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Advanced Dielectric Anomaly Detection for Non-Destructive Fruit Inspection Using Electromagnetic Microwave Technique

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Abstract— This paper presents a comprehensive investigation into the application of an electromagnetic microwave technique combined with the dielectric anomaly approach algorithm for the non-destructive inspection of fruits. The proposed antenna configuration comprises eight elements arranged in a circular array, enabling the collection of signals scattered by objects, specifically fruits, placed in their path. The collected data undergoes a series of processing steps, including Fast Fourier Transform, covariance matrix estimation, eigenvalue and eigenvector computation, and spatial spectrum construction. The dielectric anomaly algorithm is then applied to detect defects in the fruits. The study covers five different types of fruits, both healthy and defective, and gathers essential dielectric properties. Furthermore, a novel hybrid IQR method is introduced for outlier detection in the dielectric data. The results demonstrate the effectiveness of the proposed methodology in providing valuable insights into the internal structures of fruits and detecting anomalies, contributing to the enhancement of quality assessment in fruit inspection processes.

I. Introduction

In recent years, non-destructive microwave imaging has emerged as a pioneering and transformative technology with immense potential in the domain of quality assessment. This paper embarks on a comprehensive exploration of this revolutionary methodology, aiming to elucidate its underlying principles, applications, and implications, particularly within the context of quality evaluation across various fields. The significance of non-destructive microwave imaging lies in its capacity to enable meticulous inspection and characterization of materials and products without causing any harm or alteration. This unique attribute positions the technology as a game-changer in sectors such as medical diagnostics, industrial processes, and food production, where accurate and timely quality assessment is paramount.

At its core, non-destructive microwave imaging harnesses the power of electromagnetic waves within the microwave frequency spectrum to illuminate the internal attributes of materials. This method offers the ability to penetrate substances without altering their physical integrity, allowing for the measurement and analysis of properties such as composition, density, moisture content, and structural uniformity. The implications of such capabilities are profound, as they pave the way for a paradigm shift from traditional quality assessment methods that often involve destructive sampling, to an innovative approach that promises real-time, non-invasive, and comprehensive analysis.

Within the food industry, for instance, non-destructive microwave imaging has the potential to revolutionize quality assessment along production lines. The ability to scan and evaluate the internal attributes of fruits, vegetables, and other perishable items while they are in motion could substantially enhance quality control, minimize waste, and optimize resource allocation. Similarly, in medical diagnostics, this technology can enable non-invasive imaging of tissues and organs, offering insights into health conditions without the need for invasive procedures that may compromise patient well-being.This paper embarks on a journey to delve into the nuances of non-destructive microwave imaging, highlighting its theoretical foundations, technical advancements, and emerging applications. The review of recent literature and case studies will underscore the efficacy of this technology in providing detailed and accurate information about the quality and characteristics of various materials. Furthermore, the paper will shed light on potential challenges and limitations, addressing concerns such as data interpretation, system calibration, and the impact of varying sample properties.

As we stand on the cusp of a technological revolution, it becomes imperative to understand the potential and limitations of non-destructive microwave imaging for quality assessment. By presenting a comprehensive overview of this technology, this paper strives to contribute to the discourse surrounding its applications, implications, and the transformative role it can play in shaping the future of quality evaluation across diverse sectors. Through an intricate exploration of the subject matter, this paper endeavors to empower researchers, practitioners, and stakeholders to harness the power of non-destructive microwave imaging for accurate and efficient quality assessment, thereby driving innovation and progress in a multitude of industries.

II. LITERATURE REVIEW

This paper presents a novel approach for breast cancer detection using optimized planar antennas operating within the ISM frequency band, featuring a microstrip patch antenna with impressive attributes and demonstrating potential as an alternative to traditional methods for early breast tumor screening[1].This study highlights the potential of microwave radar imaging as a non-invasive and non-destructive method for detecting defects in potato samples, offering a promising solution for innovative food quality assessment and emphasizing its capacity to address global food demand and safety concerns[2].This paper presents a comprehensive evaluation of three ultra-wideband antennas for microwave breast imaging, shedding light on their performance metrics and their significant role in improving image quality and clinical utility for early breast anomaly detection and management[3].

This study introduces multi-resolution microwave imaging (MMI) as a sensitive, non-invasive, and rapid technique for early bruise detection on apples, with a methodology encompassing data acquisition, feature extraction, and model development, demonstrating its practical applicability and significance in enhancing apple product quality and preventing spoilage[4].This paper introduces a novel waveguide antenna microwave imaging system as a non-destructive and rapid method for evaluating the quality and health of food products, using eggs as an example, and showcases its effectiveness, simplicity, and potential for innovative food quality and security assessment solutions[5].

