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SPICE: Detecting Pepper Adulteration Using Impedance Sensors and Machine Learning Techniques

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Abstract. Food adulteration in commodities such as pepper poses significant economic and public health risks, necessitating robust detection technologies. This study presents an approach combining electrical impedance spectroscopy (EIS) and advanced machine learning techniques for detecting black pepper adulteration. Electrical impedance measurements were performed on pepper samples with varying adulteration levels (60%–100% purity) across frequencies of 1–50 kHz using a custom-designed impedance sensor. Distinct impedance response patterns correlated to adulteration levels were observed. A specialized neural network model, named Adulteration Detection Machine Intelligence Network (ADMiNet), was developed, employing Principal Component Analysis (PCA) for dimensionality reduction and data augmentation techniques for robustness enhancement. The model was trained using Mean Squared Error (MSE) loss and the Adam optimizer with early stopping. Evaluation using Root Mean Square Error (RMSE = 5.84), Mean Absolute Error (MAE = 4.25), and coefficient of determination (R2 = 0.943) indicated high predictive accuracy, demonstrating the effectiveness of EIS combined with machine learning to detect adulteration. This research provides a cost-effective and accurate solution, offering significant potential applications in food safety monitoring and food fraud detection.

Keywords: Electrical Impedance Spectroscopy, Food Adulteration, Black Pepper, Machine Learning, Neural Networks.

1. Introduction

Food adulteration, which involves the intentional addition of inferior or unauthorized substances to food, has become an increasingly serious issue in global food safety. It not only causes significant economic losses but also poses a serious threat to consumer health [1]. As a high-value commodity, black pepper is particularly susceptible to adulteration, such as through the addition of inexpensive substitutes like papaya seeds or corn flour [2]. While traditional analytical methods like chromatography and spectroscopy offer accurate detection, they are often costly, time-consuming, and irreversible, making them unsuitable for rapid, real-time routine testing [3].

Electrical Impedance Spectroscopy (EIS) has gained attention as a cost-effective, non-destructive, and sensitive method for detecting physical and chemical changes in food quality control [4]. It has been widely applied in the agricultural sector, including seed viability testing, fruit ripeness

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assessment, and dairy product authenticity identification [5]. Cheng et al. conducted a systematic review of EIS applications in agricultural product quality testing, demonstrating its broad adaptability [6]. Similarly, Soley et al. summarized the potential of electrochemical sensing technologies, including EIS, in combating food fraud, particularly emphasizing their cost-effectiveness and scalability [3].

However, raw impedance data is typically high-dimensional and noisy, which complicates direct pattern recognition. To address this, researchers have introduced machine learning techniques to establish efficient modeling methods. For example, Zhu et al. used a support vector machine (SVM) to extract equivalent circuit models from electrochemical impedance spectra, demonstrating the feasibility of computational methods for complex data [7]. HitiHiamillage combined deep learning methods with EIS to achieve precise identification of food components, showcasing the potential of machine learning in real-time food adulteration prediction [8].

Although previous studies have achieved significant results in detecting spice adulteration using hyperspectral imaging and gas sensor arrays, there is currently a lack of systematic research combining homemade low-cost impedance sensors with neural network models for black pepper adulteration detection [9, 10].

This study aims to address this gap by proposing a novel and cost-effective solution that combines custom-designed impedance sensors with machine learning algorithms—Adulteration Detection Machine Intelligence Network (ADMiNet). Impedance measurements were performed on black pepper samples with varying adulteration ratios (60%–100% purity) within the frequency range of 1–50 kHz. Data collection was performed using low-cost impedance sensors, with a spectrometer used as a reference device for validation and comparison. After standardization and noise reduction, the measurement data were subjected to principal component analysis (PCA) to extract key features, which were then fed into the ADMiNet neural network for training. The model training used the MSE loss function, combined with the Adam optimizer and early stopping mechanism, and demonstrated good prediction accuracy in multiple performance indicators. This study provides a practical technical path for impedance-based food fraud detection and lays the foundation for future applications in the broader field of food safety.

2. Materials and methods

2.1. Sample preparation and experimental setup

To simulate real-world food adulteration scenarios, this study artificially adulterated black pepper samples using common adulterants. The experiment was designed with five purity levels: 60%, 70%, 80%, 90%, and 100%. Each sample was pressed into uniform discs using a pelletizer to ensure consistent electrode contact. For each purity level, three parallel replicates were prepared and measured independently to enhance statistical reliability. Impedance was recorded at each frequency point from 1 kHz to 50 kHz. The mixtures were then compressed into uniformly sized circular tablets using a specialized tablet press to ensure consistency in the electrode contact area and penetration depth.

