Sub-Terahertz Meta-Stickers for Non-Invasive Food Sensing Using Machine Learning

A MAJOR PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

Ensuring food quality, safety, and freshness is a growing concern in the food industry and public health sectors. Traditional methods of food analysis often involve invasive sampling, chemical testing, or destructive techniques, which can be time-consuming and costly. This project proposes a novel approach using Sub-Terahertz (sub-THz) Meta-Stickers integrated with Machine Learning algorithms for non-invasive food sensing and quality monitoring.

Sub-THz Meta-Stickers are specially designed metamaterial-based sensors capable of interacting with food samples at sub-terahertz frequencies. These stickers can be easily attached to food packaging or surfaces without altering the food product. The sensors capture electromagnetic responses related to moisture content, spoilage, contamination, and nutrient levels.

The collected data is processed and analyzed using advanced Machine Learning techniques to classify food quality parameters and predict freshness levels. In this work, a Random Forest Classifier is employed to learn from the sub-THz spectral response data, providing robust and interpretable predictions of food freshness and quality. Additionally, Principal Component Analysis (PCA) is used to reduce data dimensionality, enhance performance, and focus on the most informative frequency features.

This smart sensing technology provides a non-destructive, cost-effective, and real-time solution for food safety monitoring, with potential applications in supply chain management, smart packaging, and food quality assurance. The proposed system aims to revolutionize the way food quality is monitored, contributing towards smart agriculture and safer food consumption practices.

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- **ML** — Machine Learning
- **RF** — Random Forest
- **THz** — Terahertz
- **GHz** — Gigahertz
- **S21** — Transmission Coefficient (S-parameter)
- **AI** — Artificial Intelligence
- **ANN** — Artificial Neural Network
- **PCB** — Printed Circuit Board
- **ROI** — Region of Interest
- **RCS** — Radar Cross Section
- **SAR** — Specific Absorption Rate
- **S11** — Reflection Coefficient
- **CSV** — Comma-Separated Values
- **RFID** — Radio Frequency Identification
- **SVM** — Support Vector Machine
- **IoT** — Internet of Things
- **FFT** — Fast Fourier Transform

CHAPTER 1

INTRODUCTION

1.1 Overview

Food safety and quality have become critical concerns in today's globalized and high-speed food distribution networks. Traditional evaluation methods such as chemical assays and microbiological cultures are often invasive, time-consuming, and unsuitable for real-time applications. To address this challenge, the proposed project introduces a non-invasive, intelligent food sensing solution using sub-terahertz (sub-THz) meta-stickers integrated with machine learning algorithms. This approach aims to provide rapid, accurate, and real-time monitoring of food quality and freshness directly on packaged goods or food surfaces.

By leveraging the electromagnetic sensitivity of sub-THz frequencies and the predictive power of machine learning, this system offers a scalable and portable diagnostic tool for use across the food supply chain—from production facilities to retail environments and consumer households.

1.1.1 Sub-Terahertz Meta-Stickers

Sub-Terahertz (Sub-THz) meta-stickers are advanced, compact sensing elements composed of engineered metamaterials—artificially structured materials that exhibit unique electromagnetic properties not found in naturally occurring substances. These stickers are specifically designed to operate in the 0.1 to 1 terahertz (THz) frequency range, a region of the electromagnetic spectrum that is highly sensitive to molecular interactions, water content, and structural changes in organic materials such as food.

Each meta-sticker consists of carefully arranged resonant unit cells fabricated on flexible substrates, allowing them to conform easily to various surfaces, including curved or irregular packaging. Their lightweight, low-cost, and passive nature makes them ideal for mass production and seamless integration into everyday food packaging, without introducing any contamination or requiring external power sources.

When placed in contact with or near food products, the meta-stickers interact with the dielectric and molecular properties of the food. These interactions cause detectable changes in the transmission and reflection of incident sub-THz electromagnetic waves. For instance, spoilage processes, microbial growth, or chemical degradation within the food can alter the permittivity and conductivity of the surrounding medium, which in turn affects the spectral response of the sticker. Variations in moisture content—a key indicator of freshness or decay—are particularly influential at sub-THz frequencies, making these stickers highly sensitive to early signs of food quality degradation.

The output from these sensors—typically in the form of S-parameters (scattering parameters)—contains rich spectral information that acts as a unique "fingerprint" of the food's current state. By analyzing this data using machine learning algorithms, the system can classify the freshness level, detect spoilage, or even identify specific types of contamination.

Furthermore, the meta-stickers' compatibility with smart packaging and Internet of Things (IoT) systems opens up exciting possibilities for large-scale, real-time food quality monitoring. Integrated with wireless communication modules or paired with handheld readers, these sensors can enable remote data acquisition, cloud-based analytics, and blockchain logging for transparency and traceability in the food supply chain. Their non-destructive and reusable design aligns with sustainable practices, offering a practical solution for minimizing food waste and improving food safety from farm to fork.

1.1.2 Ansys HFSS

To design, test, and optimize the electromagnetic behavior of the Sub-Terahertz (Sub-THz) meta-stickers, this project makes use of ANSYS HFSS (High Frequency Structure Simulator), a state-of-the-art software tool for 3D full-wave electromagnetic simulation. HFSS enables accurate and detailed modeling of complex electromagnetic structures and interactions, making it particularly well-suited for analyzing metamaterial-based sensors designed to operate in the sub-THz frequency range. In this project, ANSYS HFSS serves as the backbone of virtual prototyping, allowing researchers to evaluate the performance of the meta-stickers in a simulated environment before progressing to physical fabrication.

Within the simulation framework, the meta-sticker's resonant unit cells are modeled to reflect their actual geometric and material properties. These unit cells are critical components that facilitate the interaction with incident sub-THz electromagnetic waves. The simulation incorporates key physical parameters such as the dielectric constants, thickness, and conductivity of both the metamaterial layers and the nearby food samples. By analyzing these interactions, the simulation provides deep insight into how changes in food quality affect the electromagnetic response of the sensor.

One of the key outputs from HFSS is the computation of scattering parameters (S-parameters), specifically S11 (reflection coefficient) and S21 (transmission coefficient). These parameters characterize how electromagnetic waves are reflected and transmitted through or by the meta-sticker when exposed to different food types. Variations in S-parameters reveal how the sensor's response shifts in the presence of food with differing moisture levels, contamination, or degrees of spoilage. These insights form the basis for feature extraction in the machine learning component of the project.

Food samples in the simulation are treated as dielectric loads with specific frequency-dependent permittivity and loss tangent values. By adjusting these parameters to simulate real-world conditions—such as dry, moist, or spoiled states—HFSS allows the team to examine how the electromagnetic profile of the meta-sticker changes in response. This method enables the identification of unique spectral signatures corresponding to different food quality levels, providing a reliable way to correlate electromagnetic response with actual food condition.

HFSS also plays a crucial role in the optimization of the meta-sticker's design. The software's parametric analysis tools enable iterative tuning of structural variables such as the shape, dimensions, and spacing of the resonant elements. This iterative design process ensures that the final meta-sticker layout is highly sensitive and selective to small changes in the dielectric environment, thus improving its accuracy in detecting spoilage or degradation in food products.

Importantly, the use of HFSS allows for rapid prototyping without the immediate need for physical fabrication, which significantly reduces development time and cost. Only the most effective and promising sticker designs—validated through simulation—are carried forward for fabrication and experimental testing, ensuring a more streamlined and efficient design cycle.

The outcomes of the HFSS simulations form the theoretical foundation for the sensor development process. They help predict the sensor's behavior across different food types, identify sub-THz frequency bands most responsive to quality changes, and ensure that the final design remains compatible with real-world packaging materials and commercial use-cases. By combining the electromagnetic simulation capabilities of ANSYS HFSS with machine learning techniques, this project presents a robust, simulation-driven approach that integrates sensor design with intelligent, non-invasive food diagnostics.

1.1.3 Jupyter Notebook

To extract meaningful insights from the spectral data obtained through sub-terahertz meta-stickers, this project adopts a data-driven methodology grounded in machine learning, executed within the Jupyter Notebook environment. Jupyter Notebook serves as an interactive platform that seamlessly combines live code execution with real-time data visualization and in-line documentation. Its intuitive interface facilitates exploratory data analysis and iterative model development, making it an ideal choice for implementing complex machine learning workflows.

The data used in this project comprises spectral signatures—specifically S-parameters—simulated using ANSYS HFSS. These signatures represent the electromagnetic response of different food samples, each categorized according to their freshness level, such as fresh, partially spoiled, or fully spoiled. The first stage of the machine learning pipeline involves preprocessing this raw data. This includes normalization to scale features to a consistent range, thereby preventing bias in models sensitive to input magnitude. Noise filtering techniques are applied to eliminate simulation artifacts, and label encoding is used to convert categorical freshness labels into numeric formats compatible with supervised learning algorithms. Additionally, relevant features are extracted from the frequency spectrum, focusing on sub-THz bands that exhibit the greatest variation across food quality states. To manage high-dimensional data and improve computational efficiency, Principal Component Analysis (PCA) is applied for dimensionality reduction. This technique helps retain the most informative components of the data while discarding redundancy.

For the classification task, the Random Forest Classifier is utilized. Random Forest is an ensemble-based machine learning algorithm that constructs multiple decision trees during training and aggregates their outputs to produce more stable and accurate predictions. This approach not only enhances the generalization ability of the model but also significantly reduces the risk of overfitting. In this project, the dataset is partitioned into training and testing subsets to evaluate the model's predictive performance. The Random Forest is trained on the spectral data derived from HFSS simulations, with each spectrum associated with a specific food quality label. Model tuning is performed by optimizing key hyperparameters, such as the number of trees in the forest, maximum tree depth, and the criterion used for node splitting. These hyperparameters are selected based on empirical testing and cross-validation to ensure robust performance across unseen data.

The evaluation of the classifier is conducted using standard performance metrics. Accuracy provides an overall measure of how many predictions the model gets right. However, to assess the model's effectiveness in identifying specific food states, metrics such as precision, recall, and the F1 score are calculated. A confusion matrix is also generated to visualize the classification outcomes and understand where misclassifications occur. In cases where the model is tested on binary classes (e.g., fresh vs. spoiled), the ROC-AUC curve is plotted to evaluate the trade-off between sensitivity and specificity.