This study investigates the application of microwave imaging for non-destructive internal fruit quality assessment, highlighting its potential to address challenges by reducing views in a Huygens-based algorithm without compromising detection resolution, and proposing an automated limited-view data acquisition system design to advance cost-effective and efficient food imaging[6].This paper introduces an innovative wideband antenna design optimized for ultra-wideband microwave imaging applications, featuring that collectively enhance attributes such as bandwidth, gain, and directionality, demonstrating its efficacy for high-resolution microwave imaging and tumor detection within complex structures like breast tissue[7].This study utilizes a wide-band microstrip patch antenna operating within the 3.6 to 9.2 GHz range, combined with the Confocal Microwave Imaging (CMI) algorithm, to generate 2D breast images for enhanced, non-invasive breast cancer detection, considering factors like dielectric properties, age groups, and types to investigate their impact on Specific Absorption Rate (SAR) and temperature within breast layers, highlighting the potential of microwave imaging for accurate diagnostic approaches[8].

This paper introduces a modified Planar Inverted F Antenna (PIFA) as a microwave imaging sensor designed to detect concealed objects, particularly tumors in human tissue, through its stacked design and operation within the 1.55–1.68 GHz frequency range, showcasing its potential for medical diagnostics and tumor detection based on computational analysis and experimental validation using a realistic breast phantom[9].This paper introduces an innovative microwave imaging system featuring an eight-element microstrip patch antenna array configuration, offering a compact, cost-effective solution for diverse imaging applications, detailing the experimental setup, calibration process, and image reconstruction methodology that utilizes the antennas' unique arrangement to effectively capture dielectric properties and image quality using the distorted Born iterative method[10].This study introduces a laboratory microwave imaging system prototype for systematically evaluating its potential in imaging, detecting, and classifying human brain strokes using components like a slot bowtie antenna array holder, a reconfigurable human head phantom, and stroke phantoms, validating its efficacy in detecting and characterizing brain strokes through microwave-based technology and highlighting its utility as an advanced tool in this domain[11].

The study introduces an innovative microwave imaging system for breast tumor detection, incorporating a CPW-fed microstrip antenna with an MTM-AMC structure, a microcontroller-based imaging setup, and image processing to effectively detect tumors and enhance breast imaging accuracy[12].This review comprehensively evaluates non-destructive methods for assessing the quality of fruits and vegetables, comparing their relevance, popularity, and correlation with specific produce types' attributes, acknowledging the benefits and drawbacks of various techniques while providing valuable insights to guide informed choices for fruit and vegetable quality assessment[13].The paper presents a nondestructive approach to fruit quality assessment using millimeter waves and classification methods, highlighting the potential benefits of preserving fruit integrity, achieving objective categorization, and enabling automated, real-time quality assessment for various industries[14].

The paper focuses on noninvasive inline food inspection using microwave imaging technology, highlighting its real-time, non-damaging assessment of food quality and characteristics during production and processing, and emphasizing its potential to enhance efficiency, ensure quality, detect defects, and improve food safety and production efficiency in the food industry[15]. Microwave imaging, a cost-effective and non-invasive technology, is increasingly used for inspecting packaged food products in real-time, and this study presents a novel detection method exploiting inherent food item symmetries to identify contaminants without requiring a reference item, making it especially suitable for circular container-packaged homogeneous foods, as supported by numerical analyses[16]. In response to the continuous global increase in food consumption, this paper presents a novel microwave radar algorithm for fruit imaging, leveraging purpose-built hardware and a Huygens principle-based reconstruction approach to detect internal contrasts in fruits' dielectric properties, as demonstrated in experiments on lemons and grapefruits, promising improved consumer safety and reduced product waste[17].

The presence of foreign bodies in food products, posing safety and quality concerns, necessitates urgent detection methods, and this article provides a comprehensive review of noninvasive techniques such as X-ray, thermal imaging, near-

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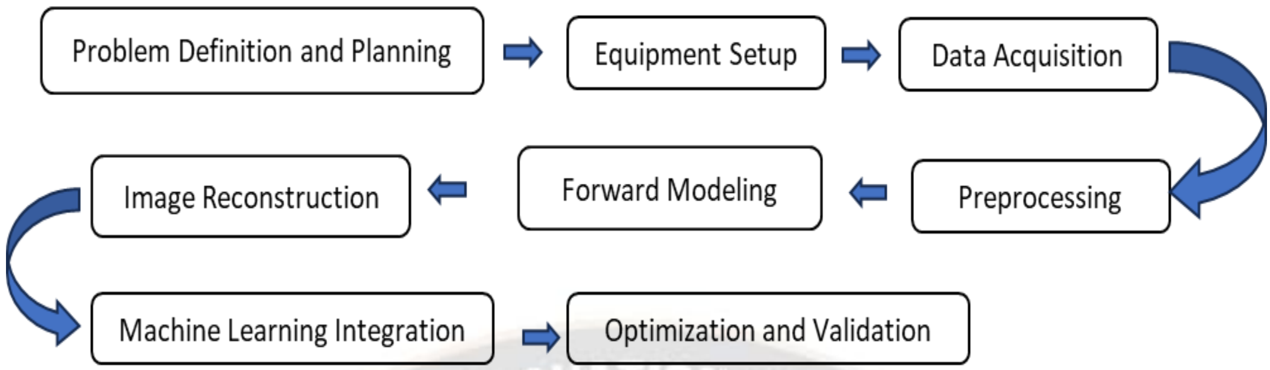

Figure 1: Overview of methodology

infrared spectroscopy, hyperspectral imaging, ultrasonic, and terahertz, detailing their principles, applications, performance, limitations, and future trends for researchers in this field[18]. This paper presents a novel microwave imaging system utilizing a circular array of 10 Coplanar Vivaldi antennas to determine watermelon ripeness, demonstrating its potential for enhancing food quality and safety assessment[19]..

