Machine learning-based classification of corn seed viability using electrical impedance spectroscopy

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Article Info

Article history:

Received Apr 28, 2024
Revised Oct 7, 2024
Accepted Oct 30, 2024

Keywords:

Agricultural technology
Digital agriculture
Non-destructive approach
Seed classification
Seed phenotyping

ABSTRACT

Corn (*Zea mays L.*), an essential global commodity, plays an ever-increasing role in agri-food systems. To support growing demand, rapid and non-invasive methods for determining seed germination rates are crucial alongside invasive techniques such as dissection, germination paper tests, and chemical assays. This study introduces electrical impedance spectroscopy (EIS) as a novel, non-invasive approach for classifying viable and non-viable corn seeds. Non-viable corn seeds were prepared by exposing them to 100 °C convection heat for 30 minutes. Impedance spectra were measured using the EVAL-AD5933EBZ evaluation board from 400 kHz to 1 MHz frequency range within 30 seconds. Furthermore, a comparison of six optimized supervised machine learning (ML) algorithms, including shallow and deep networks, was performed, setting this apart from other studies. The trained model was deployed to assess the viability of new seed samples effectively. Key impedance metrics, including their frequencies, were extracted to train and test the algorithms. The regression tree (RTree) model outperformed deep learning classifiers, achieving 95% accuracy, 90% precision, and 100% sensitivity. The results indicated an upward trend in viable seed impedance, increasing by 0.000164 Ω/Hz, peaking at 990 kHz. This approach offers a rapid, non-invasive solution for seed viability assessment, with significant potential to enhance agricultural productivity.

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1. INTRODUCTION

Corn or maize (*Zea mays L.*) plays a critical role in supporting human life and economic development in many regions of the world. It is a versatile multipurpose crop used for human food (13%), animal feed (56%), and non-food use such as ethanol and bio-oil (20%) [1], [2]. The estimated global demand for this crop is projected to increase from 1,177 million metric tons in 2023 to 1,218 million metric tons in 2024 [3]. These rising demands necessitate strategies to ensure high yields and productivity. One strategy is ensuring that the corn seeds are of high quality, and a key characteristic for this is germinability. Seed germination indicates viability and potential plant performance, meaning a high germination rate produces maximum yield [4]. Non-invasive, accurate, and faster ways of testing seed viability are being developed and utilized such as optical-based evaluation [4], thermal imaging approach [5], and spectroscopy-based assessment [6].

The germination rate of corn seed is still obtained using the standard and conventional procedure that lasts 7 to 14 days and requires a lot of work in maintaining a controlled environment inside a laboratory while monitoring it regularly [7]. However, modern techniques have been developed to acquire not just the germination rate but also detect possible diseases and abnormalities. Near-infrared hyperspectral imaging (NIR-HIS) is a rapid, non-destructive, and accurate technique used to determine the maturity classification of maize seeds [8]. Real-time detection and evaluation of normal, heat-damaged, and artificially aged sweet corn seed using near-infrared spectroscopy (NIRS) is feasible [9]. Starch and protein in corn seeds can be detected to determine viability using fourier transform NIR (FT-NIR) with higher accuracy than Raman spectroscopy [10]. HSI is being utilized to differentiate viable and non-viable white, yellow, and purple corn kernels [11]. It can also be used to detect toxins, fungal infections, and other diseases in maize seeds [12], [13]. While these techniques were proven to be effective, fast, and accurate, acquiring the needed equipment and instruments to perform these techniques is costly, which makes it difficult to industrialize related applications. Impedance spectroscopy proposes a low-cost, simple, and potential technique used for qualitative and quantitative analysis of sample components with a wide range of applications in the non-invasive testing of agricultural products [14].

Electrical impedance spectroscopy (EIS) is a method for evaluating agricultural products without causing any damage [15]. It involves applying a sinusoidal current or voltage to the sample and measuring its impedance over a range of frequencies. The impedance spectra obtained from this process reveal the electrical properties and behaviors of the sample, providing valuable insights into its characteristics [16]. Moreover, it has numerous applications in fruit and vegetable quality assessment, meat quality detection, food quality evaluation, and grain quality classification [14]. Rice seed vigor detection utilizes EIS to categorize fresh and aged seeds and to determine the moisture content using impedance as the main parameter [17]. The EIS approach is also effective in predicting snap bean and soybean seed viability, whether germinal or non-germinal [18]. However, snap bean and soybean seed moisture content must be at 40% to 45% before testing [19], [20]. Initial procedures such as boiling and humidity processing are needed prior to obtaining the impedance spectra of soybean seeds [21]. Successful characterization and differentiation between olive varieties through EIS are viable [22]. Corn, being one of the most in-demand crops worldwide, requires a rapid and non-invasive method of viability test. With these proven applications of EIS on various seeds, there is a huge gap in using this technology to evaluate corn seed viability.

