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***Abstract*—This paper presents a novel approach based on electromagnetic waves (EM) to classify food packages that hold water as one of the main ingredients from the inside into contaminated or uncontaminated products. A non-destructive technique that can handle a real-time food production line is proposed to achieve this goal. This technique combines the operation of a microwave sensing system (MW) with a machine learning (ML) classifier. An accuracy of 100% has been obtained from training the aforementioned ML tool on a dataset constructed from the retrieved scattering parameters of about 500 measuring samples.**

I. Introduction

As the food industry is growing enormously over the years, food processing companies maintain adherence to rigorous production systems and require increasing quality standards for their products. Physical contamination occurs when small objects of a few millimeters in size contaminate the food during the production process, especially in the packaging phase. For this reason, the detection of these contaminants before sending the products to the market has become of great interest to food manufacturers. During the past few years, many technologies have been developed and investigated to achieve this goal like X-rays [1], metal detectors, and other methods such as near-infrared [2], terahertz spectroscopy [3] or hyperspectral imaging [4]. The first in particular, is considered to be the most effective, capable of detecting even sub-millimeter intrusions, and whose detection principle is based on density contrast between the product and the contaminant. So, this may lead to undetected contaminants if their density is lower than the product one.

Recently, the MW sensing technology assisted by ML tools has been investigated by the authors [5]–[7] for this purpose and it appears to be one of the most effective techniques in terms of data acquisition speed, implementation, cost, safety, and penetration depth, overcoming intrinsic limitations of existing devices. The fundamental concept of our approach is based on the interaction of the emitted MW with the materials that compose the sample under test. The scattering behavior of these waves depends on the permittivity and the geometry of these materials. Thus, the dielectric contrast causes a modification in the back-scattering behavior of the EM waves. These reflected waves, if collected and processed appropriately, can lead to the detection of intrusions inside the food package.

The scope of this work is to show how the retrieved EM waves can be used to detect products to be rejected by means of ML tools, through the development of appropriate algorithm, processing the acquired scattering matrix, to classify the samples as contaminated or not. In our previous works [8], [9], we focused on the food of low-loss materials like oil and cocoa cream. Really promising results were obtained using different types of ML classifiers, or even solving an inverse problem and providing a tomographic scan of the volume under test. In this work, we deal with food packages containing lossy materials, harder to penetrate by microwaves, mainly composed of water.

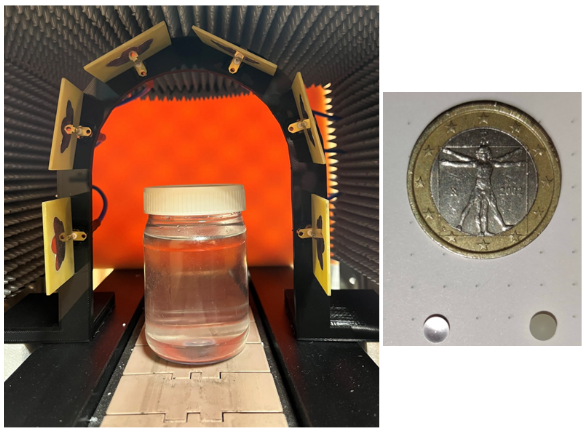
II. Experimental Setup

The MW sensing system, shown in Fig. 1, consists of an antenna array of 6 elements mounted on an arch-shaped support allowing the sample to pass through it without any obstruction. The antennas are connected to a six-port VNA that acquires in parallel both magnitude and phase of radiated signal from the transmitting antenna at multiple frequencies. The speed of the conveyor belt that carries the food bottles was set up to 20 m/min. A photocell is used to trigger the VNA to start the measurement when the item approaches the antenna array. The measurement system has been modified for being suited to the measurement of lossy medium. For this, we used a wideband antenna shown in Fig. 1 and derived from [10] which can operate at low frequencies for better penetration depth.