III. Methodology

The methodology for non-invasive object detection and food inspection using Electromagnetic Microwave Imaging (EMMI) involves a multi-step process that integrates electromagnetic theory, signal processing, data analysis, and image reconstruction. While specific methodologies may vary based on the application and equipment used, here is a general overview of the steps involved:

1. Problem Definition and Planning: Defining the objectives of the inspection (e.g., detecting contaminants, assessing moisture content). Identifying the dielectric properties of interest (e.g., permittivity, conductivity) for the specific food products.
2. Equipment Setup: Configuring the hardware components, including microwave source, antenna system, and transceiver unit. Calibrate the system to ensure accurate measurements and data acquisition.
3. Data Acquisition: Positioning the food items on the inspection platform or conveyor. Emit microwave signals and collect raw data as they interact with the objects.
4. Preprocessing: Applying signal processing techniques to clean, filter, and normalize the raw data. Account for variations in signal strength and environmental conditions.
5. Forward Modelling: Utilize numerical methods (e.g., Finite-Difference Time-Domain) to simulate how microwave signals propagate and interact with the objects. Create a model of expected interactions based on dielectric properties and material composition.
6. Image Reconstruction: Incorporate the estimated dielectric properties into the inversion process for image reconstruction. Generate images or visualizations showing the distribution of dielectric properties within the food items.
7. Analysis and Quality Assessment: Analyzing the reconstructed images to identify patterns, anomalies, or regions of interest within the food items. Compare estimated dielectric properties with reference values to assess quality and compliance with standards.
8. Machine Learning Integration: Train machine learning models to classify food items based on dielectric properties and other relevant features. Use machine learning algorithms for real-time decision-making and quality assessment.
9. Reporting and Visualization: Presenting the inspection results through visual representations, graphs, or statistical summaries. Generate detailed reports summarizing dielectric characteristics and quality assessment.
10. Optimization and Validation: Continuously optimizing the system parameters, calibration, and algorithms for improved accuracy. Validate the accuracy of dielectric property estimations through comparison with reference measurements.

This methodology combines electromagnetic principles, advanced numerical simulations, signal processing, machine learning, and data analysis to provide a comprehensive and non-invasive approach to food inspection. It offers the potential to revolutionize quality control practices, minimize waste, and ensure consumer safety in various industries.

In Figure 1, we are presented with an insightful overview of the methodology employed in this study, which encompasses the comprehensive process of non-destructive inspection of various food products based on dielectric properties. The methodology commences with the crucial initial step of problem definition, where the specific objectives and goals of the inspection process are clearly outlined. This stage involves the identification of the key challenges and requirements for the inspection of food products, setting the foundation for subsequent actions.

Following problem definition, the methodology proceeds to the collection of dielectric property values from a diverse range of food products. This data acquisition phase involves the careful gathering of dielectric constant and loss tangent values for the different food items under investigation. These dielectric properties serve as fundamental indicators of the electrical behavior of the materials and play a pivotal role in the subsequent stages of the inspection process. The accurate collection of these properties is essential for the success of the overall methodology and its ability to detect anomalies and ensure the quality assessment of food products.

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In Figure 2, we are presented with a comprehensive depiction of the essential components and the overarching flow involved in the image reconstruction process. This critical phase is pivotal for converting raw data, acquired through the electromagnetic microwave technique and dielectric anomaly approach, into meaningful visual representations that facilitate the detection of anomalies within food products.

Figure 2: Overall flow of methodology with key components required for image reconstruction

The flow begins with the collection of raw data, which is obtained by transmitting and receiving signals using the configured antenna array. These signals interact with the dielectric properties of the food products under examination, resulting in scattered data that carries valuable information about the internal structures of the items. The next step involves the application of the Fast Fourier Transform (FFT), which transforms the acquired raw data from the time domain into the frequency domain. This spectral representation is a fundamental prerequisite for further analysis.

Subsequently, the covariance matrix estimation stage plays a critical role in understanding the interrelationships between different sensor outputs, ultimately facilitating the computation of eigenvalues and eigenvectors. These eigenvectors provide valuable insights into the direction of signals within the data, while the eigenvalues offer information about signal strength in those directions. With this foundation, the spatial spectrum construction phase generates a graphical representation of signal strength across distinct directions, enabling the localization of anomalies within the food products. Overall, Figure 2 illustrates a systematic and crucial sequence of steps that transform complex data into interpretable images, laying the foundation for the subsequent detection of defects and anomalies in food products through dielectric anomaly analysis.