This study aims to fill this gap by developing a rapid and non-invasive approach to classify viable and non-viable corn seeds using EIS with advanced machine learning (ML) models. Furthermore, a comparison of remodeled supervised ML algorithms, such as regression tree (RTree), gaussian process regression (GP), support vector machine (SVM), feed-forward neural network (FFNN), spiking neural network (SNN), and deep recurring neural network (DRNN) by cascading a rounding off (RO) algorithm section (resulting models are RTree+RO, GP+RO, SVM+RO, FFNN+RO, SNN+RO, and DRNN+RO), in classifying was performed. This innovative combination of EIS with advanced ML models not only improves classification accuracy but also simplifies the viability testing process.

The study makes a substantial intellectual contribution by proposing a novel, low-cost, and efficient approach to corn seed viability testing. It highlights the potential of EIS combined with advanced ML techniques to revolutionize seed testing, offering significant benefits to the corn production industry. This method optimizes resource utilization, aligning with green production principles by reducing the environmental impact of traditional seed viability testing procedures.

The structure of this paper is as follows: section 2 details the methodology, encompassing data collection, ML modeling, and evaluation processes. Section 3 presents the data manipulation and analysis, outlines the performance metrics of each developed ML algorithm, and discusses the study's implications. Finally, section 4 synthesizes the key findings, addresses the implications and limitations, and provides recommendations for future research.

2. METHOD

The methodology has two phases: data collection and ML modeling as shown in Figure 1. For data collection, 50 viable and 50 non-viable seed samples were taken. An EIS evaluation board was utilized to extract the impedance spectra of each corn seed. From the extracted data, the impedance parameter was obtained and used in the second phase. ML modeling was performed by cleaning and transforming the dataset based on the selected features. These features were fed to train and test various supervised ML algorithms and determine the most appropriate model to classify viable and non-viable corn seeds.

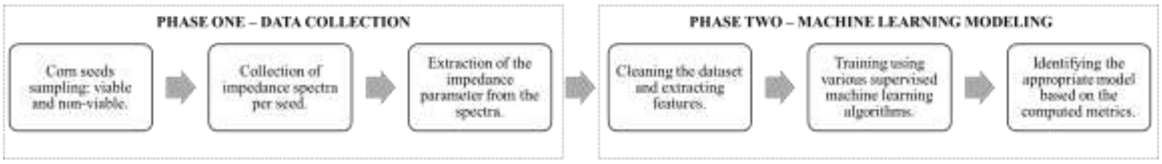


Figure 1. Step-by-step flow of classifying viable and non-viable corn seeds using various shallow to deep ML models with EIS data as input features

2.1. Data collection

2.1.1. Corn seeds

The corn seeds used in this study were the NSIC CN 282 (IES 10-04w) variant provided by the Bureau of Plants Industry (BPI), Manila, Philippines. This batch was harvested last March 31, 2023, had a moisture content of 11.5% and a germinability rate of 93%. The seeds belonged to the foundation class. As foundation class seeds, they serve as the primary source for producing certified and registered seeds. Ensuring the viability of these seeds is crucial, as it significantly increases the likelihood of achieving high germination rates in subsequent seed classes.

2.1.2. Heat-induced corn seeds

To create a dataset with both viable and non-viable seeds, a total of 100 corn seeds with comparable sizes were selected. Of these, 50 seeds were treated as viable, while the other 50 were made non-viable through heat treatment. The non-viable seeds were produced by exposing them to 100 °C for 30 minutes in a convection oven (HEO45SS Hanabishi, Philippines). The seeds were distributed without overlapping with each other. Exposure of seeds to a high-temperature environment above 40 °C reduces seeds' viability [23]. Following this induced aging process, each seed underwent EIS to extract its impedance data.

2.1.3. Electrical impedance spectroscopy

EIS is a technique used to measure the electrical impedance of a system or a body over a range of frequencies, which can be characterized based on the measured value [15]. It works by employing a sinusoidal current or voltage applied to the sample to measure its impedance over a frequency range. The resulting impedance spectra represent the sample's electrical characteristics and give an insight into its behaviors and properties [16].

