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Machine Learning to Detect Physical Contaminants in Food

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Abstract: In the realm of food safety and quality control, the detection of contaminants in consumables has become increasingly critical. Traditional laboratory methods are often time-consuming, labour-intensive, and costly. This paper presents a novel approach to food contaminant detection by leveraging microwave emission analysis combined with advanced machine learning techniques. Specifically, a Neural Network model is trained on microwave emission profiles to accurately classify contaminated versus uncontaminated food samples. By processing emission signals through deep learning architects, the system can detect subtle anomalies that traditional methods may overlook. The proposed solution integrates efficient data preprocessing, real-time signal analysis, and intelligent feedback reporting, ensuring rapid and reliable assessment without the need for extensive laboratory infrastructure. This innovation significantly reduces detection time while maintaining high accuracy, offering a scalable and cost-effective solution for industries and organizations concerned with food quality assurance. Further enhancements could include expanding the model to accommodate a broader range of food types and contaminants, further increasing the system's versatility and impact.

Keywords: Machine learning (ML), Contaminants, S-matrix, Microwave Spectroscopy (MWS)

INTRODUCTION

Food contamination is a significant global health issue that causes a huge number of illnesses, hospitalizations, and deaths annually. Contaminants of food may consist of variants Physical contaminants like micro metal objects, glass pieces, plastic & etc., or biological toxins like bacteria, viruses, and fungi or chemical toxins like pesticides, foul odour, change in chemical composition and other adulterants. Conventional detection techniques are usually based on laboratory analysis, which are mostly time-consuming, costly, and require sophisticated equipment and expertise.

Ensuring the safety of food remains one of the significant concerns within the global food industry because physical contaminants such as pieces of plastic, glass, and metal can endanger the health of consumers. Removing such contaminants from food products is important, not only for consumer welfare, but also for the image of product manufacturers. Even though manufacturers follow strict safety procedures, and conventional testing methods such as X-ray imaging and metal detection are used, these systems routinely fail to detect some plastics and glass which are of low density and non-metallic.

To address these issues, our initiative proposes a new method that incorporates Microwave Sensing (MWS) technology and Machine Learning (ML) algorithms for contaminant detection in food products. Microwave Sensing is a non-invasive procedure which employs electromagnetic radiation to investigate the internal composition of some objects. While food products travel through a microwave sensor, the interaction of the microwaves with the materials in the food yields signals. The signals fetched as scattering parameters, also referred to as S-matrix data, are valuable to detect certain anomalies with the right analysis.

The central concept of this paper is to leverage the discriminative ability of ML models to decode the intricate patterns in the S-matrix data and label food samples as contaminated or uncontaminated. By training supervised learning models on labelled data—where each sample is labelled with a known contamination status—the system can be taught to recognize minute variations in the microwave response due to varying types of contaminants. This method has the following benefits compared to classical methods: detection of a wider variety of contaminants (metallic and non-metallic), increased precision, and reduced processing time.

The execution process of this work involves some major phases. In the first, controlled datasets of food products are groomed, such as clean food samples and deliberately contaminated ones with materials like plastics, glass, and metal. These samples are then microwave scanned, and the resulting S-matrix data are collected. Then, data preprocessing operations clean the data and normalize it for training. Feature extraction and selection are performed to ascertain the most important signal or signals related to the exact classification. Next, several

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Machine Learning algorithms are trained and tested to select the best-performing model, including Support Vector Machines (SVM), Decision Trees, and Neural Networks. The combination of MWS and Machine Learning in this paper provides a new, efficient, and scalable approach to detecting food contamination in real-time.

To counter such shortcomings, interest has been growing in applying machine learning (ML) methods to food contaminant detection with speed, accuracy, and affordability. Based on patterns found in data types like spectroscopic signals, variation in di-electric properties, chemical compositions, or images, ML models can determine potential contamination without lengthy laboratory procedures. With data-driven methodology, detection becomes more rapid, paving the way for timely interventions from regulatory agencies, food companies, and consumers that lead to safer food and public health.

The paper includes the following sections as Section 2. Literature Review, Section 3. Methodology, 4. Results Discussion, 5. Conclusion and Future enhancements

LITERATURE SURVEY

In this section, different approaches to Physical Contaminants in Food are examined and compared with regard to their effectiveness in identifying physical contaminants using the various machine learning approaches.