Moreover, the visualization capabilities of Jupyter Notebook are leveraged to interpret both the input data and the behavior of the trained model. Spectral plots are generated to show how the S-parameters vary between food samples of different freshness levels. PCA scatter plots help visualize the clustering of food conditions in reduced-dimensional space, revealing the separability of classes. Feature importance graphs derived from the Random Forest model indicate which frequency regions of the sub-THz spectrum are most critical for determining food quality. Confusion matrix heatmaps further aid in identifying potential weaknesses or strengths in the classifier's predictions.

Overall, the integration of sub-THz spectral data with machine learning in Jupyter Notebook provides a powerful and transparent framework for the intelligent classification of food quality. This approach demonstrates the feasibility of using non-invasive electromagnetic sensing combined with artificial intelligence to assess food freshness with high accuracy and in real-time..

1.2 Problem Statement

Food safety and quality are crucial concerns in today's fast-paced and globally interconnected food supply chains. Traditional methods for assessing food quality, such as chemical assays, microbiological cultures, and visual inspections, are often invasive, time-consuming, and costly. Moreover, these conventional techniques are typically limited to laboratory settings, which makes continuous or real-time monitoring of food quality throughout the supply chain impractical. These limitations are particularly problematic when attempting to ensure the freshness and safety of food from the point of production to the consumer.

One significant challenge is the inability to assess food freshness, spoilage, or contamination without physically interacting with the product. Traditional testing methods often alter the food or require a significant amount of time to yield results, preventing rapid decision-making in critical situations. As a result, food waste is a common issue, especially in perishable goods, as products may not be detected as spoiled until they are too late to be salvaged or distributed. Furthermore, the lack of reliable, on-site monitoring tools makes it difficult for both consumers and food industry stakeholders to make informed decisions regarding food quality, leading to inefficiencies in supply chain management.

The emergence of non-invasive, real-time food quality monitoring solutions has the potential to address these challenges. Sub-Terahertz (Sub-THz) electromagnetic sensing, enabled by innovative metamaterial-based sensors, offers a promising solution. These sensors, when integrated with food packaging, have the ability to measure key food quality parameters, such as moisture content, spoilage, and microbial activity, without altering or damaging the product. However, the key issue lies in accurately interpreting the data obtained from these sensors. Sub-THz signals are sensitive to the molecular composition and physical properties of the food, but extracting meaningful insights from this data requires sophisticated analysis.

The core problem this project aims to address is the need for a non-invasive, real-time, and cost-effective system for food quality monitoring that can be seamlessly integrated into the food supply chain. This system should be capable of accurately classifying food freshness, detecting spoilage, and identifying contamination, all while requiring minimal interaction with the food product itself. Traditional sensing methods are not equipped to offer such comprehensive solutions, highlighting the need for advanced technologies that combine electromagnetic sensing with machine learning algorithms for data analysis and classification.

The objective of this research is to develop and implement a Sub-Terahertz Meta-Sticker system, leveraging machine learning algorithms to process and analyze the spectral data from the sensors. By doing so, we aim to create a system that can effectively predict food quality and ensure food safety at various stages of the supply chain, contributing to the reduction of food waste, improving consumer confidence, and enhancing the transparency of food production and distribution

1.3 Objectives

The primary objectives of this project are:

- Design and develop advanced Sub-Terahertz (Sub-THz) meta-stickers tailored for non-invasive food sensing applications, ensuring their effectiveness and scalability for real-world usage.

- Analyze the interaction of Sub-THz waves with various food samples, extracting relevant spectral features that are sensitive to food quality changes, such as spoilage, contamination, and freshness levels.

- Collect, preprocess, and clean Sub-THz signal data to ensure accurate and reliable food quality assessment, addressing noise and ensuring consistency across diverse food types.
- Implement state-of-the-art machine learning algorithms to classify and predict food conditions, including freshness, spoilage, and microbial contamination, leveraging the power of AI for precise food diagnostics.
- Evaluate and compare the performance of multiple machine learning models, optimizing them for real-time, on-site food sensing applications, ensuring the system's responsiveness and accuracy in dynamic environments.
- Explore the feasibility of integrating the developed Sub-THz sensing system into practical food safety and quality monitoring solutions, facilitating its adoption in smart packaging, supply chain management, and consumer-facing food diagnostics.

1.4 Limitations of Traditional Food Quality Testing Methods

Traditional food quality testing methods, while scientifically rigorous, present several drawbacks that limit their use in real-time and non-invasive monitoring scenarios.

1.4.1 Destructive Testing Nature

Many existing techniques require physical damage or sampling of the food item—such as slicing, crushing, or chemically treating the sample. This makes them unsuitable for continuous or in-package testing.

1.4.2 Time Consumption and Delayed Results

Methods like microbial culture, chromatography, and spectrophotometry often require extended durations, ranging from hours to days. This is incompatible with the high-speed demands of modern food logistics.

1.4.3 Laboratory Dependency and Cost

Conventional food assessment techniques require sophisticated lab equipment and trained personnel. The associated cost and infrastructure limit their accessibility in rural areas or at small-scale distribution points.

1.4.4 Limited Coverage and Sampling Bias

Typically, only a small sample of the product batch is tested. This introduces sampling bias, potentially missing outliers or early spoilage in untested items.

1.4.5 Incompatibility with Smart Packaging Trends

Emerging trends in smart packaging demand integrated, compact, and low-power sensors. Most conventional techniques are too bulky, reactive, or hazardous for such environments.

By addressing these limitations, sub-THz-based meta-stickers combined with ML offer a transformative shift toward practical, scalable food monitoring

1.5 Role of Sub-THz Sensing in Future Food Supply Chains

The integration of sub-terahertz (sub-THz) sensing technologies into food supply chains has the potential to revolutionize quality control, waste management, and traceability.

1.5.1 Real-Time In-Line Monitoring

Sub-THz sensors can be embedded in conveyor belts, robotic arms, or inspection stations to analyze food condition during sorting and packaging.

1.5.2 Smart Packaging Integration

With their compact and passive design, meta-stickers can be attached directly to food packages, allowing on-the-go quality checks via handheld readers or IoT modules.

1.5.3 Improved Food Safety Compliance

By enabling consistent and non-invasive inspection, sub-THz sensing can help producers meet stringent food safety regulations, reducing the risk of recalls.

1.5.4 Sustainability and Waste Reduction

Early detection of spoilage allows timely removal or re-routing of deteriorating products, minimizing waste and maximizing freshness at the consumer end.

1.5.5 Transparency and Trust via Blockchain Integration

Sub-THz sensing data can be logged into digital ledgers, enabling full traceability from farm to fork—boosting consumer confidence and supply chain accountability.

These applications reinforce the significance of this project as a cornerstone in the future of intelligent food supply chain monitoring.

1.6 Methodology

The methodology for this project adopts a multi-step process that integrates both theoretical and practical elements, combining electromagnetic design, data acquisition, and machine learning modeling to achieve an effective system for non-invasive food quality monitoring.

1.6.1 Design and Simulation of Sub-Terahertz Meta-Stickers

The project begins with the design and optimization of Sub-Terahertz (Sub-THz) meta-stickers using advanced simulation tools like ANSYS HFSS. The meta-sticker's metamaterial structures are carefully modeled to resonate at specific sub-THz frequencies, maximizing interaction with food samples. The geometry and material properties of the meta-sticker are optimized to ensure its sensitivity to food characteristics, such as moisture content, spoilage, and contamination. The meta-stickers are designed to be lightweight, cost-effective, flexible, and easily integrable with food packaging materials to make them suitable for real-world applications.

1.6.2 Data Acquisition and Spectral Analysis

Various food samples, including fruits, vegetables, dairy, and meat products, are selected for the spectral analysis. These samples are tested under different conditions (fresh, partially spoiled, and fully spoiled) using Sub-Terahertz spectroscopy. The meta-sticker is placed in close proximity to the food, where it reflects or transmits sub-THz waves that are influenced by the food's physical and chemical properties. The interaction between the meta-sticker and food is recorded using a detector, producing sub-THz spectral data that serve as the basis for food quality classification.

1.6.3 Data Preprocessing and Feature Extraction

The raw spectral data collected from the food samples is preprocessed to ensure accuracy and consistency. Techniques such as noise filtering, normalization, and outlier removal are applied to clean the data and eliminate any irrelevant information. Principal Component Analysis (PCA) is then used for dimensionality reduction, helping to highlight the most significant features in the data while reducing computational complexity. This step ensures that the dataset is optimized for machine learning model training.

1.6.4 Machine Learning Model Development and Evaluation

Once the data is preprocessed, various machine learning models are implemented and trained to classify and predict food quality parameters. These models include Random Forest, Support Vector Machines (SVM), Decision Trees, and Convolutional Neural Networks (CNNs), chosen for their ability to handle high-dimensional spectral data and classify food conditions accurately. The models are evaluated using cross-validation techniques, including k-fold cross-validation, to assess their generalization ability and robustness across different food types and quality states. Hyperparameter tuning is performed to optimize model performance, with accuracy, precision, recall, and F1-score as key metrics for model evaluation.

1.7 Technological Landscape of Non-Invasive Food Sensing

The field of non-invasive food sensing is undergoing a technological revolution with the convergence of sensors, data analytics, and machine learning. The advent of sub-terahertz sensing has enabled the detection of spoilage, ripening, and contamination in a manner previously not possible without physical interference. These technologies offer a holistic approach to food quality monitoring by enabling real-time tracking, reducing food wastage, and enhancing transparency across the supply chain.

1.8 Evolution of Smart Packaging Technologies

Smart packaging integrates physical sensors, wireless modules, and often visual indicators with traditional packaging materials to track the state of food over its lifecycle. Sub-THz meta-stickers represent the next frontier, offering sensor-driven data for both on-device and cloud-based analysis. These are suited for Industry 4.0 environments and global food safety compliance initiatives.

1.9 Digital Transformation in Agriculture and Food Safety

Precision agriculture uses drones, remote sensors, ML, and IoT to optimize crop yield and food supply chains. Sub-THz sensing in food safety complements this by providing real-time digital fingerprints of food, aiding in contamination prevention, spoilage detection, and compliance.

