WAVISION

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Executive summary

Nowadays, food companies produce large volumes of packaged **food products** to satisfy the population's demand, which keeps increasing. Maintaining consumer trust and brand reputation is essential for such companies. However, packaged food products often conceal various **contaminants** that can compromise product quality, impact consumer health, and result in product recalls. Marler Clark, an American food safety law firm, gathers all incidents where products have been recalled because of undesired contaminants. According to the firm's data, from 2018 to 2023, 199 recalls were made. In Italy, the Ministry of Health, responsible for product recalls, revoked 157 products because of food contamination. Insights from such entities underscore the frequent occurrence of product recalls resulting from contaminants like plastic and harmful bacteria. Contaminant presence harms **brand reputation** and **customer loyalty**, leading to substantial **economic losses** through compensations, penalties, and discarded production batches.

A company must prevent all physical, chemical, and biological contaminants from ending in a finished product. As food production quality assurance advances, destructive and non-destructive inspection controls play crucial roles in this task. The former requires measurements directly on the products (such as their temperature or oil content), while non-destructive techniques use faster and more efficient technologies like infrared. These approaches encounter **notable limitations**, particularly in detecting contaminants with low-density compositions or those concealed within metal packages. Our original research team proposed an innovative solution combining **Microwave sensors** and **Machine Learning (ML)** algorithms to address these challenges. This novel methodology exploits the **dielectric contrast** between the inspected material and potential intrusions. Through electromagnetic waves operating at specific frequencies, the presence of a foreign object disrupts wave patterns, enabling the detection of contaminated products via ML algorithms.

Building upon the pioneering work, the team currently working on the project aims toadvance the existing solution in five directions.

To begin, we **enhance the prototype** pipeline used for the experiments. The current setup heavily relies on a specific component, a Vector Network Analyzer (VNA), which represents the whole system's main cost and introduces several maintenance issues. The proposed alternative setup utilizes cheaper components while guaranteeing the same efficiency as the VNA.

The second step involves **expanding the current dataset** upon which the existing solution is built. This dataset expansion aims to strengthen further the tests we conduct on the robustness of the solution and, from a training perspective, enhances the algorithm'sability to identify contaminants with fewer samples accurately. The goal is to have a model able to adapt to different products with very different behavior regarding their **"dielectric properties"**. Therefore, we select a wide range of **products** to inspect: a carbonated and a low-CO2 soft drinks, soy sauce, flour, and honey. The chosen contaminants are plastic, paper, wood, glass, aluminum, glue, and cork, the **most common physical contaminants** that may fall into the product during production. Samples are also collected to cover **different positions** where the contaminant can realistically be found.

Thirdly, a theoretical examination of how most relevant biological contaminants impact food is performed. Drawing insights from the most frequently **recalled food products** by the FDA, we identify prevalent contaminants and evaluate the latest techniques in managing them. Biological hazards produce severe risks to human health if consumed. Since viruses and parasites generally cause illness, most risks can be reduced by following Good Manufacturing Practices. Even so, we found that some bacteria, **Salmonella spp.**; **Listeria monocytogenes**; and **Escherichia coli** are still a persistent problem in food manufacturing. Here, the **water activity** can be a crucial parameter to help determine whether a product is contaminated based on the metabolic activities. Water activity levels **above 80%** are conducive to microbial growth. When the water activity is higher than 0.85, heat treatment is required. The next logical step in the evolution of our technology is to focus on products with high water activity levels (such as juice, milk and butter).

Additionally, we comprehensively evaluate state-of-the-art machine learning and deep learning models compared to the initial solution proposed by Wavision (based on a neural network). Performing some **robustness tests** on the initial solution, we notice that it suffers from a number of shortcomings. In particular, it fails to attain comparable levels of accuracy on different types of products and contaminants. To **improve the detection accuracy** while minimizing the calibration time for a novel implementation and further supporting real-time processing, we adopted an **ensemble of the most effective methods** identified through our analysis (Lasso and AdaBoost). Given that a company's primary goal should be preventing the release of contaminated products into the market, thus minimizing false negatives, we focused on maximizing accuracy and achieving a zero false-negative rate. Results demonstrate promising outcomes, showcasing the potential for improved accuracy and real-time detection feasibility.