A. Equipment's required

The equipment used for non-invasive object detection and food inspection using electromagnetic microwave imaging (EMMI) typically involves a combination of hardware components and software algorithms. Here's an overview of the key components that may be involved:

1. Microwave Source: This component generates microwave signals that are directed towards the object being inspected. The source can emit controlled microwave frequencies and power levels. It is an essential part of the system as it initiates the interaction between microwaves and the object. In this paper Anritsu microwave source generator is employed to precisely synthesize and emit electromagnetic waves at a designated frequency of 0.915 GHz, facilitating targeted applications in the microwave spectrum. Figure 3 describes the picture of microwave source generator.


Figure 3: Microwave source generator

2. Antenna System: The antenna system is responsible for transmitting the microwave signals generated by the source and receiving the signals that are emitted and scattered by the object. It plays a crucial role in capturing the interactions between the microwaves and the object's properties. Transceiver Unit: The transceiver unit combines the roles of the microwave source and antenna system. It is capable of generating and transmitting microwave signals while also receiving and processing the signals that interact with the object. Receiver System: This part of the equipment is responsible for capturing the signals that are emitted, reflected, and scattered by the object. It may include amplifiers, filters, and other components to ensure accurate signal detection. The envisaged antenna structure has been designed upon an FR4 substrate, serving the dual purpose of operating as both the transmitting and receiving units within the system[20]. Figure 4 depicts the proposed antenna which radiates at 0.915 GHz frequency.Within the confines of this paper, the antenna system has been meticulously configured in a circular arrangement, wherein a total of eight antennas have been systematically positioned, maintaining an exact phase disparity of 45^0 degrees between adjacent antennas.

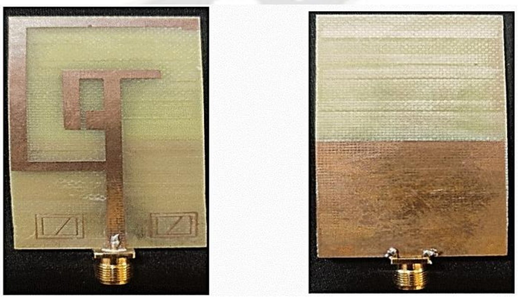
Figure 4: Proposed antenna and the antenna system

3. Signal Processing Hardware: The captured signals need to be processed to extract useful information about the object's properties. Signal processing hardware, such as analog-to-digital converters (ADCs) and digital signal processors (DSPs), is used

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to process and analyze the signals. In this manuscript, the Anritsu vector network analyzer(VNA) assumes the role of

Figure 5: Vector Network Analyzer

signal processing hardware, adeptly gathering signals emanating from the receiver antenna. Figure 5 depicts the picture of vector network analyzer.

4. Computer or Data Processing Unit: A computer or dedicated data processing unit is used to run algorithms for image reconstruction, analysis, and visualization. Advanced algorithms are employed to convert the collected signal data into meaningful images or maps of the object's properties.

5. Software Algorithms: Various algorithms are employed to process the raw signal data, reconstruct images, and interpret the information

6. Display and Visualization: The processed information is displayed and visualized for interpretation. This could involve software tools that provide images, graphs, and data representations to convey the results of the inspection.

7. Calibration and Validation Equipment: Proper calibration of the system is crucial to ensure accurate and reliable measurements. Calibration equipment and procedures are used to establish a reference for the system's measurements.

8. Sample Handling Mechanism (Optional): In food inspection, a mechanism for presenting and moving food items through the inspection system may be necessary. This could involve conveyor belts, trays, or other handling mechanisms.

It's important to note that the specific equipment used can vary depending on the application, the level of detail required, and the characteristics of the objects being inspected. Moreover, advancements in technology may lead to the development of more specialized and efficient equipment for electromagnetic microwave imaging applications in the future.

B. Experimental setup

The proposed antenna configuration comprises eight elements arranged in a circular array, with a 45-degree phase difference between adjacent elements. The experimental configuration is conducted within an anechoic chamber. A source generator is utilized to produce signals, and one antenna element serves as the transmitter, while the rest act as receivers. A receiving antenna is connected to a vector network analyzer (VNA) using a probe, enabling the collection of signals scattered by objects placed in the path of the antenna array. The VNA records S11 values for each receiving element, yielding raw signal data. Subsequently, Fourier transform is applied to convert the raw data into the frequency domain representation. These transformed signals are then processed using the dielectric anomaly algorithm for the detection of defects in fruits. Figure 6 depicts the experimental setup carried inside the anechoic chamber.