The impedance spectra of each seed are extracted using the EVAL-AD5933EBZ evaluation board (Analog Devices, Inc., Philippines). The evaluation board exploits the AD5933 integrated circuit (Analog Devices, Inc., Philippines) which is a high-precision impedance converter system that combines an onboard frequency generator with a 12-bit, 1 MSPS analog-to-digital converter (ADC) [24]. This setup allows for precise impedance measurement over a range of frequencies and is widely used in agro-industrial applications to assess impedance properties [24]-[27]. The evaluation board is paired with a dedicated software application that must be installed to perform frequency sweeps and extract the impedance spectra. The software allows users to configure the settings before running frequency sweep. Moreover, impedance data can be accessed and downloaded through the software.

To be able to perform a frequency sweep and extract impedance data of corn seed, it is important to understand which settings affect the output of the impedance spectra, as shown in Figure 2. The sweep parameters, which include the start frequency, delta frequency, number of increments, number of settling time cycles, and ref clock frequency, are used to define the frequency range where the impedance is measured. The output excitation controls the sinusoidal peak-to-peak voltage used to compute the impedance. The programmable gain amplifier (PGA) enables the user to adjust the output of the current-to-voltage amplifier, allowing for amplification by a factor of either 1 or 5. The calibration impedance sets the value of R1 used to calculate the gain factor. These settings determine the impedance readings and the equivalent line graph during the frequency sweep. Additionally, the downloaded impedance data is in a .csv file containing the frequencies and their corresponding measured impedance, phase, real part, imaginary part, and magnitude.

2.1.4. Design of experiment

The instrumentation plan is shown in Figure 3. The schematic block diagram in Figure 3(a) and the actual setup of the experiment in Figure 3(b) are comprised of the EVAL-AD5933EBZ evaluation board, 2.35 mm standard pin electrode ECG lead wire as probes (machine foil wire), a corn seed holder (non-conductive material), and a Lenovo Yoga Pro 7i laptop. Before initiating the frequency sweep, the software was configured with the appropriate settings. Figure 2 shows the actual settings used during the experiment. The frequency range of 400 kHz to 1 MHz was selected based on the experimental observations indicating that this range provided the most evident trend distinction between viable and non-viable seeds and captured the significant impedance differences needed for accurate classification. The frequency range is achieved by setting the starting frequency to 400 kHz, the delta frequency to 10 kHz with 60 increments, and settling time cycles of 15 MHz and ref clock frequency of 16 MHz. Also, the output excitation is set to 2 V_{pp} and PGA control to times one as the multiplier (gain=X1). The calibration impedance is measured based on the probe's resistance of around 0.1 Ω. With these settings, the gain factor is calculated at 5.28×10^{-4}. On average, it takes 30 s to extract the impedance spectra of each corn seed from 400 kHz to 1 MHz frequency sweep.