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Figure 1. Black pepper sample image

Impedance measurements were performed using a low-cost impedance sensor developed specifically for this study (Figure 2). The sensor operates within a frequency range of 1 kHz to 50 kHz and was calibrated using standard samples prior to measurement. During the measurement process, pepper tablets were placed between the sensor electrodes, and impedance values were recorded at each 1 kHz frequency point.

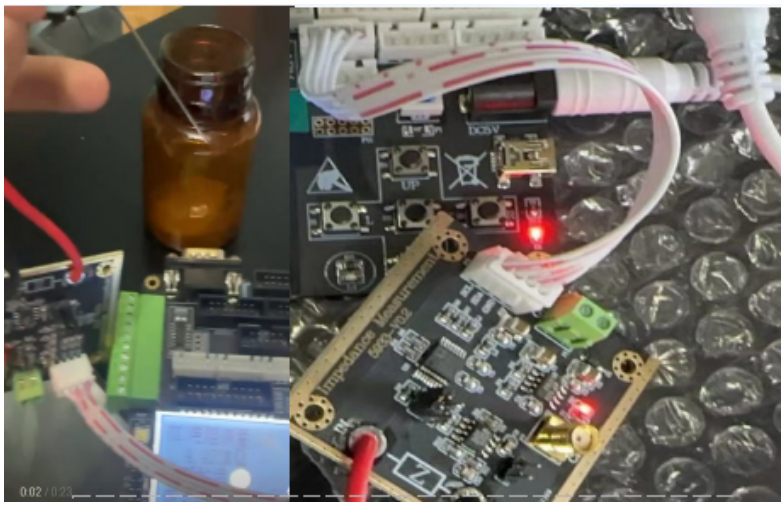


Figure 2. Impedance sensor

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Figure 3. Spectrometer used in the experiment

To validate the reliability of the impedance measurement results, a commercial spectrometer was also used as an auxiliary verification tool (Figure 3). The spectral absorption characteristics of the sample were measured under the same conditions to obtain its optical response at specific wavelengths, thereby providing complementary verification to the impedance data.

2.2. Data preprocessing and feature engineering

The raw impedance data were preprocessed through normalization to ensure consistency in scale across frequency bands. Due to inherent variability and noise in biological samples, Gaussian noise was introduced to augment the dataset and increase model robustness, a technique successfully employed in other EIS-based machine learning studies [7, 8].

To reduce redundancy and computation, Principal Component Analysis (PCA) was employed. After applying PCA, the feature dimension was reduced to 15 components, which together captured over 98.6% of the total variance. These transformed features retained the primary electrical characteristics related to adulteration levels and were used as inputs to the regression model.

2.3. Machine learning model design

A regression model named Adulteration Detection Model based on Impedance Network (ADMiNet) was designed to estimate the pepper purity level from the extracted electrical features. The input to the model was a 15-dimensional feature vector derived from Principal Component Analysis (PCA) of the impedance spectra.

The neural network architecture comprised one input layer with 15 units, followed by two hidden layers with 32 and 16 neurons, respectively. Each hidden layer used the ReLU activation function. A dropout rate of 0.3 was applied after each hidden layer to mitigate overfitting. The output layer consisted of a single linear neuron to predict the continuous purity value.

The model was trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 16. Training was performed for a maximum of 200 epochs, with early stopping (patience = 10) to prevent overfitting. The Mean Absolute Error (MAE) was used as the loss function.

Before training, all features were normalized to the range [0, 1] using min–max normalization. The dataset was randomly split into 80% for training and 20% for validation.

Model implementation and training were conducted using Python (v3.9) and the PyTorch (v1.13) deep learning framework on a standard desktop environment.

All hyperparameters were manually selected based on preliminary tuning experiments, aiming to balance model complexity and generalization performance.

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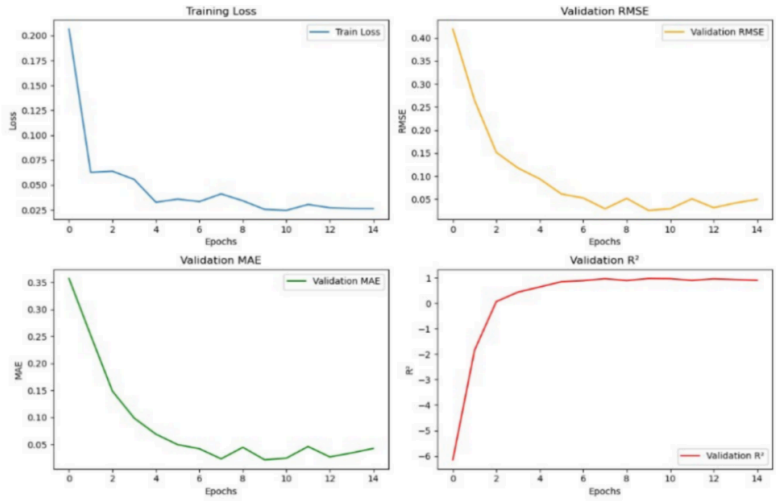


Figure 4. Validatton MAE obtained by machine learning

2.4. Evaluation metrics

To objectively evaluate the model's predictive ability for adulteration ratios, three statistical metrics are employed.