Paper [1] introduces a better machine-learning process tailored for microwave- based food sensing systems to identify contaminants in food. The authors aim to develop a system that can accurately classify food products as contaminated or safe using microwave signals and machine learning models. The authors in [2] discussed the ways in which machine learning may be used to improve microwave sensing technology for the evaluation of food quality. Also, they have illustrated with a case study in which microwave signals are employed to retrieve information from samples of food and machine learning models are used to classify them. In paper [3] work suggests a microwave sensing method along with machine learning to identify contaminants in food in a real-time, non-invasive, and economical manner. The system records microwave responses from food samples and exploits machine learning models to determine whether the food is contaminated. The authors in paper [4] adopted artificial intelligence and machine learning to predict the contamination patterns, enabling proactive risk mitigation. AI's real-time monitoring swiftly identifies contaminants, boosting consumer safety. In paper [5] authors has carried out the details review about the AI-Powered Food Contaminant Detection using around 70 papers. The paper [6] used AI-Enhanced Electrical Impedance Tomography method to detect the food contaminant and achieved 78% accuracy also. The authors in paper [7] proposed a novel approach from measurements setup to a binary classification of food products as contaminated or uncontaminated. The work focuses on combining MW sensing technology and ML tools such as MLP and SVM in a complete workflow that can operate in real time in a food production line.

MATERIALS AND METHODS

This section presents a complete picture of the proposed methodology including data preprocessing, architecture and training process for implementation of model in detail.

The primary objective of this paper is to develop an efficient and dependable machine learning-based approach for food contamination detection. The work involves data preparation pipeline, model building, training, evaluation, and prediction. Each phase was carefully considered to ensure the precision, reliability, and scalability of the model.

Data Preprocessing

A 6x6 scattering matrix (S-Matrix), which depicts certain physical characteristics of the food samples, serves as the input to the system. Important details necessary for identifying contamination are contained in this matrix. It is used the Normalisation preprocessing procedures to make sure the data was in an appropriate format for input into a neural network.

Food samples are subjected to microwave signals, and the system measures the scattering parameters (S-parameters) over a range of frequencies. With each measurement, the interaction between the electromagnetic waves and the food material is captured, indicating its internal structure and possible contaminants. The measured S-parameters are subjected to extracting prominent features like amplitude and phase data, frequency shifts of resonance, and energy absorption signatures. These features play an essential role in determining differences in uncontaminated and contaminated food samples. The feature data thus extracted is employed to validate sensing methods, optimize machine learning algorithms, and fine-tune classifiers parameters. This technique increases the system's accuracy in being able to separate contaminated and uncontaminated samples while testing. Different frequencies of microwave sensing data is combined to increase the size of dataset and to compress all different varieties of data which enables the model to identify and recodnize the pattern in data more efficiently. Combined data assists in emulating different contamination scenarios, increasing the machine learning model's ability to generalize and perform well in practical food inspection settings.

The dataset is considered from Open ML. The figure 1 illustrates an example of a microwave sensing dataset for food contaminant detection. Each row represents one food sample, and features are given by scattering parameters (S12 to S65) derived from microwave measurements. The last column, Class _Label, is the contamination status of the sample, and the entries in the figure are marked as "Contaminated." The dataset allows training and testing of machine learning models for correct classification based on microwave signal properties.