Finally, we introduce a Graph Neural Network (GNN) model trained to determine whether a container is contaminated, the **type** of contaminant, and a rough estimation of its **position** simultaneously. Given its higher parameter count and consequentially high inference time, such a model is devised to be used in a post-detection phase. The GNN architecture allows the scattering matrix to be naturally interpreted as a set of adjacency matrices by encoding the signal's features onto nodes and edges of the graph. We train the model to perform classification over both contaminant type and position in the medium, obtaining near-perfect results in tests spanning various contaminants and media. Such a technique provides the company with a powerful tool to locate and **address faults in the industrial production chain systematically**.

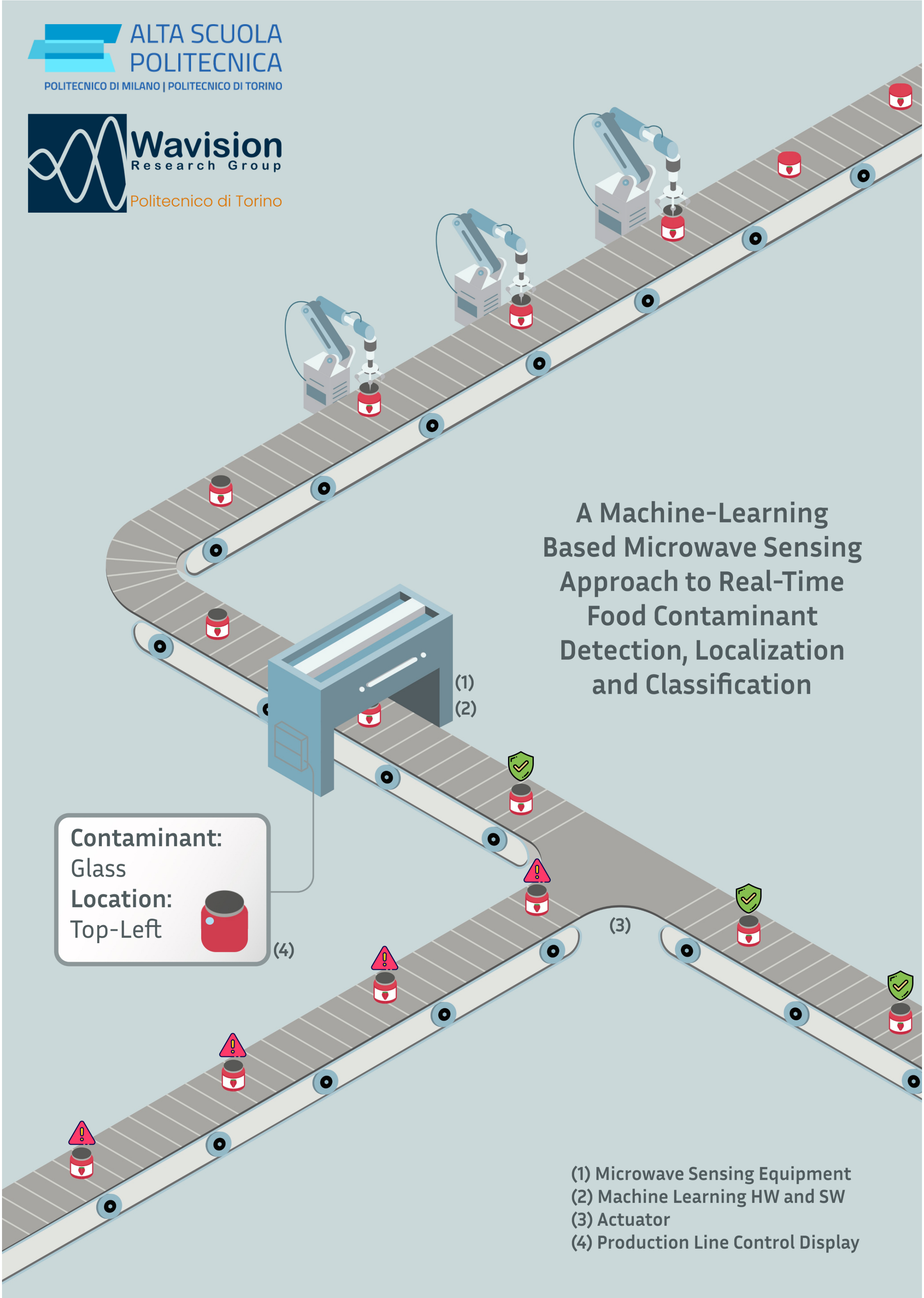
While progress has been made, some research questions remain open. Despite the system works well in the laboratory prototype, its real-world implementation requires addressing new challenges such as limited computational resources and diverse environmental conditions.