The physical dimensions of the jars, like the one shown in Fig. 1 are 6.6 cm in diameter and 7.5 cm in height. We used four different jars for the measurement phase, two of them filled with water only, and the remaining two contaminated with intrusions. The measurements were recorded for 500 samples: 300 uncontaminated, and 200 contaminated.

The intrusions employed in the procedure are 2-millimeter-radius spherical samples made up of two different materials, soda–lime glass and nylon respectively. We carried out our measurements in a frequency band ranging from 1.5 GHz and 3.5 GHz with a step of 0.2 GHz. At each frequency point, the antennas radiated in a sequence form, and when a single antenna transmits all the other antennas receive in parallel.

By this, we obtain a matrix S_{ij} formed of 6×6 entries at each frequency point, resulting in a three-dimensional structure whose size is $6 \times 6 \times 11$. The elements of the matrices obtained from the measurements are of complex nature, and thus each acquisition carries 792 features.



(a) (b)

Fig. 1. (a). A jar full of water and placed directly under the arch-shaped antenna array, which forms the MW sensing system. (b). The size of the 2 used spherical contaminants compared to the dimension of a 1 euro coin.

Fig. 2 shows the S-parameters magnitudes matrices one sample free of contamination (left) and one contaminated with soda-lime glass (right). The comparative analysis of the two images shows that the recognition of the small variation in the magnitude of the S-parameters is challenging, and then the classification process is out of reach without assistance tools, rather than simple thresholding methods. ML classification models are very powerful in pattern recognition applications and they are used in a wide diversity of classification applications. We chose the non-linear support vector machine (SVM) algorithm based on the authors' previous works in [5].

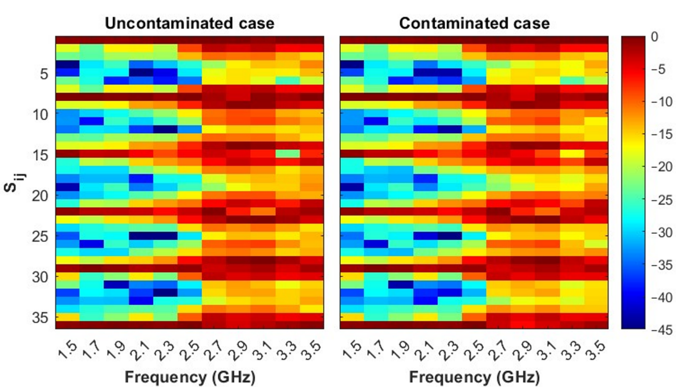


Fig. 2. The magnitude plot of two scattering matrices, obtained for two different samples under test, one is free of any contaminants, and the other is contaminated by SLG sphere.

III. Experimental Results

As a first trial, we split our data into training and test sets as follows, 60%–40% (300–200 samples) respectively. In the learning phase, 90% of the training dataset is used for training and 10% for validation. We used the Grey Wolf Optimizer (GWO) [11] to determine the hyperparameters for the optimal hyperplane that can separate the classes of the training dataset. The validation and test sets produced perfect results, achieving 100% accuracy. Even after partitioning the dataset into different percentages, such as 40%–60% for training and testing, the results remained perfect at 100%. The objective of reducing the samples in the training phase was to investigate if the same level of performance could be achieved with lighter training sets and to ensure that more samples were available for testing. Finally, we succeed in achieving the main purpose of this paper, and bringing out a complete workflow for an example of a non-destructive evaluation application in the food industry field.

Acknowledgement

This research was supported in part by PON Research and Innovation "Microwave Imaging and Detection powered by Artificial Intelligence for Medical and Industrial Applications (DM 1062/21)" and by PRIN "BEST- Food, Broadband Electromagnetic Sensing Technologies for Food Quality and Security Assessment", both funded by MUR. It was carried out partially within the Agritech National Research Center, funded by the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1032 17/06/2022, CN00000022).

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