S12	S13	S14	S15	S16	S21	S23	S24	S25	S26	S31	S32	S34	S35	S36	S41	S42
0.008627	0.000641	-0.00236	-0.00766	-0.0001	0.001068	-0.00289	0.001039	-0.00169	0.000192	0.003898	0.006663	0.001091	0.001464	-0.0008	-0.00096	0.004106
0.008815	0.00036	-0.00214	-0.0078	-0.00027	0.00123	-0.00279	0.001147	-0.00172	-3.30E-05	0.004165	0.006786	0.001077	0.001453	-0.00089	-0.00089	0.00418
0.008796	-0.00014	-0.00216	-0.00817	-0.00044	0.001705	-0.00294	0.000867	-0.00199	-0.00027	0.004673	0.006266	0.000982	0.00158	-0.0009	-0.00117	0.004334
0.00877	-7.70E-05	-0.00213	-0.00814	-0.00012	0.002109	-0.00319	0.000363	-0.00207	-0.0005	0.004284	0.006057	0.000755	0.001447	-0.0009	-0.00109	0.004661
0.007898	0.000577	-0.00294	-0.00866	-0.00076	0.001449	-0.00258	0.000335	-0.00097	0.001134	0.003977	0.006835	0.000725	0.001078	-0.00105	-0.00118	0.00352
0.0081	-0.00023	-0.00241	-0.00852	-0.00091	0.001105	-0.00278	0.000261	-0.00108	0.00097	0.003689	0.007184	0.000597	0.001049	-0.00101	-0.00097	0.003342
0.008471	2.00E-05	-0.00259	-0.0084	-0.00035	0.000616	-0.00286	0.000415	-0.00086	0.000475	0.003908	0.007098	0.000278	0.001054	-0.00113	-0.00066	0.003555
0.005155	0.002106	0.002765	-0.00151	0.000428	-0.00165	0.000192	-0.00041	-0.00066	0.000165	0.004207	0.006876	0.000173	0.00113	-0.00097	-0.00052	0.003457
0.008685	-0.00057	-0.00196	-0.00787	0.000424	0.000977	-0.00283	0.00052	-0.00053	-9.00E-05	0.004264	0.00665	0.000284	0.00108	-0.00096	-0.00049	0.003135
0.008495	-0.00064	-0.00186	-0.00768	0.000716	0.001388	-0.00275	0.000611	-0.00078	-0.00019	0.004315	0.006163	0.000255	0.001076	-0.0008	-0.0005	0.003225
0.007953	0.000313	-0.00294	-0.00848	-0.0007	0.001681	-0.00246	0.000622	-0.00085	0.001008	0.004556	0.006775	0.000872	0.000806	-0.00098	-0.00144	0.003469
0.008758	-0.00051	-0.00182	-0.00766	0.000694	0.001657	-0.00267	0.000682	-0.00098	-3.80E-05	0.004409	0.006406	6.30E-05	0.001161	-0.00073	-0.00032	0.00353
0.005168	0.001699	0.003376	-0.0014	0.000902	-0.00035	0.000133	-0.00027	-0.00102	2.20E-05	0.004474	0.006237	5.60E-05	0.001287	-0.00077	-0.00029	0.003588
0.00524	0.001733	0.003424	-0.00145	0.000811	-0.00031	5.80E-05	-0.00024	-0.00099	0.000224	0.004536	0.006428	1.30E-05	0.001365	-0.00073	-0.00037	0.003842
0.009105	-0.00018	-0.00207	-0.00778	0.000466	0.002252	-0.00279	0.000731	-0.00109	0.000104	0.004521	0.006462	8.90E-05	0.001421	-0.00078	-0.00036	0.003858
0.00547	0.001927	0.003339	-0.0014	0.000716	-0.0002	0.000138	-0.00032	-0.00093	7.70E-05	0.004626	0.006583	8.00E-05	0.001397	-0.00068	-0.00037	0.003877
0.008517	-0.00065	-0.00204	-0.00799	-1.70E-05	0.000829	-0.00287	0.000499	-0.00059	6.90E-05	0.003813	0.006705	0.000501	0.001022	-0.00107	-0.00066	0.003191
0.005018	0.001889	0.003009	-0.00147	-4.50E-05	-0.00172	0.000191	-0.00039	-0.00066	0.000297	0.004343	0.006791	0.000531	0.001063	-0.00108	-0.00072	0.00333
0.008407	-0.00073	-0.00215	-0.00833	-0.00068	0.000876	-0.0029	0.000425	-0.00088	0.000569	0.004443	0.006987	0.000648	0.001053	-0.00101	-0.00103	0.003367
0.00868	0.000578	-0.00302	-0.00913	-0.0007	0.000628	-0.00242	0.000699	-0.00053	0.001013	0.003728	0.0075	0.000666	0.000359	-0.00098	-0.00134	0.004897
0.008685	0.000617	-0.00291	-0.00923	-0.00059	0.000604	-0.00237	0.000699	-0.00048	0.000949	0.004292	0.007252	0.000764	0.000334	-0.00103	-0.00137	0.004784

Fig.1: Description of Data

Model Architecture

To tackle the binary classification job of determining whether or not a food sample is tainted, we created a deep neural network. In order to compress and extract hierarchical representations from the input characteristics, the model is composed of a series of dense (completely linked) layers with progressively smaller sizes. The following is the detailed architecture:

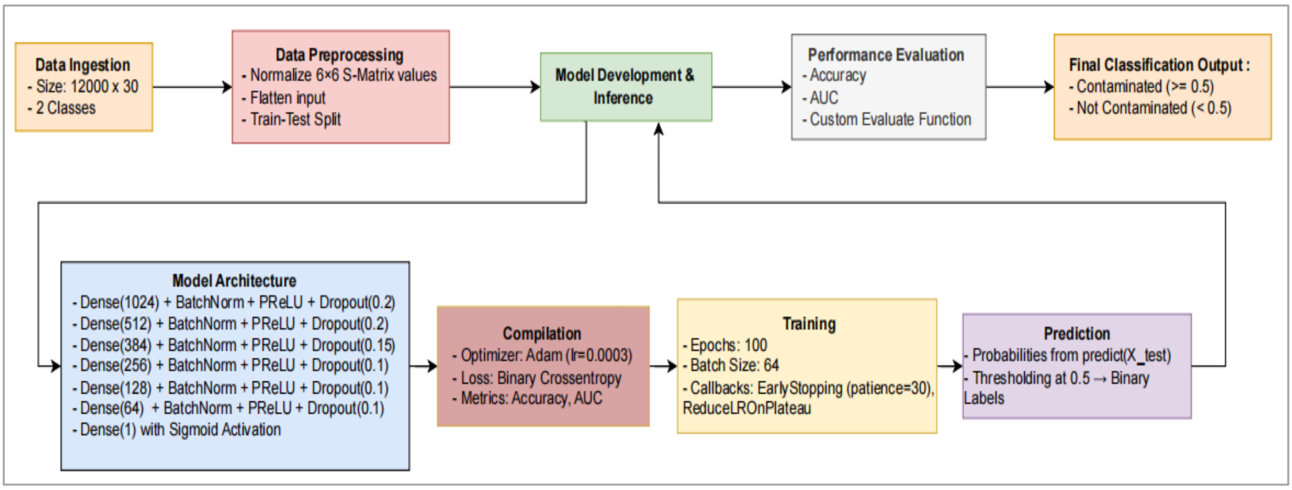

Fig. 2: Model Architecture

This is the deep neural networks model which consists of 7 fully connected dense layers with decreasing size. Each dense layer (except the last layer) is followed by Batch Normalization, PReLU activation and dropout. Final layer uses a sigmoid activation to output a probability between 0 and 1. Compilation is done using the Adam optimizer (learning rate = 0.0003), binary cross entropy loss and AUC/accuracy metrics.

Training is conducted for 100 epochs with batch size of 64 and callbacks like Earlystopping with patience of 30 and ReduceLROnPlateau. During prediction, model outputs are thresholded at 0.5 to classify samples as contaminated or not. Performance is evaluated using accuracy, AUC and a custom evaluation function.

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RESULTS

Figure 3. which shows the heatmap, the correlation between the feature. Using colour gradients, a heatmap graphically depicts the relationship between features. Neutral hues denote little to no association, blue denotes a negative correlation, and red denotes a positive correlation each feature's complete self-correlation is shown by the diagonal line. It facilitates the detection of multicollinearity and feature connections in datasets. Because of multicollinearity, highly correlated characteristics can have a deleterious impact on models such as linear regression. In order to improve model performance and interpretability, one may make well-informed judgements about feature transformation, dimensionality reduction, and feature selection by examining the heatmap. In the exploratory data analysis (EDA) stage of a machine learning project, this tool is quite helpful.