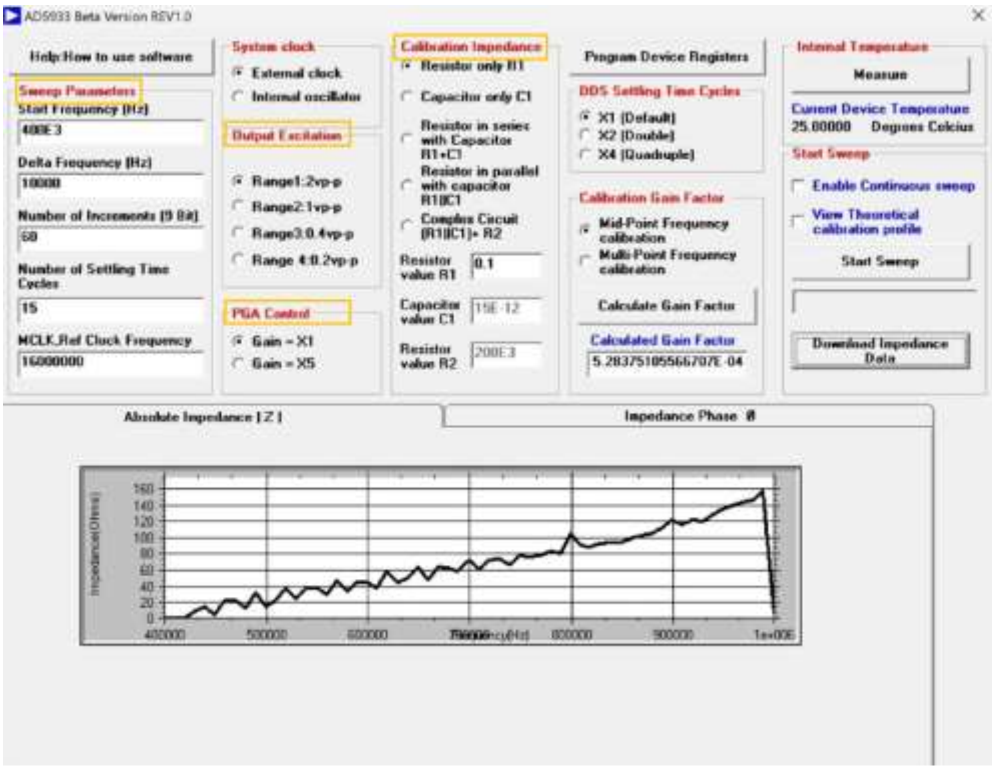
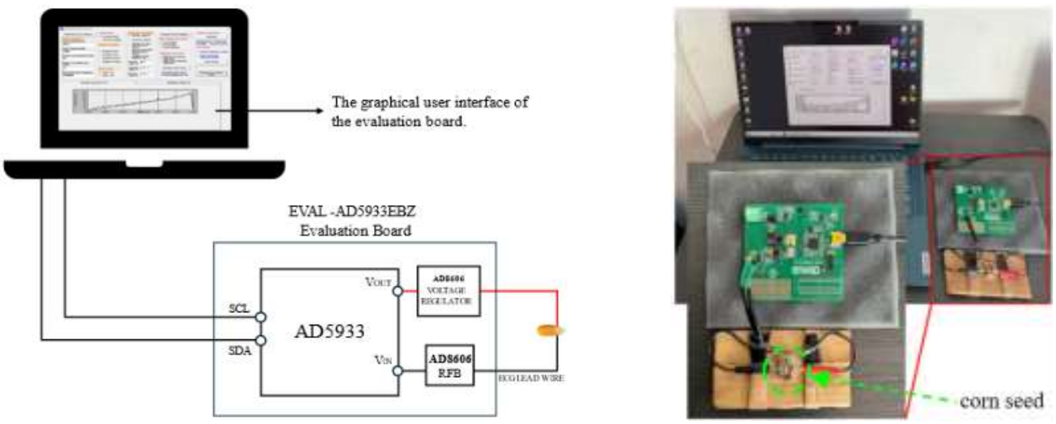


Figure 2. EVAL-AD5933EBZ graphical user interface of the software, including the actual settings used in the experiment and the option to download impedance data, highlighting the configurable sections for actual experiments



(a) (b)

Figure 3. Instrumentation plan (a) schematic block diagram and (b) actual configuration of the setup

The target positions of the probes on the surface of the corn seed are shown in Figure 4. The probes are placed along the surface of the embryo or germ part of the corn seed 3 to 5 mm from the tip cap (bottom) presented at Figure 4(a). The placement must be consistent, as probe placement is crucial for reliable and comparable impedance data illustrated in Figure 4(b). Ensuring precise and uniform probe placement across all measurements is essential for maintaining the integrity of the experimental results.

(a) (b)

Figure 4. Probes' positions (a) on the corn seed's surface and (b) at side view

To acquire the impedance spectra from the 100 corn seed samples, the EVAL-AD5933EBZ evaluation board must first be calibrated. Begin by configuring the appropriate settings and necessary parameters through the software. Then, click the 'Program Device Registers' button to enable the 'Calculate Gain Factor' button. Ensure that the probes are shorted before pressing the 'Calculate Gain Factor' button to determine the gain factor for the experiment. Once calibration is completed, place a single corn seed onto the holder so that it makes contact with the probes. Execute the frequency sweep, which will measure the impedance across the range from 400 kHz to 1 MHz. After the sweep, the software will display a line graph illustrating the measured impedance over the range of frequencies. Finally, the impedance data in a .csv file will be readily available for download to perform further analysis.

2.2. Machine learning modeling

The ML modeling phase involved training and testing various supervised ML algorithms using the impedance data collected from the corn seeds. MATLAB R2023b was used for this purpose. The dataset is comprised of 100 impedance spectra, each representing a single corn seed (50 viable and 50 non-viable). The maximum and minimum impedance, Z_{max} (Ω) and Z_{min} (Ω), and their corresponding frequencies, f_{Zmax} (Hz) and f_{Zmin} (Hz), were extracted as key features from each seed's impedance spectra and were used as predictors for the models. These features were chosen since they represent the extremities of impedance values, which are directly related to the seed's electrical properties. Variations in impedance can indicate changes in seed viability and internal conditions, making these features sensitive indicators of seed health.

The key features represent the whole impedance data of each corn seed fed to the ML models for training and testing. The dataset was split into a training set (80% of the data) for training the ML models and a test set (20% of the data) for evaluating the performance of the trained models. Stratified sampling was employed to ensure that both the training and test sets were balanced, maintaining a proportional representation of viable and non-viable seeds in each subset.