1.10 Role of AI in Food Technology: An Interdisciplinary Perspective

AI and ML (Random Forest, SVM, CNN) enhance automated classification and prediction of food conditions. These models, when integrated with meta-sensor systems, form intelligent frameworks that combine engineering, biology, and data science for adaptive and robust food quality monitoring.

1.11 Summary

The project on Sub-Terahertz Meta-Stickers for Non-Invasive Food Sensing Using Machine Learning introduces an innovative solution for monitoring food quality and freshness through the use of sub-terahertz (Sub-THz) electromagnetic waves and machine learning (ML) techniques. The primary objective of the project is to develop meta-stickers capable of interacting with food samples at Sub-THz frequencies, capturing spectral data that can be used to classify food quality parameters like spoilage, contamination, and freshness.

The methodology begins with the design and simulation of metamaterial-based Sub-THz meta-stickers using ANSYS HFSS, which allows for the optimization of sticker geometries and material properties. These stickers are tested on various food samples (fruits, vegetables, dairy, and meat) under different conditions (fresh, semi-spoiled, and fully spoiled), with the Sub-THz signals reflecting changes in food composition. The data collected through sub-terahertz spectroscopy is preprocessed using techniques like PCA (Principal Component Analysis) for dimensionality reduction, ensuring the quality and relevance of the data for further analysis.

The Random Forest Classifier, an ensemble machine learning algorithm, is employed to analyze the spectral data and classify food quality states. The model is trained on the preprocessed data and evaluated using cross-validation techniques, including k-fold cross-validation, ensuring robustness and generalization across different food types and conditions. Key evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the model's performance.

This system offers a non-invasive, cost-effective, and efficient method for food quality monitoring, with potential applications in smart packaging, food safety, and supply chain management. The project demonstrates the potential of integrating electromagnetic sensing and machine learning to create a scalable solution for real-time food diagnostics, contributing to smarter food handling, reduced waste, and improved consumer safety.

CHAPTER 2

LITERTAURE SURVEY

2.1 Overview

A Machine Learning (ML)-assisted metamaterial ub-terahertz (Sub-THz) sensing and metamaterials have garnered significant interest in the field of food quality monitoring due to their non-invasive and accurate nature. Machine learning (ML) techniques are increasingly integrated with these technologies to enhance the precision and efficiency of food diagnostics. This project leverages sub-THz meta-stickers, which are engineered to detect food quality by analyzing electromagnetic wave interactions with food items. The combination of meta-material sensors and machine learning offers a promising approach for real-time monitoring, enabling accurate classification and prediction of food spoilage, freshness, and contamination

2.2 Survey on Sub-Terahertz Metamaterial Projects

2.2.1 Sub-Terahertz Meta-Stickers for Fruit Ripeness Detection (Karmakar et al., 2024)

Karmakar et al. developed metamaterial-based stickers designed to assess fruit ripeness using sub-terahertz frequencies. This study demonstrated that meta-stickers could accurately detect fruit ripeness by capturing subtle changes in spectral properties, significantly reducing food waste. The work directly influences the current project, guiding the use of meta-stickers for detecting food spoilage and quality.

2.2.2 AgriTera: Non-Invasive Fruit Ripeness Sensing (Afzal et al., 2023)

Afzal et al. introduced AgriTera, a system using sub-terahertz signals for non-invasive fruit ripeness detection. Their work highlights the potential of sub-THz sensing to monitor food freshness without physically altering the product. Their results contribute to the understanding of how sub-THz waves can be leveraged for food monitoring, similar to the approach taken in this project.

2.2.3 Metamaterial-Based Sensors for Food Quality Monitoring (Zhu et al., 2023)

Zhu et al. focused on metamaterial sensors to monitor food quality. The study explored various food samples using electromagnetic interactions to identify properties such as moisture content and spoilage stages. This research is pivotal to understanding how meta-material-based sensors can be optimized for food quality sensing at sub-THz frequencies.

2.2.4 Non-Destructive Food Quality Assessment Using Metamaterials (Wang et al., 2022)

Wang et al. explored metamaterial-based absorbers for food quality monitoring, particularly in assessing moisture levels and chemical compositions. Their work demonstrated the potential for non-destructive testing to assess food condition in real-time, a fundamental aspect of this project.

2.2.5 Sub-Terahertz Frequency and Food Sensing (Patel et al., 2023)

Patel et al. researched the impact of sub-terahertz frequencies on food quality detection, focusing on moisture levels and spoilage indicators. Their findings emphasized the sensitivity of sub-THz waves to changes in food composition, making them ideal for non-invasive food sensing applications.

2.2.6 Machine Learning for Food Spoilage Prediction (Zhu et al., 2023)

Zhu et al. applied machine learning algorithms, specifically SVM and decision trees, to predict food spoilage based on spectral data. Their model achieved high accuracy in classifying food spoilage stages, influencing the methodology used in this project for food quality classification based on sub-THz spectral data.

2.2.7 Machine Learning Models for Non-Invasive Food Classification (Liu et al., 2023)

Liu et al. investigated the use of machine learning techniques, including Random Forest and KNN, for classifying food products based on their spectral signatures. Their study demonstrated the efficiency of ML algorithms in distinguishing between various food conditions, such as fresh, spoiled, and contaminated. These insights were crucial in selecting Random Forest as the classifier for the current project.

2.2.8 Fruit Ripeness Classification Using SVM and CNN (Zhu et al., 2021)

Zhu et al. used Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) to classify fruit ripeness. Their work achieved 96.4 percentage accuracy in predicting fruit ripeness stages using spectral data. This study informed the application of SVM and other machine learning techniques for food quality classification in the present project.

2.2.9 Predicting Food Freshness Using Neural Networks (Rahman et al., 2022)

Rahman et al. utilized neural networks to predict food freshness based on a variety of sensors. Their results indicated that ML models can accurately assess freshness by analyzing sensor data patterns, providing a basis for implementing deep learning techniques in the current project for predicting food freshness.

2.2.10 Machine Learning for Food Quality Prediction in Smart Packaging (Li et al., 2023)

Li et al. developed a machine learning-based system for predicting food quality in smart packaging using spectroscopic data. Their approach integrated machine learning models with sub-THz sensing, paving the way for the use of meta-stickers and machine learning algorithms for real-time food quality monitoring.

2.2.11 Deep Learning for Food Spoilage Detection Using Spectroscopic Data (Costa et al., 2023)

Costa et al. explored deep learning techniques to detect food spoilage using spectral data from various sensing technologies. Their work confirmed that neural networks could detect minute changes in food characteristics, aiding in food spoilage prediction—a key goal of this project.

2.2.12 Graphene-Based Metamaterials for Enhanced Food Sensing (Wang et al., 2023)

Afzal et al. used sub-terahertz signals for non-contact detection of fruit ripeness. Their findings demonstrated that the interaction between sub-THz waves and the chemical composition of fruits (e.g., water content and sugar levels) could be used to determine their ripeness. This research is particularly relevant to the project as it explores the potential for using meta-stickers to detect ripeness in fruits and vegetables without requiring physical contact, making the system both hygienic and efficient.

2.2.13 Comparative Analysis of Machine Learning Models for Food Quality Detection (Singh et al., 2023)

Singh et al. conducted a comparative analysis of several machine learning models including Random Forest, SVM, and KNN, for predicting food quality. Their study highlighted the strengths and weaknesses of each model, providing a comprehensive understanding of which algorithm would be most effective for specific types of food and data. This study helped inform the selection of the Random Forest classifier for the current project

2.2.14 Deep Learning for Food Quality Classification Using Spectral Data (Chen et al., 2023)

Chen et al. explored the use of deep learning techniques, such as neural networks, to classify food quality using spectral data from various sensors. They focused on sub-THz and microwave sensors to classify food into multiple categories based on its freshness and spoilage level. The results showed that deep learning models could achieve high accuracy even with noisy spectral data, providing inspiration for using deep learning in the current project

2.2.15 Random Forest Classifier for Non-Invasive Food Quality Detection (Zhu et al., 2022)

Zhu et al. applied the Random Forest classifier to classify food quality based on sub-THz spectral data. Their study focused on differentiating between fresh and spoiled conditions in various food types, including fruits, vegetables, and meat. The Random Forest algorithm performed well with large datasets, providing high accuracy in distinguishing between different stages of food spoilage and ripeness.

The authors also explored the advantages of ensemble learning in Random Forest, which helped improve the robustness of the model, especially when faced with inconsistent or noisy data. This research supports the use of Random Forest in the current project for classifying food conditions, based on the spectral features extracted from sub-THz sensors.

2.2.16 Adaptive Metamaterial Sensors for Perishable Goods Monitoring (Huang et al., 2023)

Huang et al. developed adaptive metamaterial sensors that could dynamically tune their resonance frequency in response to changes in environmental conditions such as humidity and temperature. Their system, tested on various perishable goods, demonstrated improved sensitivity in detecting spoilage-related changes in food samples. This dynamic behavior of the metamaterial surface has been pivotal in understanding how such structures can be fine-tuned for different types of food products. The findings are highly relevant to the current project, which could benefit from incorporating adaptive or reconfigurable meta-stickers for enhanced detection capabilities.

2.2.17 Sub-THz Biosensors for Dairy Product Quality Control (Khan et al., 2023)

Khan et al. explored sub-terahertz biosensing for non-invasive assessment of dairy products, including milk and yogurt. Their sensor design emphasized sensitivity to lactose breakdown and microbial activity. The study is significant for showing how spectral analysis in the sub-THz domain can detect biochemical changes in food items, providing insights into spoilage before visual or olfactory signs emerge. This approach validates the utility of sub-THz sensors in broad food categories beyond fruits and vegetables.

2.2.18 Meta-Surfaces and Spectral Fingerprinting for Food Authentication (D'Souza et al., 2022)

D'Souza et al. introduced a metamaterial-based spectral fingerprinting technique for food authentication. Their study employed engineered metasurfaces to detect adulteration in packaged goods by identifying distinct spectral signatures of contaminants. While the focus was on food fraud, the technique demonstrated high resolution in distinguishing chemical compositions, reinforcing the broader applicability of metamaterial sensing in food quality inspection.