Additionally, the study's scope of contaminants and food products may not fully reflect what food companies encounter, which requires further research and validation along with different packaging materials. Despite these limitations, the Wavision team's innovative approach addresses many of the limitations in non-invasive contaminant detection methods today, aiming to help food companies save on costs, reduce waste, and ensure customer safety.

Key Words

Microwave sensing | Machine learning | Imaging | Graph neural networks | Food technology

A Machine-Learning Based Microwave Sensing Approach to Real-Time Food Contaminant Detection, Localization and Classification



Project description written by the Principal Academic Tutor

The food and beverage industries, even with technology improvements in recent years, are still facing issues related to contamination during the production processes. As a matter of fact, it is quite common to find on media news about foreign bodies found by final consumers, or to read about recalls due to contaminated batches at the distribution segment.

The European Union set up an entity, called RASFF (Rapid Alert System for Food & Feed), aimed at collecting all the customers' complaints related to the aforementioned issue; the reports during the years, confirm the existence of an intrinsic problem of production facilities. The consequences are multiple: first, the potential consumers health hazards, but also brand reputation, legal expenses and costs for recalls affecting the production companies.

Current employed technologies have some drawbacks: check-weigher and metal-detectors are limited respectively in accuracy and composition of potential foreign bodies; X-rays devices have multiple matters: high costs, ionizing radiations, and source disposal, and mostly the detection principle, based on density, thus limiting the detection capability particularly for low-density contaminant, as plastic, glass, and wood, quite common in such industries.

Wavision is focused on giving an alternative system, to complement the existing ones, offering an innovative solution to significantly increase the quality assessment of production output. The technology is based on a totally different detection principle, the dielectric contrast at microwave frequency, another physical property of each different material, allowing to correctly detect many of the contaminants which are currently non-visible by any other device. It is based on an array of antennas, emitting low-power non-ionizing radiation (not altering at all the product properties), crossing the sample under test, and looking for discrepancies of the transmitted signals between a reference case and the current one. Ad-hoc AI-based algorithms have been developed to discern the good and item to discard.

The patented system is under further development, and the goal of this project is to further validate the technology, by testing the working prototype with a wider set of different products, with varying dielectric properties and consequently different contrast with potential foreign bodies, by system readaptation, i.e., tuning the working frequency and the corresponding antennas architecture based on each product dielectric and physical features, or improving the components in the prototype

Team description by skill

The challenge of a multidisciplinary project has encouraged a work organization that fully leveraged the cross-functional nature of the team, composed of members with diverse academic backgrounds.

More in details, our team comprised engineers from different departments.
We decided to allocate tasks based on our competencies and expertise.

The team included two *Computer Science Engineers*, **Margherita** and **Filippo**, one *Mathematical Engineer*, **Francesco**, one *Chemical Engineer*, **Sebastian**, one *Management Engineer*, **Chiara**, and one *Engineer* specializing in *Industrial Production*, **Claudio**.

The management and industrial production engineer were assigned higher-level tasks with a long-term perspective on the project. They were responsible for engaging with stakeholders, defining short-term objectives, managing the budget, and ensuring that the project development remained consistent with the final objectives and deadlines throughout the project duration. They also handled the physical data collection in the laboratory, testing the detection equipment on various products contaminated with elements of different natures and placed in various positions.

The chemical engineer played a crucial role in analyzing the dielectric properties of the new materials, both as products and contaminants, and correlating these properties with statistical insights derived from machine learning classification.

The mathematical engineer developed a Graph Neural Network to model the signals from the antennas and reconstruct the relative positions of the product and contaminant during detection.