A comparison of the six ML models is performed in this study. This includes shallow networks such as SVM, FFNN, GP, and RTree. Moreover, this study also utilized deep network algorithms such as DRNN and SNN to classify corn seed viability. These models were executed by categorizing the outputs into 1 and 0 (one-hot encoding) for viable and non-viable classifications, respectively. Unlike the conventional way of classification problems, this study used the tandem of regression model with RO algorithm to enhance classification performance and as a package to make a classifier model.

The shallow network algorithms are optimized straightforwardly to train the datasets with complex patterns and nonlinear relationships to develop a model. In this study, the hyperparameters of each model were optimized. SVM+RO was configured using 694.2586 box constraint, 34.10 epsilon, and 1.42 kernel scale with solver sequential minimal optimization (SMO). GP+RO was configured using 0.0889 sigma, and 0.2877 beta with squared exponential as kernel function. For FFNN+RO was configured with 63 hidden layers with limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm (L-BFGS) as solver, sigmoid as activation, glorot for layer weights initializer, $1e^{-6}$ for loss tolerance, and $1.25e^{-7}$ for lambda. RTree+RO has a minimum leaf size of 3. Additionally, the deep network algorithms can be configured more in-depth to train the model more effectively by selecting appropriate settings as shown in Figure 5. DRNN+RO integrates deep learning and neural networks to create multiple hidden layers, resulting in enhanced memory storage capability as shown in Figure 5(a). This study uses the Elman backpropagation network with four 4 layers configured with 100, 50, 30, and 10 hidden artificial neurons. Activation functions between the hidden layers include two tangential sigmoid and three logarithmic sigmoid. Moreover, the algorithm was trained using the scaled conjugate gradient (SCG) algorithm with a $1e^{-7}$ goal error. On the other hand, SNN+RO in Figure 5(b) is primarily based on generating and transmitting action potentials (spikes) between neurons. The SNN was optimized using 4 input neurons, 80 hidden neurons, 1 output neuron, 1000 epochs, and a 0.001 learning rate for classifying viable and non-viable corn seeds.

Optimized models were tested using a new seed dataset, and confusion matrices were created to represent the testing results alongside the calculation of accuracy, specificity, precision, sensitivity, F1-score, and Matthews correlation coefficient (MCC) based on [8].

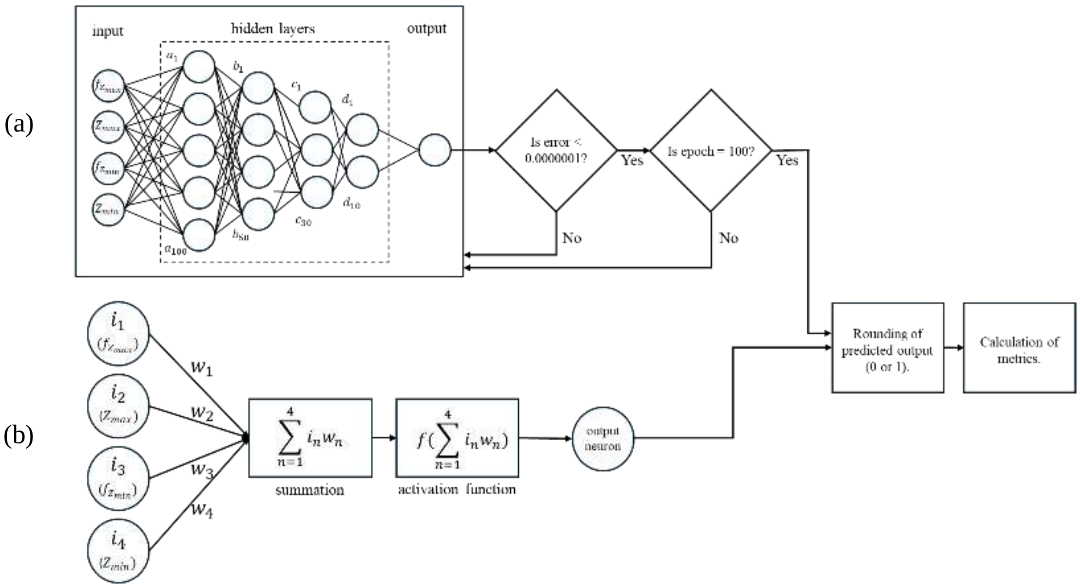


Figure 5. Deep regression networks for classifying viable and non-viable corn seeds (a) DRNN and (b) SNN