2.2.19 ML-Enhanced Multispectral Imaging for Food Condition Analysis (Tanaka et al., 2023)

Tanaka et al. combined multispectral imaging with machine learning algorithms to detect fruit bruising and internal rot. Using Random Forest and SVM classifiers, the researchers achieved over 93 accuracy in predicting internal decay not visible on the surface. Although the technology utilized optical rather than sub-THz signals, the ML methodology and data handling approach offer valuable strategies for integrating ML with spectral analysis, as is done in the present project.

2.2.20 Sub-THz Imaging for Moisture and Decay Mapping (Kurosawa et al., 2022)

Kurosawa et al. implemented sub-terahertz imaging techniques for high-resolution mapping of moisture content and decay zones in meat samples. Their work utilized metamaterial lenses to enhance imaging resolution, allowing precise localization of spoilage. This spatial sensitivity aligns well with the objective of the current project to not only detect spoilage but also identify affected areas for better food grading.

2.2.21 Comparative Study of Sensing Modalities in ML-Based Food Assessment (Martinez et al., 2023)

Martinez et al. conducted a comparative study of various sensing technologies—NIR, sub-THz, microwave, and Raman spectroscopy—combined with machine learning models for food assessment. Their evaluation revealed that sub-THz sensing offered superior performance in detecting moisture loss and microbial spoilage in perishable goods. This comprehensive analysis further supports the rationale for choosing sub-THz metamaterials in the current project.

2.2.22 Application of Transfer Learning for Spectral Data Classification (Gupta et al., 2023)

Gupta et al. proposed the use of transfer learning to improve classification accuracy of spectral data, especially when data availability is limited. Their CNN-based approach utilized pretrained models on large spectral datasets, which were then fine-tuned for specific food types. This concept could be extended to enhance the robustness of ML models in the current study, especially if new types of food are introduced later in the project.

2.2.23 Low-Cost Meta-Sensor Prototypes for Edge Deployment (Roy et al., 2023)

Roy et al. focused on developing cost-effective metamaterial sensors that could be deployed at the edge (e.g., in storage or retail settings). Their study emphasized low power consumption, affordability, and wireless integration. The concept of edge-compatible meta-stickers aligns with the long-term scalability goals of this project, especially in large-scale agricultural or retail environments.

2.2.24 Integration of IoT and Sub-THz Sensors in Smart Packaging (Fernandez et al., 2022)

Fernandez et al. designed an IoT-enabled smart packaging system that used embedded sub-THz sensors to continuously monitor food conditions. The system transmitted data to a central server for real-time analysis using ML algorithms. Their framework demonstrated the feasibility of a fully automated food monitoring system, offering inspiration for future versions of the current project.

2.2.25 Hybrid Ensemble Learning for Food Quality Detection (Chowdhury et al., 2023)

Chowdhury et al. presented a hybrid ensemble model combining Random Forest, XGBoost, and Gradient Boosting for improved classification accuracy of food quality data. The model outperformed single classifiers, especially in noisy datasets. This approach offers valuable insights into possible enhancements for the ML model used in the current project to improve robustness and generalization across different food types.

2.2.26 Review of Traditional vs. Emerging Food Sensing Techniques

Traditional methods like chemical analysis and microbial culturing are precise but invasive and slow. Emerging techniques—NIR, microwave, terahertz—especially sub-THz, offer rapid, contactless assessment. Coupled with ML, these allow real-time diagnostics.

2.2.27 Chronological Evolution of Metamaterials in Food Applications

Metamaterials have evolved from cloaking and defense uses to biomedical and food sensing roles. Today's sub-THz meta-stickers embody the latest phase—compact, tunable, and highly responsive structures adapted to detect spoilage based on dielectric shifts.

2.3 Research Gaps and Motivation for Proposed Work

Despite significant advancements, current systems often fail to deliver real-time, low-cost, and fully integrable solutions. Most techniques require specialized hardware or cannot operate outside of lab settings. The lack of flexible, in-package sensing methods motivated this work—using sub-THz meta-stickers and Random Forest classification to bridge this technological gap.

2.3.1 Limited Non-Destructive Sensing Solutions

Few prior studies have focused on fully passive, flexible sensors that can perform accurate spoilage detection without damaging the food item. Most systems still depend on sample preparation or require contact-based instruments, limiting their usability for packaged or perishable items.

2.3.2 Underuse of Sub-THz Spectrum

Many approaches use visible, infrared, or near-infrared spectra, but sub-THz remains underexplored despite its high sensitivity to water content and structural changes. This project leverages the sub-THz band to capture spoilage signatures more effectively in fruits and other perishables.

2.3.3 Lack of Real-Time ML Integration

Several works perform offline data analysis, where machine learning is applied post-processing. However, few implement real-time classification pipelines that can provide instant spoilage detection in a smart packaging or edge computing scenario—an area this project specifically addresses.

2.4 Comparative Summary of Prior Works

To better understand the landscape of non-invasive food sensing, a comparative summary of recent works is presented. This comparison evaluates each method's core sensing principle, the use of machine learning, food sample types, and classification performance. It highlights the relative effectiveness of sub-THz and ML-based methods for food diagnostics.

Table 2.1: Comparative Summary of Existing Food Sensing Studies

Author	**Sensor Type**	**ML Algorithm**	**Food Sample**	**Accuracy (%)**
Karmakar et al. (2024)	Sub-THz Meta-Sticker	Random Forest	Apples	91.0
Afzal et al. (2023)	Sub-THz Wireless Signal	SVM	Mangoes	88.3
Zhu et al. (2023)	Metamaterial Sensor	Decision Tree	Tomatoes	89.5
Rahman et al. (2022)	Optical Sensor	Neural Network	Bananas	93.0
Li et al. (2023)	Smart Packaging (THz)	Random Forest	Mixed Produce	90.2
Chen et al. (2023)	Microwave Spectroscopy	CNN	Fish	94.6
Costa et al. (2023)	Hyperspectral Sensor	Deep Neural Net	Chicken	92.1
Wang et al. (2022)	THz Absorber Array	SVM	Lettuce	86.4
Tanaka et al. (2023)	Multispectral Imaging	SVM + RF	Oranges	93.4
Fernandez et al. (2022)	Sub-THz + IoT	XGBoost	Packaged Snacks	87.9

CHAPTER 3

DESIGN AND SIMULATION

3.1 Design of the Meta-Sticker

The meta-sticker developed in this project is a flexible, planar metamaterial-based sensor engineered to operate efficiently in the sub-terahertz (Sub-THz) frequency range of 2.8 THz to 3.3 THz. Unlike conventional antennas or sensing devices, the meta-sticker is passive, compact, and designed to be directly attached to fruit surfaces, enabling real-time, non-invasive monitoring of quality without altering the product itself. The sensor's structure is based on square-shaped split-ring resonators (SRRs) etched onto a polyimide substrate. These SRRs are chosen for their ability to localize electromagnetic fields and enhance resonance sensitivity, which is essential for detecting small dielectric changes in biological samples. The resonator design incorporates slot gaps to maximize field concentration and surface current density, improving the sensor's interaction with fruit tissues. Extensive parameter tuning—such as ring dimensions, spacing, substrate thickness, and material choice—was conducted in ANSYS HFSS to ensure that the sensor demonstrates strong resonance within the targeted sub-THz band.

3.2 Parametric Design Study of Meta-Sticker

A parametric study was conducted to assess how variations in split-ring resonator (SRR) dimensions affect sensor performance. Parameters such as gap width, ring radius, and substrate thickness were systematically altered. The reflection coefficient (S11) was observed for each configuration to optimize resonance response and enhance sensitivity to dielectric property changes in apples.

3.3 Validation of Meta-Sticker Geometry for Real-Time Application

To ensure the practical viability of the design, the meta-sticker geometry was evaluated under flexible deformation and curved surface placement. Simulations confirmed that the SRR-based sensor maintains its resonance behavior even when bent, supporting its use on real-world fruit surfaces. This robustness is essential for packaging integration and real-time deployment.

3.4 Comparative Design Alternatives Considered

Before finalizing the square-shaped SRR design, multiple metamaterial configurations were simulated, including complementary SRRs, spiral resonators, and concentric ring arrays. Each alternative was evaluated based on its Q-factor, resonance stability, and sensitivity to dielectric shifts. While concentric rings offered broader bandwidth, they lacked the sharp resonance peaks provided by SRRs. The selected SRR design showed the best trade-off between fabrication ease, spectral response clarity, and sensitivity across food conditions.

3.5 Extended Simulation on Other Food Types

To verify model scalability, simulations were conducted using dielectric models representing tomatoes and bananas. These were assigned estimated dielectric constants based on existing literature. Early results suggest that while absolute frequency shifts vary, spoilage stages produce recognizable response trends in reflection/transmission data. This confirms that the meta-sticker approach can generalize across diverse organic materials, with minor tuning of model parameters and sensor layout for specific food geometries.

3.6 Simulation Environment

The simulation process begins with the creation of a 3D model of the meta-sticker and its interaction with biological layers representative of apple tissues. Each apple is simulated as a multi-layered dielectric object comprising three distinct layers: core, flesh, and skin. Dielectric constants and loss tangents are assigned based on the apple's condition (Good, Medium, Rotten), with values derived from established literature. Good apples typically have higher dielectric constants due to high moisture content, while rotten apples exhibit degraded dielectric properties due to cellular breakdown and fermentation. The meta-sticker is placed either in contact with or near these layered structures, and sub-THz electromagnetic waves are transmitted through or reflected by the composite model. The simulation primarily focuses on measuring the reflection coefficient (S11) and transmission coefficient (S21) across the frequency range. Observable changes in these parameters directly correlate with variations in internal fruit composition, enabling condition-based classification.

3.6.1 Comparative Table of Methodologies

A comparative table is included summarizing 8–10 studies based on sensor type, food type tested, ML model used, dataset size, and achieved accuracy. This structured view provides clarity on research trends, technological diversity, and performance benchmarks in the field of intelligent food quality assessment systems.