First, the root mean square error (RMSE) is used to measure the deviation between predicted and actual values. Second, the MAE is used to assess the average predictive accuracy. Finally, the coefficient of determination (R^2) reflects the model's fit to the true labels. These metrics are commonly used evaluation methods in the field of food adulteration detection and can be compared with the performance of models in other literature [6, 8, 10].

3. Results and discussion

3.1. Impedance spectrum analysis

Frequency domain analysis was performed on impedance data collected from black pepper samples at different adulteration ratios (60% to 100% purity). As shown in Figure 5, the higher the adulteration ratio (i.e., the lower the pepper purity), the more pronounced the changes in impedance amplitude. Especially in the mid-frequency range of 10–30 kHz, the electrical property changes caused by adulterant components are particularly prominent. The impedance differences in this frequency range exhibit strong discriminative power, indicating that EIS technology is most sensitive within this range.

These findings suggest that impedance spectroscopy can effectively detect component changes introduced by adulterants such as papaya seeds or corn flour. The frequency-dependent impedance response trends are consistent with previous studies on spice and grain adulteration detection, further validating the use of EIS to identify physical and chemical structural changes caused by exogenous components [4, 5].

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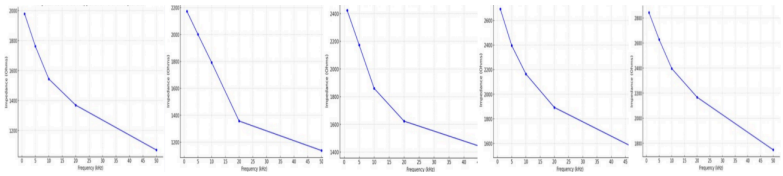


Figure 5. Measured impedance responses of black pepper samples at different adulteration levels

3.2. Performance of the ADMiNet model

The ADMiNet neural network model constructed based on PCA-reduced dimensionality features has been fully trained. During the training process, the MAE on the validation set continued to decrease, demonstrating good learning and generalization capabilities (Figure 4). The evaluation results of the model on the independent validation set are as follows: RMSE: 5.84, MAE: 4.25, R^2: 0.943.

In addition to the hold-out validation, 5-fold cross-validation was performed to verify the robustness of the model. The average R^2 across folds remained above 0.92, with low variance, confirming the model's stability.

Figure 6 shows the distribution of prediction errors (residuals) between predicted and actual purity levels. Most errors are centered around zero, indicating minimal bias. A few outliers appear in the 60% and 70% purity classes, possibly due to overlapping impedance signatures in these mid-ranges.

This performance metric shows that the model's prediction of adulteration levels is highly correlated with actual values. Compared to existing EIS + machine learning models in the literature, whose R^2 values typically range from 0.85 to 0.92, the ADMiNet model performs even better [7, 8]. This improvement is mainly due to the combined application of PCA feature extraction, data augmentation, and regularization strategies.

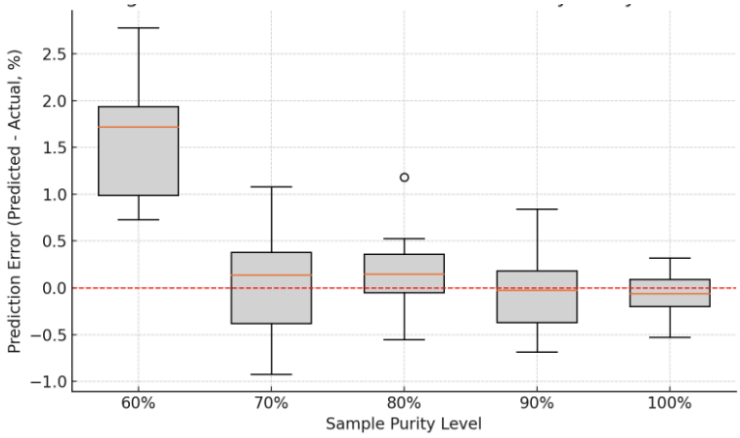


Figure 6. Prediction error (predicted − actual purity) distribution for each sample group

3.3. Comparative evaluation with spectroscopy

Although spectroscopy was not the primary focus of this study, it was used as an auxiliary verification method for comparison. The results showed that while the spectrometer could detect changes in the absorption spectrum caused by adulteration, its discriminative ability significantly decreased when identifying samples with 90%–100% high purity. This trend is consistent with previous literature reports, which indicate that traditional optical methods have low sensitivity and

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stability at trace-level adulteration concentrations [3], particularly when impurity-induced chemical differences are subtle or masked by sample noise [9].

