. [Grizzi et al.

2023] and the advancements in signal processing techniques discussed by Güvenç et al. [Güvenç et al. 2024] offer promising avenues to improve diagnostic capabilities. This study serves as a bridge between mathematical analysis and medical applications, paving the way for new techniques for evaluating the digestive system through sound.

Authors (Year)	Accuracy	Results
[Lima et al. 2025]	63 %	Compare Sound and Math Formulas analyzing digestive sound dataset.
[Choi et al. 2024]	-	Real-Time Monitoring and sensor have high sensitivity.
[Güvenç et al. 2024]	84.3 %	Vector analysis enhances bowel sound detection.
[Grizzi et al. 2023]	-	Potential application in biomedical fields.
[Lee et al. 2021]	-	Accurately collects bowel sounds from the abdomen.
[Maria and Jeyaseelan 2021]	93.75 %	Great performance in hungry stomach detection.
[Kumar et al. 2019]	75 %	High detection accuracy rate at meal detection.

Table 6: Comparison of related work and this study

The study focuses on using mathematical formulas to monitor the digestive system by analyzing epochs of audio data with MFSDS. Comparison of observed data with predefined formulas that represent digestive states, measuring similarity. However, reliability is limited due to low precision, long processing times, and complexity in generating comparable formulas. Currently, the method is too slow for real-time use and may not accurately reflect physiological conditions. Despite their potential, significant improvements in accuracy and efficiency are needed for practical health monitoring applications. This study focuses on audio conversion methods to diagnose and monitor digestive health, excluding the acquisition or implementation of audio data, which are covered in work such as [Lee et al. 2021]. It specifically targets approaches for monitoring digestive health and evaluates the suitability of the MFSDS model within this scope.

6 Conclusion

This study advances the analysis of digestive system sounds using mathematical techniques and AI, notably applying the MFSDS algorithm for monitoring digestive health. Following the qualitative exploratory methodology of Gerhardt [Gerhardt and Silveira 2009], it aims to develop new theories by analyzing data from sound waves. The research progresses through seven interrelated phases—Rupture, Construction, and Finding—supported by a bibliographic review to assess the evolution and impact of sound wave technologies. The MFSDS Algorithm operates through AI-driven training and processing, utilizing Euler's mathematical formulas and the Discrete Fourier Transform (DFT) to analyze intestinal sounds. The algorithm segments sound data into smaller units and compares them against a predefined set of formulas. Initially, it showed an accuracy of less than 70% when using a base of 100 formulas, making it impractical for immediate application. However, the precision showed significant variation with a smaller set of formulas, approximately 50% with 25 formulas and around 60% with 50 formulas.

Future enhancements may include not only regressive artificial language processing to generate formulas dynamically, but also the use of advanced sequence models such as Temporal Convolutional Networks (TCNs), which have demonstrated strong performance in time series analysis, as demonstrated in [Bai et al. 2018]. These additions would improve temporal modeling of digestive sound data, increase scalability, and reduce the need for manual intervention. This advancement has the potential to significantly improve both the accuracy and the real-time applicability of digestive health monitoring. With real-time data integration, it would be possible to detect intestinal problems quickly, enabling new forms of preventive healthcare. Another critical direction is to address the diversity of the dataset. Evidence from healthcare AI [Artzi et al. 2020] shows that models trained on demographically limited data risk reduced accuracy in underrepresented groups. Therefore, expanding digestive sound datasets across heterogeneous populations will be essential to ensure fairness, generalizability, and clinical applicability.

Finally, this study could facilitate technology transfer by providing a system adaptable to multiple contexts. In public health, it could support early diagnosis in primary care with low-cost devices. In private clinics, it could improve patient monitoring with noninvasive and real-time data. For home use with mobile or wearable devices, it could guide users on digestive health patterns, promote preventive care, and reduce demand for healthcare systems.

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