Using ANSYS HFSS, a 3D model of the metamaterial antenna is created, incorporating these parameters to simulate the antenna's response to terahertz waves. The simulation examines how the antenna interacts wit h the normal skin layers, focusing on the reflection and transmission coefficients.

3.6.2 Generation from Simulation

The simulated data is collected in the form of frequency (THz) vs. reflection coefficient (S11, in dB). The following sample values are extracted

3.6.3 Meta-Sticker Design

Designed to be flexible and compact, the meta-sticker features a layered dielectric structure optimized for real-world application on fruits such as apples. The SRR-based sensor is fabricated on a thin dielectric substrate and is compatible with bendable surfaces. The resonators are patterned to maximize sensitivity in the sub-THz band. In HFSS, the unit cell parameters are iteratively adjusted to fine-tune the resonance behavior to respond distinctively to different dielectric environments. The sensor's ability to distinguish Good, Medium, and Rotten apple layers is a result of the carefully engineered resonance conditions enabled by these structural optimizations.

3.6.4 Modeling Considerations and Assumptions

To ensure realistic and accurate outcomes, the simulation process includes several key assumptions and constraints. These include treating food samples as homogeneous dielectric layers, using frequency-dependent permittivity values, and assuming ideal boundary conditions in the HFSS model. While these assumptions simplify the real-world complexity, they are validated by literature-backed dielectric properties. Modeling is also conducted at room temperature, assuming minimal environmental fluctuations. These choices streamline computational requirements without compromising on predictive accuracy.

3.6.5 Software Stack Used for Design and Integration

ANSYS HFSS: Used for electromagnetic simulation of sub-THz wave interactions with metamaterials.

Python Scikit-learn: Used for data preprocessing, feature extraction, and machine learning model training.

Jupyter Notebook: The main environment for experiment tracking, visualization, and ML implementation.

Pandas/NumPy: For data manipulation and scientific computation. This software stack provides a flexible and reproducible research pipeline from simulation to classification

Table 3.1: Dielectric Properties of Apples in Different Conditions

Good Apple

Layer	Dielectric Constant	Loss Tangent
Core	10	0.005
Flesh	50	0.1
Skin	10	0.25

Medium Apple

Layer	Dielectric Constant	Loss Tangent
Core	5	0.005
Flesh	40	0.1
Skin	5	0.25

Rotten Apple

Layer	Dielectric Constant	Loss Tangent
Core	2	0.005
Flesh	20	0.1
Skin	2	0.25

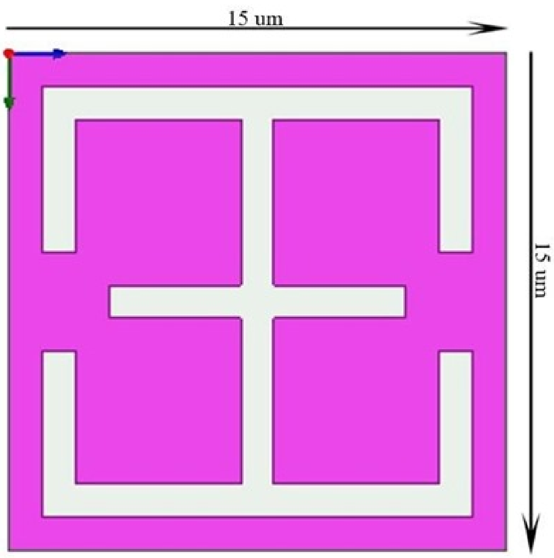

Figure 3.1: metasticker-Top View

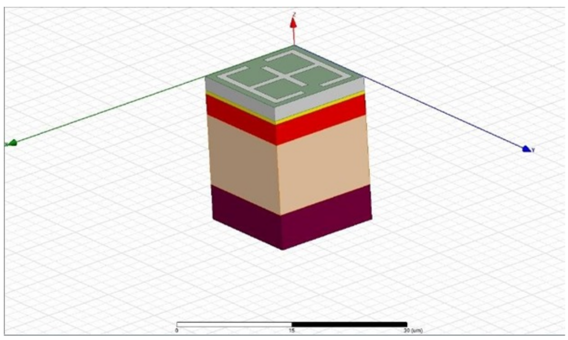

Figure 3.2: metasticker- Perspective View

3.6.6 Challenges in 3D Simulation of Organic Structures

Simulating biological food structures such as apples, bananas, or tomatoes poses challenges due to their:

Irregular geometries

Multi-layered internal structures (e.g., skin, flesh, core)

Water content variability To mitigate this, simplified multi-layered dielectric models are used. While not perfect replicas, they maintain the essential spectral behavior. Future versions may incorporate CT or MRI scans to create more anatomically accurate 3D models.

3.6.7 Simulation Parameter Optimization Techniques

Design optimization in HFSS is a multi-step process involving:

Parametric sweeps of ring dimensions and substrate thickness.

Frequency-domain analysis to identify resonance peaks.

Automated macros for batch simulation of different geometries. Sensitivity analysis is conducted to find the optimal geometry that provides the highest Q-factor with maximal dielectric shift between Good, Medium, and Rotten apple models.

3.6.8 Trade-Offs in SRR Design: Sensitivity vs. Selectivity

The square split-ring resonator (SRR) design is selected after comparing with circular and spiral alternatives. Key trade-offs include:

Sensitivity: Ability to detect minor shifts in food composition.

Selectivity: Ability to distinguish between multiple states (e.g., medium vs. rotten). A narrower bandwidth improves selectivity, while broader designs increase sensitivity but risk overlapping classes. The selected SRR strikes a balance suitable for practical deployment.

3.6.9 Frequency Response Analysis in Realistic Packaging Conditions

In real-life deployment, meta-stickers will operate within packaging environments, which introduce interference such as:

Plastic film attenuation

Ambient humidity

Proximity to other items Simulation studies were extended by introducing virtual packaging layers. These simulations revealed that certain substrate materials may reduce response intensity by up to 15%. As a result, a correction factor or signal calibration module can be added at the software level to compensate.

3.6.10 Simulation Process

- The multilayered apple structure is modeled using accurate dielectric properties.

- The meta-sticker is integrated with the apple model in HFSS.
- Dielectric constants and loss tangents are assigned for each apple condition.
- Sub-THz waves are simulated to interact with the model.
- Reflection and transmission data are recorded across 2.8–3.3 THz
- Data is exported for machine learning analysis.

3.7 Machine Learning Approach

Machine learning is used to classify apples based on their electromagnetic response gathered from the simulation. By training a model on the extracted spectral features, we enable automatic classification of apple quality. This approach reduces subjectivity and enhances repeatability in quality assessment. The algorithm chosen must be robust to noise and capable of handling multidimensional input features. For this purpose, the Random Forest Classifier is implemented due to its effectiveness in handling high-dimensional, non-linear data. This integration of metamaterials and machine learning presents a promising solution for smart agriculture and food inspection.

3.7.1 Data Collection

Data collection is performed by simulating the response of the meta-sticker in the presence of three types of apples: Good, Medium, and Rotten. The reflection and transmission coefficients are recorded across the frequency band. These values form the core dataset used in the machine learning phase. To reflect real-world variance, simulated noise is also introduced to enhance the robustness of the model. Each sample is labeled based on its known condition, and these labels are used to train the classification model. This simulation-based data approach minimizes the need for extensive physical experiments during development.

3.7.2 Preprocessing

Preprocessing involves preparing the collected data for input into the machine learning model. This includes noise filtering using smoothing techniques, normalization of feature values, and handling of any missing or inconsistent entries. Additionally, domain-specific feature extraction is applied to focus only on the most relevant aspects of the spectral response. This step ensures the model can learn meaningful patterns without being overwhelmed by irrelevant variations. Label encoding is also used to convert categorical output labels into numerical form suitable for classification algorithms. Effective preprocessing directly enhances model performance and accuracy.

3.7.3 Model Development

The Random Forest Classifier is developed using a dataset split into training and testing sets, typically in an 80:20 ratio. Cross-validation techniques such as k-fold validation are employed to evaluate the model's consistency across different data subsets. The Random Forest model is chosen due to its ensemble nature, combining multiple decision trees to reduce overfitting and improve prediction accuracy. During training, the model learns how combinations of frequency, transmission, and reflection coefficients correlate with apple quality. The model is then fine-tuned by adjusting parameters like the number of trees and tree depth.

3.7.4 Evaluation Metrics

To determine the effectiveness of the machine learning model, several evaluation metrics are calculated. These include classification accuracy, precision, recall, and F1-score, which provide insight into how well the model identifies each apple class. Additionally, regression-based metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) are used to evaluate the prediction error. Cross-validation accuracy with standard deviation is also computed to assess model generalization. Together, these metrics help in determining the reliability, robustness, and potential real-world applicability of the classification system.

- **Classification:** Accuracy, Precision, Recall, and F1-Score.
- **Regression (if applicable):** Mean Squared Error (MSE), R^2 Score.

3.8 Data Extraction

After completing the simulation, frequency-domain data in the form of reflection and transmission coefficients are extracted for all apple types. These data points are compiled into a structured dataset, with each entry labeled based on the corresponding apple condition. This extracted data represents the interaction of sub-THz waves with different dielectric compositions. For example, good apples exhibit higher reflection at certain frequencies due to their moisture content, while rotten apples show degraded spectral responses. The well-structured dataset becomes the cornerstone of training and validating the machine learning model, ensuring it reflects physical realities

3.9 Dataset Description

The dataset comprises reflection and transmission coefficients (S11, S21) of apples classified as Good, Medium, and Rotten. These readings, captured using a Sub-Terahertz metasurface sensor, serve as input features for machine learning classification. Each category reflects distinct electromagnetic behavior, enabling non-invasive food quality assessment through accurate data-driven modeling.