3. RESULTS AND DISCUSSION

3.1. Corn seed's impedance spectra

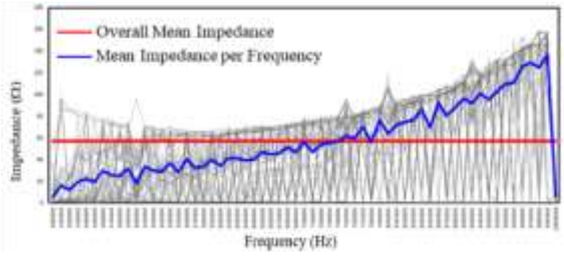
From the downloaded impedance data using the evaluation board's software, the .csv file contains the seed's impedance, phase, real part, imaginary part, and magnitude per frequency. This study only uses the maximum and minimum impedance values and their corresponding frequencies as predictors to classify viable and non-viable corn seeds as they represent the extremities of impedance values, which are directly related to the seed's electrical properties. The impedance value of each viable and non-viable seed from 400 kHz to 1 MHz is plotted and analyzed in Figure 6, together with the average impedance per frequency and the overall mean impedance.

3.1.1. Bioelectric impedance of viable corn seeds

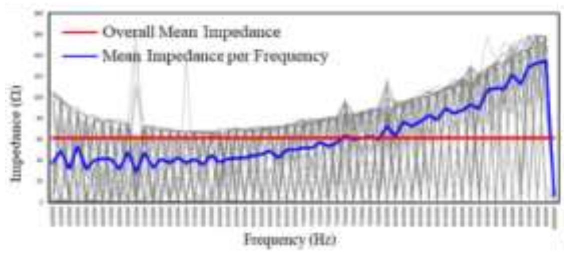
The impedance data trend of the viable corn seeds acquired from the evaluation board is shown in Figure 6(a). Based on the graph, it can be observed that the maximum impedance of the mean per frequency (MPF) trend happens at 990 kHz frequency with a value of 136.134 Ω. On the other hand, the minimum impedance of the MPF trend can be seen at 440 kHz with a 5.004 Ω impedance value. It can also be perceived that the impedance value, although fluctuating at some frequencies, trends upward by a factor of 0.000164 Ω/Hz, peaking at 990 kHz. The mean overall impedance (MOI) across all frequencies is 57.042 Ω for viable corn seeds.

3.1.2. Bioelectric impedance of non-viable corn seeds

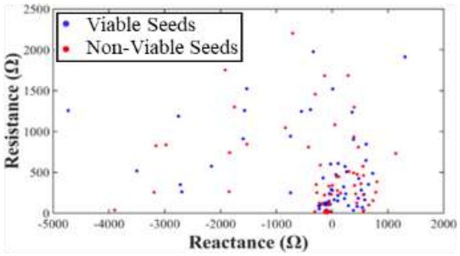
The graph in Figure 6(b) illustrates the impedance data trend of the non-viable corn seeds obtained from the evaluation board. The maximum impedance of the MPF trend can be observed at 990 kHz, with a value of 134.845 Ω. Conversely, the minimum impedance of the MPF trend is observed at 1 MHz with a 6.337 Ω impedance value. Although the impedance value fluctuates at some frequencies, it also has an upward trend by a factor of 0.0001271 Ω/Hz, peaking at 990 kHz. The MOI across all frequencies for non-viable corn seeds is 61.541 Ω. Moreover, distinct points and reactance in relation to resistance values were observed between viable and non-viable corn seeds as shown in Figure 6(c).



(a)



(b)



(c)

Figure 6. Impedance spectra of: (a) viable, (b) non-viable corn seeds, and (c) Resistance and reactance dynamics as measures of impedance variations on viable and non-viable seeds

3.1.3. Physical comparison of viable and non-viable corn seeds

Upon observation, the non-viable corn seeds have a whiter and more solid-looking appearance than viable seeds in their endosperm part as shown in Figure 7. It can be observed on the front or germ area shown in Figure 7(a), back area in Figure 7(b), and top area in Figure 7(c). The reason could be that the non-viable seeds are drier due to exposure to a high temperature.