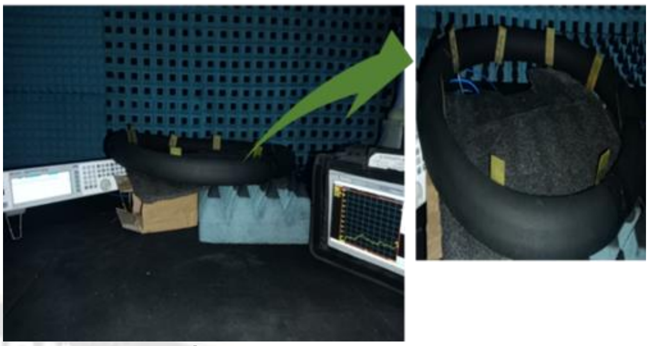
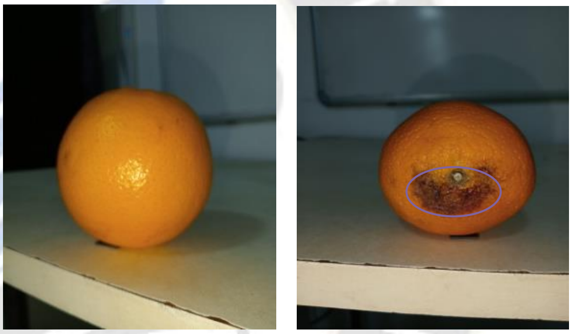


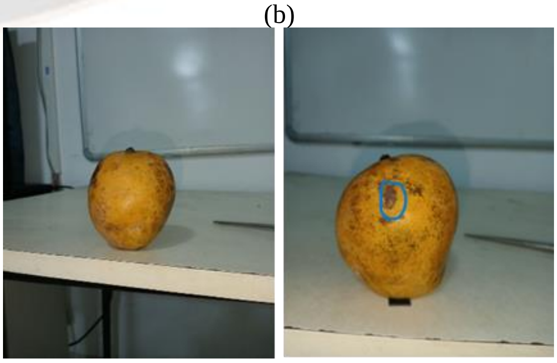
Figure 6: Experimental setup

The experiment involves the examination of five distinct types of fruits, namely orange, avocado, lemon, kiwi, and mango. For each of these fruits, we have gathered essential dielectric properties, including dielectric constant and loss tangent values, as part of the testing process. Both healthy fruits and fruits exhibiting defects have been meticulously considered in our investigation. In Figure 7, visual representations of the fruits subjected to the experimental procedures are presented.



(a)

(b)



(c)

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(d)

(e)

Figure 7: Healthy and Defected fruits, a) orange, b) lemon, c) mango, d) kiwi, e) avocado

In Figure 7, a compelling visual representation is provided, showcasing a side-by-side comparison of both healthy and defective specimens of various fruits. This comprehensive display serves as a vital component of the study's findings, offering a clear and concise means of understanding the differences between the two conditions.

a) Orange: This subfigure (a) underlines the distinction between a healthy orange and a defected one. The image effectively captures the external characteristics and structural attributes of both types of oranges, allowing for the identification of any irregularities or blemishes on the fruit's surface. This visual insight can be instrumental in quality assessment and sorting processes for oranges.

b) Lemon: Subfigure (b) presents healthy and defected lemons side by side, facilitating a direct visual comparison. By examining the external features and surface conditions of these lemons, one can easily identify any anomalies or deformities, which is critical for ensuring product quality in the lemon market.

c) Mango: The mango representation in subfigure (c) provides a visual depiction of both a healthy mango and one with defects. This visual comparison helps in discerning any imperfections, such as bruises or irregular shapes, which are essential factors in determining the market value and consumer appeal of mangoes.

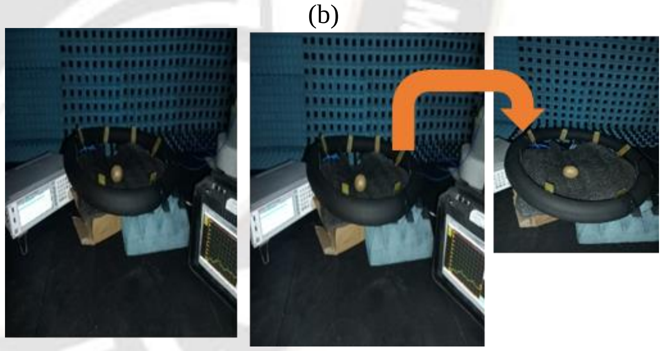
d) Kiwi: Subfigure (d) offers a visual contrast between a healthy kiwi and a defected one. The external appearance of these kiwis is crucial for assessing their quality and market readiness. Any deviations from the expected appearance can be readily observed and analyzed through this visual representation.

e) Avocado: The last subfigure (e) focuses on avocados, illustrating the differences between healthy and defected avocados. This visual insight aids in the evaluation of external characteristics, such as skin texture and color, which are vital indicators of avocado ripeness and quality.

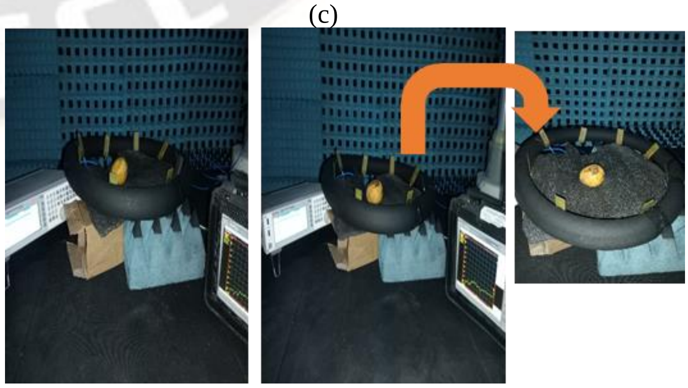
In summary, Figure 7 provides a comprehensive visual reference for healthy and defected fruit specimens across various types, enabling a rapid and effective assessment of their external attributes. This visual data is a valuable resource for quality control and decision-making processes in the food industry, ensuring that only high-quality products reach consumers.