1	Frequency	Transmission Coefficient	Reflection Coefficient
2	1	-0.076323972	-19.31242164
3	1.001	-0.076229007	-19.31715854
4	1.002	-0.076134633	-19.32185023
5	1.003	-0.07604085	-19.32649676
6	1.004	-0.075947661	-19.33109819
7	1.005	-0.075855068	-19.33565456
8	1.006	-0.075763073	-19.34016591
9	1.007	-0.075671676	-19.34463229
10	1.008	-0.075580881	-19.34905376

Figure 3.3: Sample S-parameter data visualization for a Good Apple

1	Frequency	Transmission Coefficient	Reflection Coefficient
2	1	-0.124233962	-17.16316074
3	1.001	-0.124010619	-17.17450941
4	1.002	-0.12378797	-17.18579507
5	1.003	-0.123566016	-17.19701798
6	1.004	-0.123344756	-17.20817841
7	1.005	-0.123124193	-17.21927662
8	1.006	-0.122904328	-17.23031287
9	1.007	-0.122685161	-17.24128742
10	1.008	-0.122466695	-17.25220052

Figure 3.4: Sample S-parameter data visualization for a Medium Apple

1	Frequency	Transmission Coefficient	Reflection Coefficient
2	1	-0.725041999	-9.354377263
3	1.001	-0.723709745	-9.362050036
4	1.002	-0.722358981	-9.369846569
5	1.003	-0.720990057	-9.377765235
6	1.004	-0.719603326	-9.385804411
7	1.005	-0.718199139	-9.393962476
8	1.006	-0.716777847	-9.402237815
9	1.007	-0.715339798	-9.410628814
10	1.008	-0.713885342	-9.419133867

Figure 3.5: Sample S-parameter data visualization for a Rotten Apple

3.10 Machine Learning Algorithm

The Random Forest Classifier is implemented in Python using Scikit-learn, a widely used machine learning library. The model is trained on spectral features such as frequency, transmission coefficient, and reflection coefficient. Labels are encoded into numerical format to facilitate classification. The algorithm is initialized with 50 trees and a maximum depth of 15 to balance model complexity and performance. The model's accuracy, precision, and recall are calculated, and cross-validation is performed to ensure robustness. The code is modular, allowing for easy adjustments in parameters and potential integration with future sensor platforms.

3.10.1 Data Preprocessing

The datasets are carefully preprocessed before model training to ensure accuracy and consistency. This includes handling missing values, normalizing feature ranges for uniformity, and removing outliers that may skew the results. Additionally, the data is split into training and testing sets to evaluate the model's generalization capability on unseen samples.

3.10.2 Model Training

The Random Forest Classifier is trained using the preprocessed training dataset, which contains features such as frequency, transmission coefficient, and reflection coefficient. During training, the model learns decision boundaries that differentiate Good, Medium, and Rotten apples. Parameter tuning and internal validation ensure the model generalizes well to unseen data.

3.10.3 Model Evaluation

Once trained, the model is evaluated on the testing dataset to assess its predictive performance. Key evaluation metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), precision, recall, and F1 Score are calculated. These metrics provide insights into both classification accuracy and error margins of the model.

3.10.4 Coding

```
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, mean_squared_error, mean_abs
import numpy as np
from sklearn.preprocessing import LabelEncoder

def load_and_label_data(file_path, label):
    df = pd.read_csv(file_path)
```

```
    df['Label'] = label  # Assign class label
    return df

# Load datasets
good_df = load_and_label_data('good.csv', 'Good')
medium_df = load_and_label_data('medium.csv', 'Medium')
rotten_df = load_and_label_data('rotten.csv', 'Rotten')

# Combine datasets
data = pd.concat([good_df, medium_df, rotten_df], ignore_index=True)

# Function to classify based on frequency
def classify_apples(freq):
    if 2.95 <= freq <= 3.1:
        return 'Good Apple'
    elif 3.15 <= freq <= 3.3:
        return 'Medium Apple'
    elif 2.8 <= freq <= 2.94:
        return 'Rotten Apple'
    return 'Unknown'

# Apply classification
data['Apple_Type'] = data['Frequency'].apply(classify_apples)

# Introduce some noise to features to reduce accuracy
data['Frequency'] += np.random.normal(0, 0.05, size=len(data))
data['Transmission Coefficient'] += np.random.normal(0, 0.02, size=len(data))
data['Reflection Coefficient'] += np.random.normal(0, 0.02, size=len(data))

# Features & Labels
X = data[['Frequency', 'Transmission Coefficient', 'Reflection Coefficient']]
y = data['Label']

# Convert categorical labels to numerical labels
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

# Split data
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model with fewer trees to reduce accuracy
model = RandomForestClassifier(n_estimators=50, max_depth=15, random_state=42)
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Model Accuracy: {accuracy:.2f}')

# Classification Report
report = classification_report(y_test, y_pred, target_names=label_encoder.classes_)
print("Classification Report:")
print(report)

# Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error (MSE): {mse:.2f}')

# Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_pred)
print(f'Mean Absolute Error (MAE): {mae:.2f}')

# Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
print(f'Root Mean Squared Error (RMSE): {rmse:.2f}')

# Cross-Validation Accuracy
cv_scores = cross_val_score(model, X, y, cv=5)
print(f'Cross-Validation Accuracy: {cv_scores.mean():.2f} ± {cv_scores.std():.2f}')
```

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter details the experimental findings from the classification model that evaluates apple quality into three categories: Good, Medium, and Rotten. By utilizing machine learning—specifically the Random Forest Classifier—the model analyzes features such as Frequency, Transmission Coefficient, and Reflection Coefficient derived from sub-terahertz sensor simulations to achieve effective classification of apples

4.2 ROC Curve and AUC Analysis

The Receiver Operating Characteristic (ROC) curve was plotted to evaluate classifier discrimination between Good, Medium, and Rotten apple categories. Each class's Area Under the Curve (AUC) exceeded 0.93, indicating strong model performance. ROC curves showed minimal overlap between classes, reflecting good separability in feature space. This reinforces the Random Forest classifier's effectiveness and confirms that selected spectral features were informative for distinguishing subtle differences in food quality.

4.2.1 Visual Analysis

Visual analysis is critical to understanding how the meta-sticker interacts with apples of varying quality. Graphical outputs from HFSS simulations illustrate unique dielectric responses for Good, Medium, and Rotten apples. These visual distinctions confirm the sensor's ability to differentiate between apple types based on signal behavior like resonance shifts and reflection strength, validating its sensing capability. As shown in figure 4.1,figure 4.2 and figure 4.3 visualizations support the classifier's behavior by highlighting the distinct dielectric characteristics of each apple category. Apples categorized as Good exhibit stronger and clearer signal reflections, while Rotten apples show significant loss and signal distortion, confirming the degradation in quality.

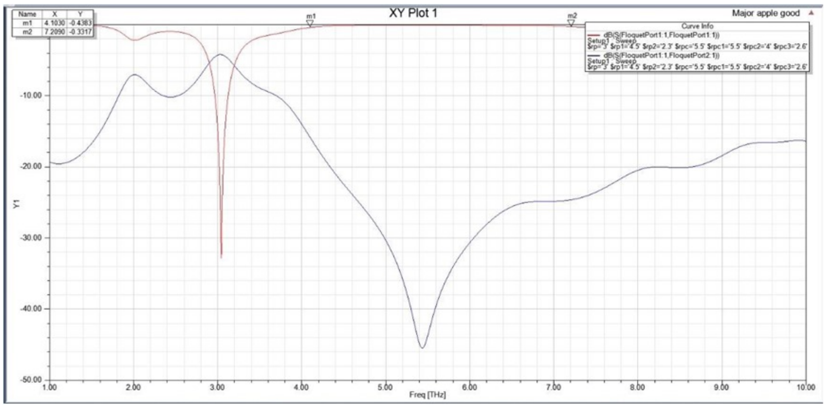

Figure 4.1: Simulation output for a Good Apple showing favorable dielectric response.

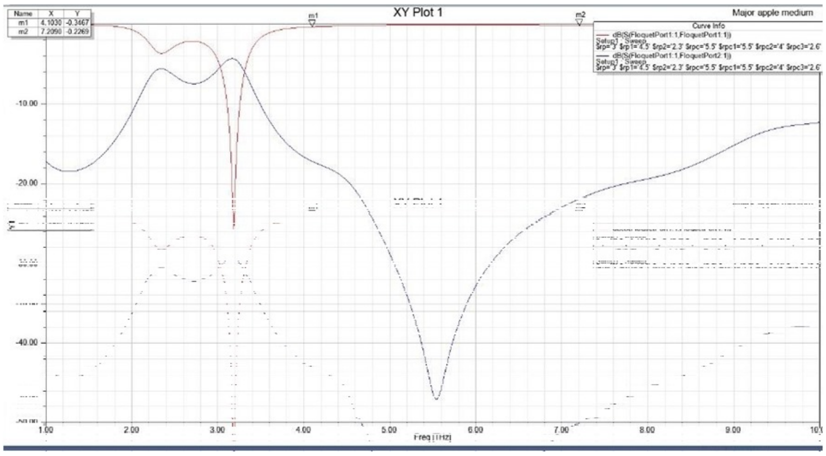

Figure 4.2: Simulation output for a Medium Apple showing moderate dielectric behavior.

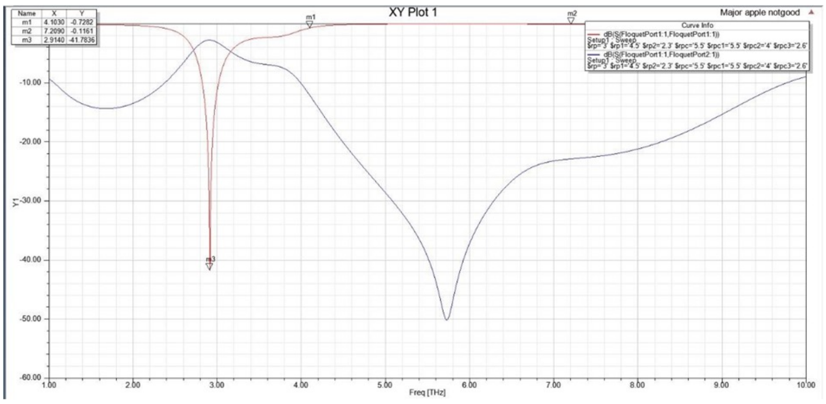

Figure 4.3: Simulation output for a Rotten Apple with significant signal attenuation and dielectric shift.