(a)

(b)

(c)

Figure 7. Corn kernel architectural views: (a) germ or front that is indicative of indention, (b) back, and (c) top

3.2. Comparison of machine learning models

The features extracted from the impedance spectra, which are the maximum and minimum impedance values and their corresponding frequencies, are used to train and test the ML models in MATLAB. Figure 8 shows the confusion matrix generated by each ML algorithm. Regarding the shallow network ML algorithms, RTree+RO model yielded 95.00% accuracy, 100% sensitivity, 90.90% specificity, 90% precision, 94.74% F1-score, and 90.45% MCC during testing as shown in Table 1. The decision tree has six pruning levels and utilizes 'Var3' (Z_{max}), 'Var4' (f_{Zmin}), and 'Var5' (Z_{min}) to identify the viability of corn seeds. Figure 8(a) illustrates that the SVM+RO model correctly identified 9 viable seeds, achieving an accuracy of 51.25%. In contrast, the FFNN+RO model, with an accuracy of 57.50%, accurately classified 9 viable and 2 non-viable seeds, as shown in Figure 8(b). Figure 8(c) presents the confusion matrix for the GP+RO model, which attained 82.50% accuracy, correctly identifying 8 viable and 2 non-viable seeds.

Finally, Figure 8(d) shows the confusion matrix for the RTree+RO model, which achieved 95.00% accuracy, correctly classifying 10 non-viable and 9 viable seeds.

Between the deep network models, the SNN+RO algorithm achieved 51.25% training accuracy, 45% testing accuracy, 0% specificity, 100% sensitivity, 45% precision, 62.07% F1-score, and 0% MCC. In comparison, DRNN+RO achieved 70% training accuracy, 70% testing accuracy, 63.63% specificity, 77.78% sensitivity, 63.64% precision, 70% F1-score, and 41.41% MCC in classifying viable and non-viable corn seeds during testing. The SNN+RO algorithm correctly classified zero non-viable and nine viable seeds, as shown in Figure 8(e). Moreover, the DRNN+RO algorithm has accurately predicted seven non-viable and seven viable seeds, as illustrated in Figure 8(f). Table 1 summarizes the metrics of each algorithm used. The RTree+RO model outperformed all other algorithms across every metric measured, which makes it the most appropriate model for classifying viable and non-viable corn seeds. Its training and testing accuracies are at least 20% better than the deep network models in Table 1.

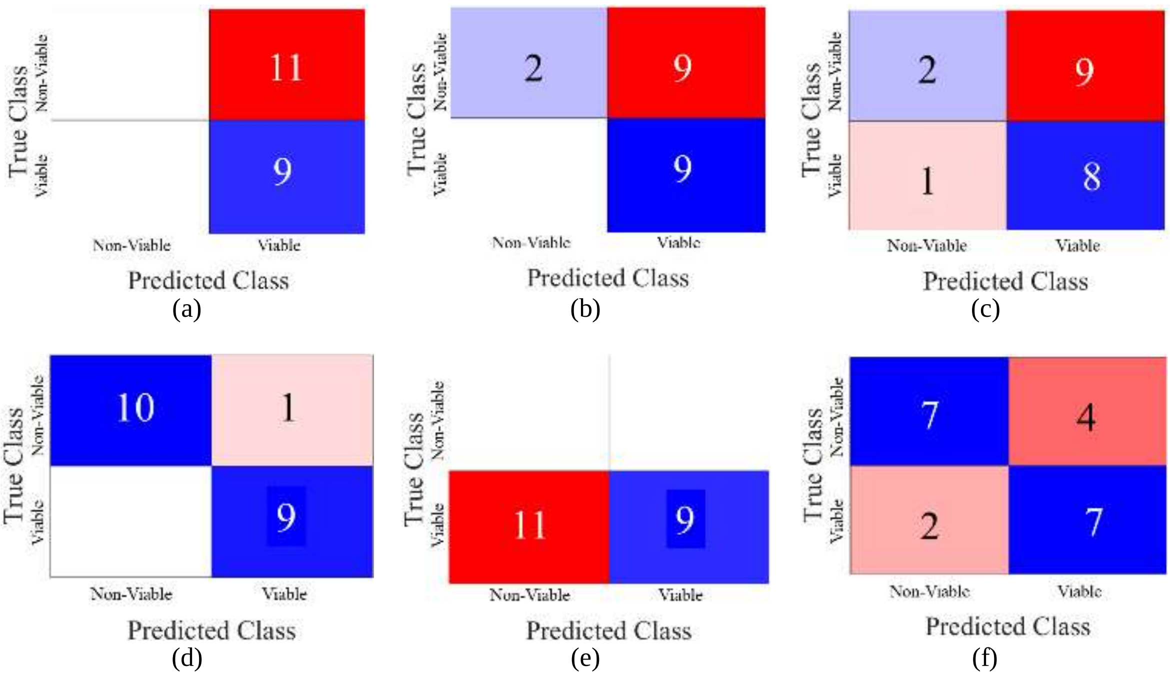


Figure 8. Confusion matrices of (a) SVM+RO, (b) FFNN+RO, (c) GP+RO, (d) RTree+RO, (e) SNN+RO, and (f) DRNN+RO