Finally, the two computer science engineers conducted extensive training and testing of various machine learning solutions, aiming to identify the best approach that could generalize effectively to unseen combinations of products and contaminants while maintaining a high level of accuracy.

Goal

The operational principle proposed by the research team we collaborated with relies on detecting variations in electromagnetic waves' behavior due to differences in dielectric properties between the inspected medium and potential contaminants.
The working frequency is selected based on the medium's characteristics, and any foreign bodies alter the recorded waves, making contaminated products detectable.

The primary goals for the project assigned to the team were as follows:

1. **Analyze an alternative setup** for the current prototype using cost-effective components readily available in the market.

2. **Expand the dataset** used for training the machine learning algorithm, enhancing its ability to detect unclassified contaminants with fewer training samples.

3. **Improve the neural network's capabilities** through optimized training procedures.

4. **Develop a tomography technique** for 3D Microwave Imaging of the target.

5. **Explore the possibility** of detecting previously challenging forms of contamination, such as those caused by chemical or biological agents, to determine if the sensing system can recognize such alterations.

The team pursued the aim of enhancing the current system's flexibility and adaptability, for being able to detect contaminants in diversified positions and in a wider range of products.

In order to make the product easily marketable, the team aspired to expand the prototype into a robust system version that could, with minimal model training, generalize its detection capability over a broader spectrum of contaminants

Understanding the problem

Packaged food products often conceal a variety of contaminants that have the potential to compromise the nutritional quality of the product, inflict harm to consumers' oral health, or in severe cases, lead to poisoning.
According to data provided by the American food safety law firm specializing in food safety, Marler Clark, a total of 199 food product recalls occurred between 2018 and July 2023 due to the presence of undesired contaminants. The two primary causes of these recalls were the discovery of plastic within the products and the presence of harmful bacteria.
In Italy, the Ministry of Health is responsible for informing consumers in the event of a product recall. From 2018 to 2023, 157 products were recalled due to food contamination. Despite efforts to prevent contaminated products from reaching consumers, low-density contaminants often evade detection.

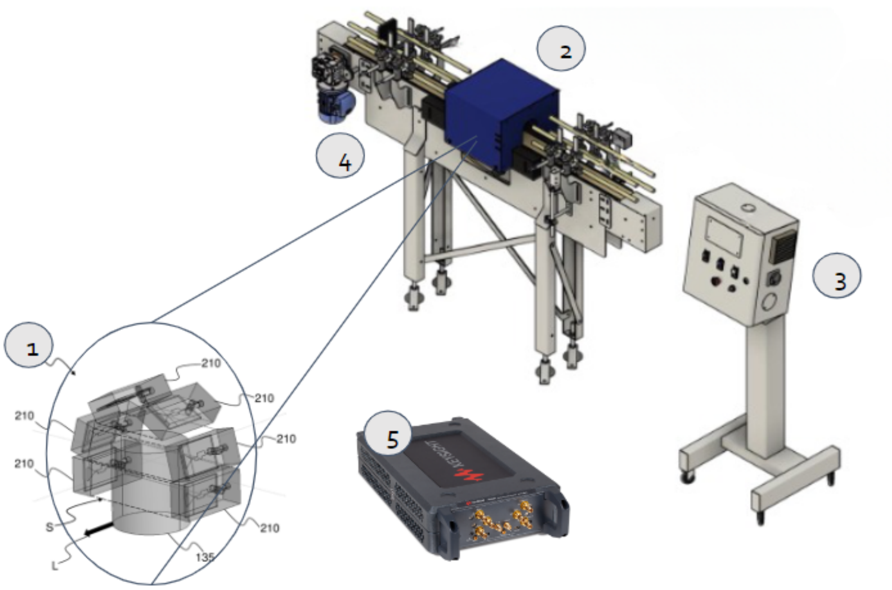
These contaminants can be of a physical, chemical, or biological nature and may enter products at various stages of production. In the food industry, quality control measures can be either invasive or non-invasive, with X-ray monitoring being a commonly used method.
The presence of contaminated products not only damages brand reputation and customer loyalty but also results in tangible economic losses, including compensation, penalties, and the disposal of entire production batches, among other consequences for food companies.