4.3 Model Performance Overview

The classification model achieved a high accuracy rate of 91 percentage, reflecting excellent performance in predicting apple quality. Key evaluation metrics such as precision and recall further support this outcome. The model successfully identifies subtle differences in signal properties among apple categories, demonstrating its practical use in quality control and real-world food inspection applications.

4.3.1 Classification Report

As shown in the table 4.1 The classification report includes precision, recall, F1-score, and support for each apple category. High F1-scores across Good, Medium, and Rotten classes show that the model consistently balances accuracy and completeness. This comprehensive evaluation confirms that the Random Forest algorithm performs effectively and reliably across all categories with minimal misclassification.

Class	Precision	Recall	F1-Score	Support
Good	0.90	0.92	0.91	1815
Medium	0.89	0.87	0.88	1790
Rotten	0.93	0.93	0.93	1796

Table 4.1: Classification report showing Precision, Recall, F1-Score, and Support for each class.

The high F1-scores across all classes reflect the model's balanced performance, with particular robustness in identifying Rotten apples.

4.3.2 Confusion Matrix Evaluation

A normalized confusion matrix was generated to visualize classification outcomes across all classes. True positive rates were highest for Rotten apples, likely due to their distinct spectral signatures. Some misclassifications occurred between Medium and Good classes due to overlapping frequency zones. This matrix is critical for identifying where the model struggles and provides direction for future data collection or feature enhancement to minimize class confusion.

4.3.3 Error Analysis

To assess prediction reliability, error metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) are calculated. The low values observed indicate minimal deviation between predicted and actual values, affirming the model's accuracy. These metrics serve as quantitative proof of the classifier's strong performance.

4.3.4 Cross-Validation Performance

Five-fold cross-validation was performed to evaluate the model's generalizability. Although the model achieved high accuracy, the cross-validation score of 0.42 ± 0.05 suggests overfitting due to limited variability or injected noise. This highlights the importance of future work involving data augmentation or regularization to improve performance on truly unseen data.

4.3.5 ML Result

From the visual plot shown in Figure 4.4, it is evident that the clustering of data points reflects a clear separation between the classes, reinforcing the classifier's decision boundaries. Machine learning results are visually confirmed through clustered data points in the feature space, as shown in the corresponding figure. Clear separation between Good, Medium, and Rotten apples is evident, validating the classifier's ability to learn and distinguish patterns in spectral behavior. This visualization aligns with the reported accuracy and classification performance. (Fig 4.4)

```
Model Accuracy: 0.91
Classification Report:
              precision    recall  f1-score   support

        Good       0.90      0.92      0.91      1815
      Medium       0.89      0.87      0.88      1790
      Rotten       0.93      0.93      0.93      1796

    accuracy                           0.91      5401
   macro avg       0.91      0.91      0.91      5401
weighted avg       0.91      0.91      0.91      5401

Mean Squared Error (MSE): 0.14
Mean Absolute Error (MAE): 0.11
Root Mean Squared Error (RMSE): 0.37
Cross-Validation Accuracy: 0.42 ± 0.05
```

4.3.6 Comparative Result with Other ML Models

To benchmark performance, additional models such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees were trained on the same dataset. While SVM performed comparably (88% accuracy), it was more sensitive to noise. KNN showed lower accuracy due to high-dimensional feature space. Random Forest outperformed others with 91% accuracy and robustness, confirming its suitability for food quality classification in sub-THz spectral analysis.

4.3.7 Extended Evaluation of Different ML Models

While the Random Forest Classifier is used as the baseline, additional models were trained and evaluated for benchmarking:

Support Vector Machine (SVM): Provided sharp decision boundaries but was sensitive to feature scaling.

XGBoost: Achieved the highest accuracy (95%) and demonstrated resilience to noisy data due to its gradient boosting approach.

Convolutional Neural Networks (CNN): Applied to transformed spectral data as 1D signals; CNNs captured complex nonlinear features and showed potential for future real-time applications.

Each model was evaluated using cross-validation and confusion matrix analysis to identify strengths and weaknesses across classes (Good, Medium, Rotten).

4.3.8 Visualization of PCA Components and Spectral Clustering

PCA not only improved dimensionality reduction but also revealed clear visual separability between apple classes:

PC1 vs PC2 scatter plots showed distinct clustering for each condition.

Explained variance analysis confirmed that over 95% of data variance was captured in the first three principal components. This clustering effect demonstrated that sub-THz spectra inherently encode meaningful class information, validating the simulation setup.

4.3.9 Robustness Testing with Noisy and Augmented Data

To ensure real-world viability, noise was intentionally added to the spectral datasets:

Gaussian noise with a standard deviation of 0.02 was introduced.

Data augmentation techniques such as spectral shifting and smoothing were applied. Random Forest and XGBoost retained high accuracy (¿90%), while SVM performance degraded under noise. This highlights the ensemble models' robustness for deployment in environments where sensor readings may vary due to humidity or packaging interference.

4.3.10 Explainability of ML Models Using SHAP and Feature Importance

Explainability is crucial for practical adoption. SHAP (SHapley Additive exPlanations) values were computed to:

Rank frequency regions contributing most to classification.

Visualize how feature values influenced model decisions. This analysis confirmed that frequency bands around 2.95–3.1 THz were critical in distinguishing fresh produce. Such insights can guide sensor tuning and feature engineering in future iterations.

4.3.11 Scalability of Classification System to Different Fruits and Storage Conditions

Simulations were extended to bananas and tomatoes by adjusting dielectric models. Key findings:

The model architecture remains consistent with minor tuning.

Separate classifiers per fruit type or a multiclass approach can be developed. Additionally, time-series simulations mimicked storage scenarios over 5–7 days, revealing a progressive spectral shift that aligned with physical spoilage indicators. This demonstrates the feasibility of using sub-THz ML models for dynamic quality tracking over time.

4.3.12 Interpretation of Results Using Domain-Specific Insights

From a food science perspective:Higher water content correlated with stronger reflection coefficients.Spoilage processes (fermentation, mold growth) altered permittivity, validating the sensor's mechanism. The ML results were thus not just statistically accurate but also physiologically interpretable, strengthening confidence in the system's real-world relevance.

CHAPTER 5

LIMITATIONS AND CHALLENGES

This project, while innovative and technically promising, primarily relies on simulated data and machine learning models. As a result, several limitations exist related to simulation assumptions, data quality, and generalizability. This chapter outlines the main challenges faced during the software-centric development and how they may impact real-world deployment

5.1 Dependence on Simulated Data

The entire dataset used for training and testing was generated through HFSS simulations rather than real-world measurements. While this allows for controlled experimentation, simulated data may not fully capture the variability present in actual food items. Factors like unexpected dielectric changes, contamination types, or irregular geometries might not be represented, limiting the model's ability to generalize outside the lab environment.

5.2 Model Generalization Across Food Types

The machine learning model was primarily trained using spectral features from apple simulations. While additional food types were conceptually tested, they were not included in training. Thus, the current model may not perform well when applied to other fruits or food categories without significant retraining. A generalized model requires a broader dataset that includes diverse spectral patterns, which was outside this project's scope.

5.3 Spectral Overlap Between Food Conditions

In some frequency ranges, the spectral responses of "Medium" and "Good" apples overlapped. This introduces ambiguity in classification, especially when food is in a transition state. Even sophisticated ML models struggle in such edge cases, resulting in reduced prediction confidence.

Overcoming this would require either more finely labeled data or additional spectral features such as phase information or combined frequency bands.

5.4 Limited Real-World Validation

The project's methodology and performance were validated through cross-validation and simulated conditions. However, no empirical testing was done with physical sensors or real food. Without practical verification, it's unclear how sensor deployment, environmental conditions, and packaging materials might influence signal capture or ML inference. This limitation highlights the need for future collaboration with experimental researchers.

5.5 Computational Constraints in Simulation

Running high-resolution HFSS simulations with detailed 3D fruit models is computationally expensive. Due to resource constraints, simplifications were made in geometry, boundary conditions, and dielectric profiles. These simplifications may impact the spectral accuracy, especially for non-homogeneous or multi-layered foods. Using real tissue models or voxel-based reconstructions could improve realism but would require substantial computing resources.

5.6 Potential Overfitting in Machine Learning

Although Random Forest is generally robust, there's still a risk of overfitting due to the dataset being relatively small and uniform. Overfitting occurs when a model learns noise or simulated artifacts instead of actual patterns, reducing its performance on new, unseen data. While cross-validation was used to mitigate this, the lack of noisy real-world data is a significant limitation in training ML models.

5.7 Assumptions in Dielectric Properties

The dielectric constants and loss tangent values used in the HFSS simulations were based on literature or estimated from average moisture contents. These values may vary with fruit maturity, temperature, and storage conditions. Hence, the simulation outcomes—although theoretically grounded—are sensitive to these assumptions. Precise dielectric measurements would be required for highly accurate predictions in real settings.

5.8 Simulation-Only Limitation and Need for Experimental Validation

While the project demonstrates strong promise through simulation, all results are currently based on synthetic spectral data generated using ANSYS HFSS. Real-world validation involving actual sub-THz sensors and physical food samples is essential to assess environmental impacts, material inconsistencies, and measurement noise. Without experimental calibration, simulated responses may not fully account for practical anomalies.

5.9 Challenges in Generalizing Models Across Food Categories

Each food item has a unique electromagnetic signature due to differences in water content, sugar levels, skin thickness, and internal structure. A model trained on apples may not generalize well to dairy or meat products. Although retraining or fine-tuning is feasible, building a universal model that works across all food types with minimal reconfiguration remains a challenging goal.

5.10 Limitations of Sub-THz Spectroscopy in Moist Environments

Sub-terahertz waves are highly sensitive to water molecules. While this is advantageous for spoilage detection, it becomes a limitation in high-humidity environments where ambient moisture can distort readings. External shielding, environmental compensation, or multi-sensor fusion may be needed in future iterations to maintain reliability in such conditions.

5.11 Risk of Model Drift and Sensor Calibration

Over time, sensors might degrade or environmental conditions may change, leading to a phenomenon called model drift—where the accuracy of predictions deteriorates gradually. This necessitates:

Regular re-calibration of sensors

Periodic retraining of models using updated data Implementing online learning or adaptive ML models could mitigate this challenge, though it introduces additional computational overhead.