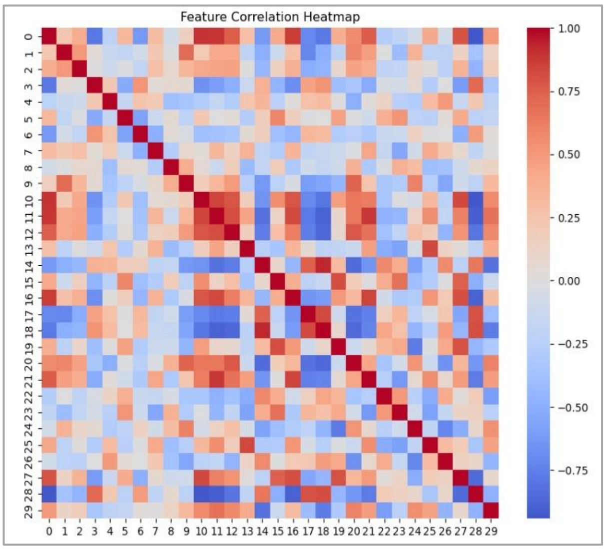

Fig. 3: Heat map

24	25	26	27	28	29	True_Label	Predicted_Probability	Predicted_Label	True_Label_Text	Predicted_Label_Text
-1.253269	1.535350	0.570838	1.536259	-1.744774	0.852400	0	0.006791	0	NON Contaminated	NON Contaminated
-1.064193	-0.850203	0.738792	0.345029	0.535529	-0.992440	1	0.927541	1	Contaminated	Contaminated
-3.283877	-1.578605	1.977657	-0.095585	0.671082	-3.516901	0	0.001574	0	NON Contaminated	NON Contaminated
-0.509272	1.522470	0.762073	0.876126	-1.289583	1.112886	1	0.995159	1	Contaminated	Contaminated
-3.085851	-0.367940	2.218779	0.787216	0.790570	-3.236048	0	0.005963	0	NON Contaminated	NON Contaminated
1.100671	-1.149291	-1.582625	0.422136	-0.823013	0.268183	0	0.577966	1	NON Contaminated	Contaminated
1.104027	-1.227999	-1.441278	0.570843	-0.856483	0.188858	1	0.962228	1	Contaminated	Contaminated
0.221300	0.191598	0.785353	-0.927244	0.443822	-0.458605	1	0.948626	1	Contaminated	Contaminated
-0.966858	-1.094911	0.627377	0.359191	0.543227	-0.949561	1	0.905609	1	Contaminated	Contaminated
-0.851622	-1.049118	0.050349	0.165636	0.479969	-1.136082	0	0.001099	0	NON Contaminated	NON Contaminated

Fig.4: Prediction of food is

Following successful data processing, the fig.4 shows the Microwave Sensing Contaminant Detection system displays the Analysis Results page. It offers a thorough synopsis of the detection outcomes. The user can export the entire report when the interface verifies that the analysis is finished and the findings are available. The relevant contamination probability, risk level, confidence level, and prediction status (contaminated or not) are reported for each sample. Users can swiftly determine whether samples are possibly dangerous and need additional attention thanks to this output. Effective decision-making in food quality assurance is encouraged by the platform's structure and clarity, which make it simple to understand machine learning predictions.

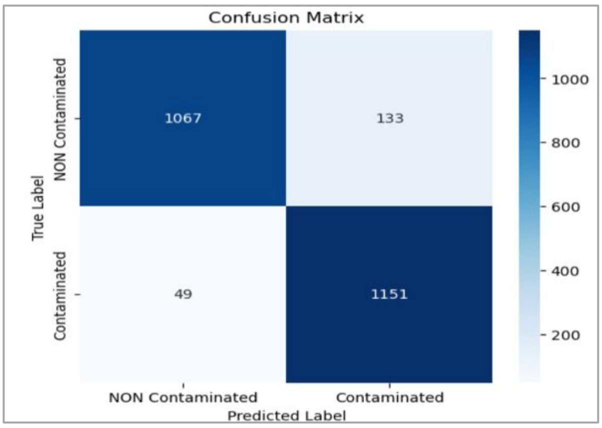

Fig. 5: Confusion Matrix

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The distribution of accurate and inaccurate predictions is displayed in fig. 5. While the classifier misclassified 133 positives as negatives and 49 negatives as positives, it correctly predicted 1067 positives and1151 negatives. This high percentage of accurate classifications indicates that the model is balanced and works well for both groups.