To address this issue, food companies seek levels of precision higher than those mandated by regulations, often necessitating the use of costly monitoring equipment.
These companies employ various measures, such as quality control, material selection, improved manufacturing processes, barrier technologies, traceability systems, and consumer education, to mitigate the risk of contaminated products.
However, there is no one-size-fits-all solution, and a combination of strategies is required to minimize contamination while managing costs and ensuring safety.
A holistic strategy that incorporates improved manufacturing processes, meticulous material selection, rigorous quality control, and efficient traceability systems is crucial to mitigate the potential hazards associated with packaging contaminants.
Nevertheless, it's essential to recognize that the amalgamation of these measures can result in added expenses that some companies may find challenging to manage.

However, the fundamental objective persists—to provide consumers with safe products and assist food companies in implementing measures that enhance their ongoing endeavors to minimize the presence of contaminated products.

Therefore, the food industry is actively exploring innovative approaches to overcome the limitations of current detection methods.

In this frame the Wavision project plays a significant role.



Existing Wavision's solution: 1) Antenna Array; 2) Metal case; 3) Controller; 4) Production line; 5) Vector Network Analayzer

Visual inspection quality control system

Exploring the opportunities

Opportunities are plentiful due to the increasing need for rigorous quality and safety checks, particularly in industries like baby food.
The limitations of conventional systems, such as X-rays, in detecting specific contaminants create a compelling argument for the adoption of Wavision's technology.

However, there is an underlying risk; failing to meet these urgent demands or experiencing a drop in the effectiveness of their technology could turn this strength into a weakness, causing a rapid erosion of market trust.

In conclusion, while Wavision possesses a solid technological foundation and a clear competitive advantage, it requires a strategic vision that leverages its strengths, addresses weaknesses proactively, capitalizes on external opportunities, and effectively manages potential threats.

Generating a solution

Building upon prior research, this project seeks to enhance detection outcomes by improving data collection, employing a combination of machine learning algorithms, and utilizing imaging techniques to pinpoint the contaminant's location.
Furthermore, the research broadens the scope of considered products, resulting in improved detection precision across a broader spectrum of contaminants with fewer samples, and proposes an upgraded prototype version.

To begin with, we replicated the findings of previous studies by implementing the same neural network architecture on identical data as presented in reference [1]. Our objective was to validate their results.

Subsequently, we aimed to simplify the neural network architecture by adopting a single-layer neural network with a reduced number of neurons, referred to as a "mini neural network". This approach allowed us to decrease the classifier's complexity while maintaining the same level of generalization accuracy.

The next step involved reducing the number of training samples while still achieving 100% accuracy. By adjusting certain hyperparameters in the learning process, we successfully utilized only 13% of the original data to maintain a 100% generalization accuracy.
To further minimize the required number of samples, we introduced augmentation techniques. Data augmentation involves expanding the dataset by creating synthetic data using existing data and domain knowledge. For instance, if we were building a face classifier based on images, we would expect the classifier to correctly identify the person regardless of factors like lighting conditions or orientation.

To increase the dataset size without collecting more data, we applied rotations and lighting effects to the existing images while preserving the same labels and added these augmented images to the training dataset. This approach helps the classifier learn transformations that are independent of rotation and lighting.

Building on this straightforward yet essential concept, and recognizing the need to reduce the volume of data that companies must collect to adopt our software, we developed a tailored data augmentation solution for the problem.

Our idea was to create new samples while maintaining the same labels and features as older samples, simply by rearranging the order of features. In other words, by swapping the measurements between antennas, we could generate new samples in which the product and contaminant remained the same, but their rotation or position under the antennas changed. While this was a promising idea, it did not significantly improve classifier performance due to the strong non-linearity in the measurement system.

As a result, our strategy shifted towards collecting more data from various additional contaminants, which ultimately led to an enhancement in the system's performance.

Main bibliographic references

[1] Ali Darwish, Marco Ricci, Flora Zidane, Jorge A. Tobon Vasquez, Mario R. Casu, Jerome Lanteri, Claire Migliaccio, and Francesca Vipiana. Physical contamination detection in food industry using microwave and machine learning. Electronics, 11(19), 2022