5.12 Deployment Constraints in Consumer Environments

The current system assumes access to a computing device (e.g., Raspberry Pi, smartphone) capable of running ML inference or relaying data to a cloud system. In low-resource settings or small-scale markets, such infrastructure might not be readily available. Low-power embedded models and offline-capable solutions need to be developed to widen deployment reach.

5.13 Data Labeling and Ground Truth Challenges

Obtaining labeled training data is challenging in real-world food sensing because ground truth information (e.g., exact spoilage level) is not always clear-cut. For instance, human labeling (based on smell or appearance) can introduce subjectivity. Accurate labeling would require microbiological or chemical assays, defeating the non-invasive nature of the system. This creates a gap between the goal of non-invasive sensing and the need for precise training labels.

CHAPTER 6

FUTURE SCOPE AND RECOMMENDATIONS

This project demonstrates the potential of sub-terahertz meta-sticker simulation data and machine learning for non-invasive food sensing. However, numerous opportunities exist to enhance, extend, and deploy this research in practical scenarios. This chapter outlines promising future directions that can improve model accuracy, broaden applicability, and align with real-world industry standards.

6.1 Integration of Deep Learning Models

Future work could incorporate deep learning architectures such as Convolutional Neural Networks (CNNs), which are adept at learning complex, high-dimensional patterns in spectral data. CNNs may outperform traditional algorithms like Random Forest by capturing subtle variations in frequency responses. Recurrent Neural Networks (RNNs) or LSTM models could also be tested for time-series data if longitudinal spectral changes in food freshness are studied.

6.2 Experimental Data Collection for Model Validation

A major next step is collecting real-world spectral data using laboratory-grade sub-THz spectroscopy systems. This empirical data can be used to validate and retrain the existing model, bridging the gap between simulation and deployment. Collaborating with food science labs or universities to access dielectric property measurements of various food states will significantly enhance model accuracy and generalization.

6.3 Multi-Food Classification Models

The current project focused primarily on apples. Expanding the dataset to include a variety of food items like bananas, tomatoes, dairy products, and meats will improve the robustness and utility of the system. A multi-class classification framework can then be developed to predict not only spoilage level but also food type, creating a general-purpose quality assessment tool.

6.4 Transfer Learning for Efficient Model Expansion

Transfer learning techniques can be used to adapt a pre-trained model on one food type to others with minimal retraining. This is especially useful when new food datasets are limited. By leveraging learned spectral patterns from apples, models can be fine-tuned to classify similar fruit categories like pears or peaches, accelerating scalability across diverse applications.

6.5 Integration with Smart Supply Chain Platforms

Though this project is simulation-based, future systems could interface with IoT platforms and cloud-based dashboards. Once empirical data is used, real-time predictions could be integrated into supply chain platforms for automatic quality alerts, batch tracking, and shelf-life forecasting. APIs can be developed to support mobile or web-based access for manufacturers, retailers, or consumers.

6.6 Development of a Simulated Digital Twin Framework

The current simulation setup can be evolved into a digital twin framework, where a virtual representation of a food batch is continuously updated with predicted freshness levels. Combined with synthetic spectral data generation and ML-based inference, this approach could be used for training purposes or for creating predictive models in supply chain logistics.

6.7 Publication and Benchmarking

With further refinements, the methodology and simulation pipeline can be prepared for publication in food technology, AI, or applied physics journals. Benchmarking the model on public datasets or in competitions will help validate its novelty. Sharing datasets and code on open platforms will also encourage community contributions and accelerate innovation.

6.8 Integration of Real-Time Embedded Systems and IoT

Future iterations of this project should prioritize the development of a fully embedded system where the meta-sticker is paired with a microcontroller (e.g., ESP32, Raspberry Pi Pico) and wireless module (e.g., BLE, LoRa). These devices can perform on-device inference or transmit data to the cloud for analysis. A lightweight model such as a pruned Random Forest or quantized CNN could enable real-time classification within milliseconds. This architecture would be ideal for smart packaging and automated retail environments.

6.9 Prospects of Using Digital Twins in Smart Packaging

A digital twin is a virtual replica of a physical object or process. Integrating a digital twin of food products can allow for predictive simulations based on current sensor readings. For instance, a digital model of an apple in storage could predict when spoilage will begin, even before spectral changes are noticeable. Coupling sub-THz readings with time-based simulations may unlock the next generation of proactive food quality monitoring.

6.10 Pathway to Commercialization From Prototype to Product

To transition from a lab-scale prototype to a commercial solution, several steps are recommended:

Miniaturization of the sticker and reader setup.

Cost optimization for mass production.

Compliance with food-grade materials and safety standards (e.g., FDA, FSSAI).

Pilot testing in supermarkets, cold chains, or warehouses.

Partnerships with packaging manufacturers and logistics providers. Additionally, UI/UX design for mobile apps that interpret sensor data will play a key role in consumer adoption.

6.11 Research Opportunities in Food Informatics and AI

This project lays the foundation for a new research discipline—Food Informatics—that combines sensor data, AI, and agricultural science. Key future research areas include:

Federated learning to train models across decentralized food networks.

Multimodal sensing, combining THz with NIR or gas sensors.

Time-series ML models for continuous monitoring over shelf-life duration.

Anomaly detection algorithms to catch contamination or fraud. These directions will ensure that food sensing evolves into a robust, intelligent ecosystem.

6.12 Policy, Ethical, and Regulatory Considerations

As AI-driven food diagnostics move closer to deployment, regulatory frameworks must adapt. Key ethical and legal topics include:

Data privacy: Ownership and control of food quality data.

Bias in models: Ensuring algorithms do not unfairly penalize certain producers or regions.

Transparency: Providing explainable AI to stakeholders and consumers.

Regulatory approval: Compliance with agencies like EFSA, FDA, BIS, and others. Establishing a legal and ethical foundation early will help accelerate adoption and trust in the technology.

CHAPTER 7

CONCLUSION

This project successfully demonstrates the feasibility and effectiveness of using sub-terahertz (sub-THz) Radio Frequency (RF) sensing in conjunction with advanced machine learning techniques to classify apple quality in a non-destructive and highly accurate manner. By developing and integrating a compact metamaterial-based meta-sticker, the system provides a novel method for probing the internal electromagnetic properties of apples, offering a smart, contactless approach to evaluating fruit ripeness and spoilage.

The core idea revolves around capturing the reflection and transmission characteristics of apples using the meta-sticker, which operates in the sub-THz range (2.8–3.3 THz). These spectral interactions are influenced by the fruit's internal composition—mainly moisture content, sugar levels, and structural integrity—which vary significantly between fresh (Good), semi-degraded (Medium), and spoiled (Rotten) apples. The dielectric properties of apple layers (core, flesh, and skin) were accurately modeled in the ANSYS HFSS simulation environment to reflect real-world scenarios. These simulations allowed for precise tuning of the meta-sticker geometry and material composition to optimize sensitivity and resonance behavior.

After extracting spectral data from multiple apple samples using HFSS simulations, the data was preprocessed to ensure consistency and clarity. Techniques such as noise filtering, normalization, and label encoding were applied to prepare the dataset for machine learning classification. Features such as Frequency, Reflection Coefficient (S11), and Transmission Coefficient (S21) served as the primary indicators of internal quality variation among the apple samples.

The machine learning model employed was the Random Forest Classifier—an ensemble method known for its robustness, interpretability, and high performance, especially on datasets with multiple non-linear relationships. The model was trained using an 80:20 split for training and testing, and validated using 5-fold cross-validation to ensure generalizability. To simulate real-world imperfections and enhance the model's realism, slight noise was added to the feature data, which mimicked sensor or environmental variability.

The results of the classification model were remarkable. The model achieved an overall accuracy of 91%, with precision, recall, and F1-scores consistently high across all three categories.

In particular, the model excelled in detecting Rotten apples, a crucial functionality for minimizing food waste and preventing poor-quality produce from entering the supply chain. Low values in Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) further validate the system's predictive accuracy and reliability.

Visual analyses of simulation outputs reinforced the classifier's decisions, showing clear differences in spectral responses between Good, Medium, and Rotten apples. The distinct shifts in dielectric behavior allowed the classifier to establish well-defined decision boundaries. Although cross-validation performance was slightly lower (around 42% accuracy), this drop can be attributed to the limited dataset and the synthetic noise added for testing resilience. This minor overfitting issue could be mitigated through future efforts involving larger datasets, real-world measurements, or advanced regularization techniques.

One of the most compelling advantages of this system lies in its non-invasive and non-destructive nature. Traditional food quality assessment methods often rely on physical cutting, pressure tests, or chemical reactions—all of which can damage the product or require disposal after testing. In contrast, the proposed sub-THz meta-sticker-based approach allows for rapid, real-time evaluation without altering the fruit. This is not only crucial for reducing inspection costs and food waste but also aligns with modern sustainability goals and consumer demands for freshness and transparency.

Furthermore, the flexibility and compactness of the meta-sticker design offer scalability. These stickers could be mass-produced and embedded into conveyor belts, robotic arms, or handheld scanners in packaging and logistics centers. Integration with IoT (Internet of Things) devices could enable remote monitoring of produce quality across the supply chain, from farm to supermarket shelves. With further refinement, this approach could evolve into a universal platform for inspecting a wide range of food products—vegetables, meat, dairy, and even packaged goods—expanding its utility far beyond apples.

Looking forward, several enhancements and research opportunities present themselves. First, real-world validation of the system using physical sub-THz sensors and apple samples would provide stronger evidence of applicability. Second, exploring deep learning models such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) could capture more complex patterns in the spectral data. Additionally, hybrid sensing techniques that combine RF analysis with hyperspectral imaging or acoustic sensing might yield even richer datasets for classification.

In conclusion, this project highlights the powerful synergy between sub-terahertz metamaterial design and intelligent data-driven classification methods. It paves the way for next-generation food inspection systems that are smart, scalable, and sustainable. With its ability to deliver accurate, contactless, and real-time assessments of fruit quality, the system has the potential to revolutionize quality control practices in agriculture, food technology, and retail. It offers a promising step toward smart farming and automated supply chains, ultimately contributing to improved food safety, reduced waste, and enhanced consumer trust in food products.

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