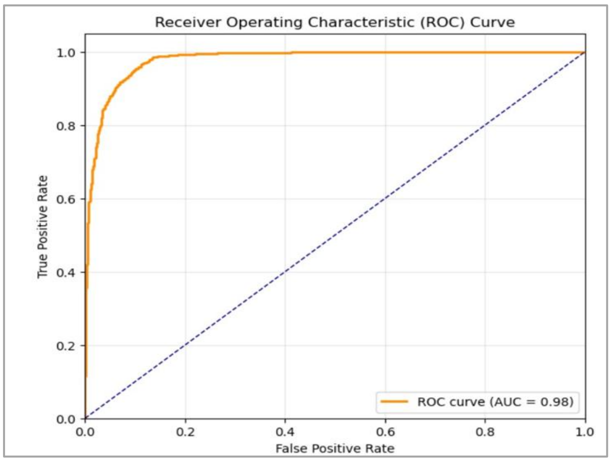

Fig. 6

The receiver operating characteristic, or ROC curve, shows in Fig.6 how the True Positive Rate (TPR) and False Positive Rate (FPR) are traded off at different threshold values. With a TPR of 0.880 and an FPR of 0.060, a prominent point on the curve indicates a high capacity for class distinction. A ROC curve that bends in the upper-left corner indicates superior classification performance.

CONCLUSION

A productive machine learning-driven approach to discriminating between contaminated and non-contaminated samples is provided by the Contaminant Detection using Microwave Spectroscopy (MWS) program. The device attains high prediction accuracy using dimensionality reduction methods such as Principal Component Analysis (PCA) and classification techniques, rendering it suitable for initial-stage screening of food or water samples. Improved understanding and verification of the findings are facilitated by the addition of a clear visual representation of model performance in the form of confusion matrices, ROC curves, and accuracy/loss plots. The system also includes a well-designed results section that provides users with detailed insights into the research by presenting the prediction probability, contamination status, and confidence levels for every sample. In conclusion, this research marks a significant step in the application of MWS for smart, data-driven contamination detection. It is a sound basis for developing an improved and more valuable solution in the future due to its flexibility, modularity, and strong performance metrics. It has vast potential for application in public health, food safety, environmental surveillance, and industry with further developments.

Future Enhancement

Future development might include a number of sophisticated features to improve the Contaminant Detection utilising MWS system's capabilities. Currently, the system acts as a binary classifier predicting whether a sample is infected or not. However, real-time data gathering would be made possible by incorporating hardware elements, such as microwave spectroscopy sensors that are coupled to microcontrollers (like Arduino or Raspberry Pi). This may change the system from a static analytic tool to a deployable, dynamic solution that can be used in labs, industries, or field testing.

REFERENCES

1. Štitić, B., Urbinati, L., Di Guglielmo, G., Carloni, L. P., & Casu, M. R. (2024). Enhanced Machine-Learning Flow for Microwave-Sensing Systems for Contaminant Detection in Food. *IEEE Transactions on AgriFood Electronics*.
2. Ricci, M., Štitić, B., Urbinati, L., Di Guglielmo, G., Vasquez, J. A. T., Carloni, L. P., ... & Casu, M. R. (2021). Machine-learning-based microwave sensing: A case study for the food industry. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, *11*(3), 503-514.
3. Urbinati, L., Ricci, M., Turvani, G., Vasquez, J. A. T., Vipiana, F., & Casu, M. R. (2020, October). A machine-learning based microwave sensing approach to food contaminant detection. In *2020 IEEE International Symposium on Circuits and Systems (ISCAS)* (pp. 1-5). IEEE.
4. Kuppusamy, S., Meivelu, M., Praburaman, L., Alam, M. M., & Al-Sehemi, A. G. (2024). Integrating AI in food contaminant analysis: Enhancing quality and environmental protection. *Journal of Hazardous Materials Advances*, *16*, 100509.
5. Shehzad, K., Munir, A., & Ali, U. AI-Powered Food Contaminant Detection: A Review of Machine Learning Approaches. *Global Journal of Computer Sciences and Artificial Intelligence*, *1*(2), 1-22.
6. B. Alsaid, T. Saroufil, R. Berim, S. Majzoub and A. J. Hussain, "Food Physical Contamination Detection Using AI-Enhanced Electrical Impedance Tomography," in IEEE Transactions on AgriFood Electronics, vol. 2, no. 2, pp. 518-526, Sept.-Oct. 2024, doi: 10.1109/TAFE.2024.3415124.
7. Darwish, A., Ricci, M., Zidane, F., Vasquez, J. A. T., Casu, M. R., Lanteri, J., ... & Vipiana, F. (2022). Physical contamination detection in food industry using microwave and machine learning. *Electronics*, *11*(19), 3115.

***Corresponding Author:** Dr. Shweta S. Kaddi