(a)

(b)



(c)



(d)

(e)

Figure 8: Experimental setup with different fruits, (a) orange, (b) lemon, (c) mango, (d) kiwi (e) avocado

The experimental setup involves a diverse selection of fruits, including oranges, lemons, mangoes, kiwis, and avocados, and employs electromagnetic microwave imaging as a technique. Figure 8 illustrates the experimental configuration organized with various types of fruits. This suggests that these fruits are being utilized as test subjects in the context of microwave imaging, likely to evaluate the feasibility and effectiveness of this imaging method for various applications. The experiment aims to capture and analyze microwave-based images of these fruits, potentially for purposes such as non-invasive inspection, quality assessment, or research into microwave imaging techniques for agricultural or medical applications.

The core procedural steps within the proposed system can be delineated as follows:

1. Data Acquisition: In the initial phase, data is acquired through an array of sensors, such as a microphone array or antenna array. Typically, this data is collected in the time-domain format, representing a sequential set of temporal samples.
2. Fast Fourier Transform (FFT) Utilization: Following data acquisition, the Fast Fourier Transform (FFT) is employed to convert the acquired data into its frequency-domain representation. This transformation is fundamental for spectral analysis.
3. Covariance Matrix Estimation: Subsequent to the FFT, the system proceeds to estimate the covariance matrix derived from the received signal. This matrix captures the intricate relationships among various sensor outputs and forms the cornerstone for subsequent calculations involving eigenvalues and eigenvectors.
4. Eigenvalue and Eigenvector Computation: Computation of eigenvalues and eigenvectors is carried out based on the covariance matrix. These eigenvectors elucidate the directions from which signals originate, whereas eigenvalues provide insights into signal strength within each of these directions.
5. Spatial Spectrum Construction: Utilizing the calculated eigenvectors in conjunction with the FFT-transformed received signal, the system meticulously constructs a spatial spectrum. This visual representation graphically illustrates signal strength distributed across distinct directions, enabling effective spatial analysis.
6. Application of Dielectric Anomaly Detection Approach for Class Labels: Employing a dielectric anomaly detection approach, the system proceeds to assign class labels to the data points, facilitating the identification of anomalies.
7. Validation of Class Labels: Ensuring the accuracy of class labels is crucial. This is achieved through meticulous assessments involving inter and intra similarity distance calculations, further enhancing the reliability of the classification.
8. Training Data Retention: Data collected is systematically retained as training data for subsequent phases, serving as a valuable reference for model optimization and refinement.
9. Ensemble Classification Framework Implementation: The ensemble classification framework is strategically applied to predict anomalies within the dielectric test data, leveraging the collective wisdom of multiple models for enhanced accuracy.
10. Statistical Metric Assessment: Lastly, the system conducts a thorough scrutiny of statistical metrics to gauge the effectiveness and performance of the ensemble classification framework, providing valuable insights into the anomaly detection process.

C. Software Algorithms

Various algorithms are employed to process the raw signal data, reconstruct images, and interpret the information. These algorithms may include inversion algorithms for image reconstruction, machine learning algorithms for pattern recognition, and data analysis tools. In the context of this paper, the algorithm employed is denoted as the "Dielectric Anomaly Detection Approach."

Compute the following hybrid IQR method as

DF [] =Features ();

R1=V(|DF|/4)); (1)

R2=(V(|DF|/2) +V(|DF|/2+1))/2; (2)

R3=(V(|DF|-|DF/4-1) +V(|DF|-|DF|/4))/2; (3)

U_E []=R3+η.log(Γ(R3-R1)) (4)

L_E []=R1-η.log(Γ(R3-R1)) (5)

U_Outlier=R3+η.min(χ(R3+R1,9)),exp(Γ(R3-R1))) (6)

L_Outlier=R3-η.min(χ(R3+R1,9)), exp(Γ(R3-R1))) (7)

For i=1 to |FS|

perform

if F(i) lies above or below the upper and lower range, it is labelled as anomaly

Else

Labelled as non-anomaly

In this paper, aforementioned algorithm outlines a hybrid methodology for detecting outliers in dielectric data using the interquartile range (IQR). Here is a comprehensive step-by-step elucidation of the algorithm:

Initialize the array DF[], which represents the input features containing dielectric data.

Calculate the first quartile range R1: This value is determined as the 25th percentile of the absolute values within DF[].

Compute the second quartile range R2: This range corresponds to the average of values at the 25th and 75th percentiles of the absolute values within DF[].

Calculate the third quartile range R3: This range is derived as the average of values located at the 75th percentile and the 25th percentile from the end of the absolute values within DF[].