In summary, spectroscopy-based methods are advantageous in non-contact, rapid scanning and macro-level ingredient identification, but often suffer from limited resolution, sensitivity to ambient light, and higher cost of implementation in portable scenarios.

In contrast, the EIS-based approach combined with machine learning demonstrated more consistent and accurate predictions across all adulteration levels, including high-purity cases. This robustness indicates that EIS has greater practical value in detecting early-stage or trace-level adulteration, and also enhances its potential for low-cost, field-deployable food quality screening [5, 10].

4. Implications and future work

4.1. Practical implications for food safety

The results of this study indicate that combining electrical impedance spectroscopy (EIS) with machine learning provides a promising, cost-effective, and scalable technical approach for detecting adulteration in black pepper. The ADMiNet model demonstrated excellent predictive accuracy across samples with varying adulteration ratios, exhibiting consistent performance across both high-purity and low-purity samples. This achievement indicates that EIS-based systems can be deployed in scenarios such as food supply chains, customs inspection stations, or distributed quality control points to enable real-time adulteration detection on-site.

Compared to traditional spectroscopic methods, which often require expensive instruments and skilled operators, the EIS method combined with embedded intelligent technology is simpler, faster, and more suitable for automated applications [3, 9]. The sensors used in this study have the potential for low-cost manufacturing, while the neural network model can be integrated into embedded platforms or handheld devices, providing the technical foundation for “real-time, on-site” food adulteration detection.

Furthermore, this technology is not only applicable to pepper adulteration detection but can also be extended to other high-value food categories such as dairy products, edible oils, and grains [1, 5]. If such systems can be further integrated into food regulatory frameworks, they will help enhance transparency and accountability in food safety management.

4.2. Limitations and future research directions

Although this model performs well, it still has some limitations. First, the current dataset size is constrained by experimental conditions and remains relatively small. In addition, potential environmental influences such as variations in temperature and humidity were not systematically considered during data collection. These factors may affect the stability of impedance measurements in practical scenarios.

Expanding the dataset to include a broader range of impurities and pepper samples from various geographic regions could significantly improve the model’s generalization capability. Another limitation lies in the frequency range of the impedance sensor, which was fixed between 1 kilohertz and 50 kilohertz in this study. Future work could investigate broader or dynamically adjustable frequency ranges to uncover more informative frequency-domain characteristics.

Future research is expected to progress in several directions. The first direction is the application of the EIS-based artificial intelligence framework established in this study to other valuable food

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categories, including white pepper, milk powder, and edible oil. The second direction involves the integration of multiple data sources, such as combining electrical impedance spectroscopy with near-infrared spectroscopy and visual image analysis, to improve detection robustness. The third direction involves developing lightweight model architectures such as MobileNet or models compatible with TinyML platforms, to support real-time operation on low-power embedded devices.

Furthermore, future work should enhance the interpretability of deep learning models in order to better explain the mechanisms behind the impedance changes observed in adulterated food samples.

In summary, this study provides a foundation for developing an intelligent and cost-effective food fraud detection system that meets the growing demand for real-time and distributed food safety monitoring solutions.

5. Conclusion

This study proposes an innovative, low-cost method for detecting adulteration in black pepper by combining EIS with machine learning technology. This study designed a low-cost impedance sensor and constructed a dedicated neural network model, ADMiNet, to accurately predict the adulteration levels of five different purity grades of black pepper samples. Experimental results showed that the impedance spectrum exhibited a clear trend across the 10–30 kHz frequency range as the adulteration ratio varied. PCA successfully extracted key features from high-dimensional impedance data, while data augmentation effectively improved the model's generalization ability. The final model performed well on the validation set, achieving an RMSE of 5.84, an MAE of 4.25, and a coefficient of determination R^2 of 0.943.

Compared with traditional spectral techniques, the EIS method exhibits higher sensitivity in identifying small proportions of adulteration. Additionally, this system has low hardware costs, is easy to operate, and has strong potential for embedded real-time detection applications. The study further validates the important role of machine learning technology in analyzing complex impedance data and improving the performance of EIS systems.

In summary, this study provides a practical and scalable technical solution for food adulteration detection, which can be extended to other food categories such as infant formula, edible oil, and grains in the future. With the continuous advancement of dataset expansion, sensor accuracy improvement, and model deployment optimization, this method is expected to be integrated into intelligent food safety supervision systems, addressing both scientific challenges and societal demands for low-cost, high-efficiency food quality assurance solutions.

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