Compute the upper outlier threshold U_E[]: This threshold is defined as R3 plus a parameter eta, multiplied by the logarithm of the gamma function evaluated at the difference between R3 and R1.

Calculate the lower outlier threshold L_E[]: This threshold is defined as R1 minus a parameter eta, multiplied by the logarithm of the gamma function evaluated at the difference between R3 and R1.

Compute the upper outlier limit U_Outlier: This limit is defined as R3 plus eta times the minimum of the chi function evaluated at R3 plus R1 with 9 degrees of freedom and the exponential of the gamma function evaluated at R3 minus R1.

Calculate the lower outlier limit L_Outlier: This limit is defined as R3 minus eta times the minimum of the chi function evaluated at R3 plus R1 with 9 degrees of freedom and the exponential of the gamma function evaluated at R3 minus R1.

Begin the outlier detection process:

Iterate through each feature F(i) within the dielectric data FS[].

If the value of F(i) lies above the upper outlier threshold U_E[] or below the lower outlier threshold L_E[], it is classified as an outlier.

Otherwise, further processing or analysis can be performed using the data points that are not classified as outliers.

The algorithm ingeniously amalgamates the IQR methodology with supplementary statistical measures such as the gamma function and chi function, alongside threshold values (U_E[], L_E[], U_Outlier, L_Outlier), to effectively discern and label outliers within the dielectric data set.

D. K-class membership validation approach

Step 1: To each dielectric labelled partition data PD

Step 2: To each data point p[i] in PD

Step 3: Perform weightage density to each data object using the Gaussian transformation function as

$$wd_i = \sum_{j\in I, i!=j} \exp(-(d_{ij}/d_c)^2) \quad (8)$$

$$d_{i,j} = \sqrt{\sum_{t=1}^{m} \left(x_i^t - x_j^t\right)^2}$$

Where dc: Threshold

Step 4: To each object, find the highest density using the following measures.

$$hd_j = \max\{wd_i\} \quad (9)$$

Step 5: Computing the k nearest neighbors by using the k-randomized centres as k initial clusters. The set of k nearest neighbors of center CPi is defined

$$NP_i^k = \{P_j / \min(d_{ij}), i! = j\} \quad (10)$$

Step 6: Compute the inter cluster similarity and intra cluster similarity to each k-neighbor initial clusters using the following formula.

$$\lambda 1 = \mathrm{IntraClu}(p_c, p_i) = \frac{1}{n_i - 1} hd_c . \sum_{m=1} d(p_c, p_m) \quad (11)$$

$$\lambda 2 = \mathrm{InterClu}(p_c, p_i) = \min_{1<=m<=k}\left(\frac{1}{n_m} hd_c . \sum_{r=1} d(p_c, p_r)\right) \quad (12)$$

$$\alpha = Q1;$$
$$\beta = Q2;$$
$$\chi = Q3;$$

$$\mathrm{Upp\_Outlier} = \chi + \Gamma \max\{\lambda 1, \lambda 2\}.(\chi - \alpha) \quad (13)$$

$$\mathrm{Lower\_Outlier} = \chi - \Gamma \max\{\lambda 1, \lambda 2\}.(\chi - \alpha) \quad (14)$$

Step 7: Iterate until all points are assigned to k=clusters or no more changes in clusters.

The algorithm initiates its process by individually assessing every data point within a designated partition. In this assessment, a weightage density is meticulously computed utilizing a Gaussian transformation function. Subsequently, among the neighboring data points, the most pronounced density is determined for each individual object.Initial clusters are then established through the method of selecting k centers in a randomized manner, which are subsequently paired with their k nearest neighbors. Following this initial formation, a two-fold assessment is undertaken, involving both inter-cluster and intra-cluster similarity evaluations for each of the preliminary clusters. The algorithm proceeds iteratively, effecting a series of updates to the cluster assignments. This iterative process continues either until a point of convergence is reached, signifying stable cluster assignments, or until a predefined stopping condition is satisfied. the core objective of the algorithm lies in the clustering of data points based on their density and proximity. The iterative nature of the algorithm seeks to refine cluster assignments through successive steps, ultimately culminating in a clustered representation of the data.

E. Proposed Ensemble learning model

Ensemble learning emerges as a potent methodology that amalgamates predictions from numerous foundational models to heighten overall performance and enhance generalization. When harnessed to tackle the intricate challenge of localizing dielectric anomalies – a task that entails the identification of regions harboring atypical electrical characteristics within a given material – the ensemble strategy exhibits the potential to furnish heightened accuracy and robustness in outcomes. This approach capitalizes on the aggregated predictions stemming from the ensemble of models to accurately pinpoint and localize instances of dielectric anomalies within the material. Consequently, the technique assists in unveiling these distinctive regions characterized by deviating electrical properties. A noteworthy facet involves the visualization of these outcomes, which can be achieved by superimposing the predictions of anomalies onto the initial maps portraying dielectric properties or other pertinent visual representations. This overlay not only facilitates a clear comprehension of the detected anomalies but also empowers researchers and practitioners to readily identify and interpret the irregularities within the material's electrical attributes.

1) Initialization of ensemble learning process

Set of proposed classifier and base classifiers are represented as ensemble classifiers as

$$EC = \{KNN, HDT, ProposedModel\},$$
$$MC = \{\};// \text{Model classifier}$$

CO={};Classifier output

2) Procedure

Let, D:=Input data PAi is the set of input random variables. PIj is the instance of attribute.
To each attribute PAi in data PD.
Construct the Bayesian network graph using the input data and naïve Bayesian estimations.
Estimate Bayesian network node variables using the two cases. If the attribute type is discrete, then the Bayesian discrete parameters are estimated using the following measure as

$$P(A_i = I_k/c_j) = \frac{N_{ijk}}{N_j} \quad (15)$$

Where Nijk is the number of instances of class cj having the value Ik in attribute Ai.
If the attribute type is continuous type, then the Bayesian continuous parameters are estimated using the following measure as

$$P(A_i = I_k/c_j) = G(I_k, \mu_{ij}, \sigma_{ij}) \quad (16)$$

$$G(I_k, \mu_{ij}, \sigma_{ij}) = \frac{1}{\sqrt{2\pi}\sigma_{ij}} e^{\frac{(I_k-\mu_{ij})^2}{2\sigma_{ij}^2}} \quad (17)$$

In order to optimize the decision tree construction process, a novel feature ranking measure is proposed to optimize the problem of pruning.

To each feature in DF[]
do
Finding rank of the feature as
s=D.log(D);
p1=-s/(($\sqrt{\sum D[i]})^3 * \sqrt{\chi(D) * \sum D[i]}$ (18)
p2=-(s*CE(D))/($\chi(D) * \sum D[i])^3$ (19)
done

IV. Results

Utilizing the electromagnetic microwave technique coupled with the dielectric anomaly approach algorithm, a meticulous investigation was carried out on five distinct fruit specimens in a controlled anechoic chamber environment. This comprehensive study culminated in the successful generation of tomographic image reconstructions. Within Figure 9, (a) depicts the resultant output for the orange fruit, (b) portrays the output for the mango, (c) illustrates the output for the lemon, (d) displays the output for the kiwi, and (e) exhibits the output for the avocado. These visual representations offer intricate details of the internal structures and deviations present within the fruits, serving as invaluable tools for the identification and analysis of irregularities and anomalies. Such insights are pivotal in the realm of quality assessment and defect detection in fruit inspection processes, showcasing the efficacy of the employed technique and algorithm for non-destructive testing and evaluation. Permittivity, or the dielectric characteristics of foods, elucidate the material's capacity to either retain or disperse electromagnetic radiation energy. These dielectric properties govern the reflection, transmission, and absorption of radiation at the material's surface. The complex permittivity, denoted as ε and defined as ε =ε'± ε''j, encapsulates both the real and imaginary components of dielectric behavior. The real value ε',is the dielectric constant and the imaginary part ε'',is the dielectric loss factor. The values of the dielectric properties of fruits like avocado is 47±16j, kiwi is 70±18j, lemon is 73±15j, mango is 64±13j, orange is 73±14j.

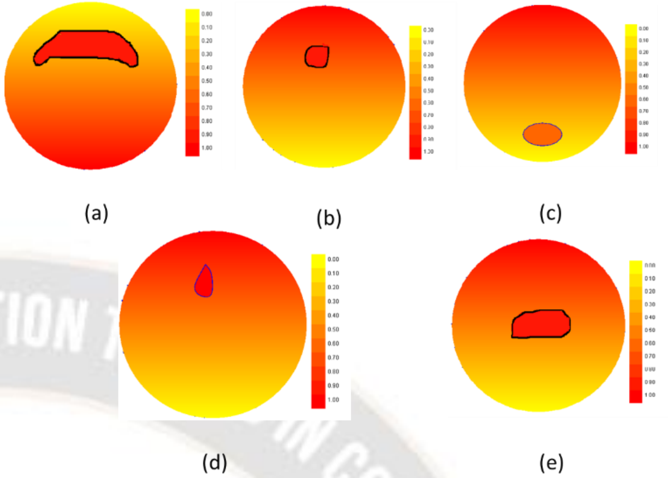


Figure 9: Image Reconstruction of different fruits, a) orange, b) mango,c) lemon,c) kiwi d) avacado

V. Conclusion

In this paper, we have presented a comprehensive approach for the non-destructive inspection of fruits using electromagnetic microwave techniques and the dielectric anomaly approach algorithm. Our experimental setup, consisting of an antenna array and signal processing steps, successfully reconstructed tomographic images of fruits, allowing for the detection of defects. We examined five different types of fruits, both healthy and defective, and gathered essential dielectric properties. The introduction of a novel hybrid IQR method for outlier detection further enhanced the accuracy of anomaly identification. The results showcase the potential of this approach in revolutionizing the fruit inspection process, enabling efficient quality assessment and defect detection. As future work, we intend to explore additional machine learning techniques to further improve the accuracy and efficiency of fruit inspection, making it an invaluable tool for the food industry.

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