Table 1. Comparison of developed model metrics in classifying viable and non-viable corn seeds

Classifier model	Training accuracy	Testing						
		Accuracy	Specificity	Sensitivity	Precision	F1-score	MCC	Inference time (s)
SVM+RO	51.25%	45.00%	0.00%	100.00%	45.00%	62.07%	0.00%	23.74
FFNN+RO	57.50%	55.00%	18.18%	100.00%	50.00%	66.67%	30.15%	37.03
GP+RO	82.50%	70.00%	81.82%	55.56%	71.43%	62.50%	38.98%	15.21
RTree+RO	95.00%	95.00%	90.90%	100.00%	90.00%	94.74%	90.45%	11.55
SNN+RO	51.25%	45.00%	0.00%	100.00%	45.00%	62.07%	0.00%	0.32
DRNN+RO	70.00%	70.00%	63.63%	77.78%	63.64%	70.00%	41.41%	1.43

Furthermore, the RTree+RO model has demonstrated performance comparable to other EIS-based models, such as those that classified olive variants into five categories with 98% accuracy [22] and detected leaf phosphorus in various crops with 82% accuracy [28]. The results of this model are also on par with image-based analysis techniques, including HSI, which achieved approximately 97% accuracy in classifying white corn as viable or non-viable [11]. Notably, this study is distinctive in its integration of EIS with ML specifically for seed viability classification. Previous research has primarily focused on applying EIS and ML to plants and fruits, leaving a gap in corn seed viability studies as shown in Table 2.

Table 2. Comparison of developed techniques and models to existing related works

Seed variety	Nature of seed	Phenotyping technique	Optimal classifier model	Major finding	Reference
Sweet corn	Normal, heat-damaged, and artificially aged	NIRS	Partial least squares discriminant analysis (PLS-DA) model	The research shows that spectral data from seed positions can reflect activity and enable real-time detection and classification in the detection area. Accuracy: 97%-100%	[9]
White, yellow, and purple corn	Heat-aged and healthy	FT-NIR	Principal component analysis (PCA) and PLS-DA models	The starch and protein in corn seeds help distinguish viable from nonviable kernels. The study also found FT-NIR spectroscopy more effective than Raman spectroscopy for evaluating seed viability. Accuracy: 95%-100%	[10]
White, yellow, and purple corn	Heat-aged and healthy	HSI	PLS-DA model	The study suggests that seeds of varying colors, shapes, and sizes require different radiation and instrument settings. However, overall results indicate that HSI accurately classifies viable and nonviable seeds in a non-destructive way. Accuracy: 95%-97%	[11]
Japonica rice	Naturally aged and fresh	EIS	Fisher linear discriminant analysis	The vigour of rice seeds was successfully distinguished in the low-frequency region, with impedance influenced by water state and micromorphology. Accuracy: 90%	[17]
Snap bean	Heat-aged and healthy	EIS	Complex non-linear least squares (CNLS)	The study found that the most sensitive EIS parameters for differentiation of viable and non-viable seeds were $\log(C_2)$, R_2, R_2/R_1 ratio, and the apex ratio. Moisture content strongly affects the EIS parameters, especially on non-viable seeds.	[20]
Yellow corn	Heat-aged and healthy	EIS	Hybrid RTree model with RO (RTree+RO)	This study is the first to successfully integrate EIS with ML for rapid, non-invasive classification of corn seed viability. Accuracy: 95%	This work

3.3. Relevance in green production and future implications

Green manufacturing or green production refers to pioneering production techniques designed to minimize adverse environmental effects by decreasing waste, promoting waste recycling, optimizing natural resource utilization, and implementing related initiatives [29]. The substantial contribution of this study is to significantly lessen the time for viability assessment or germination test of corn seeds from 7 to 14 days [7] to approximately 1 day. The standard procedure to assess seed viability through a germination test involves placing seeds on a clear, well-lit medium with proper moisture. The containers are sealed to maintain humidity and placed in warm conditions. Seed germination is then monitored at regular intervals, and success is evaluated based on established criteria like root emergence or shoot development after a designated period [7]. By utilizing the proposed method of this study, resources used in the germination test can be optimized and repurposed. The non-invasive approach to assessing seed viability promotes preservation, ensuring seeds remain unharmed for future planting. Faster analysis may result in faster distribution of corn seeds which could optimize land utilization due to the availability. Reducing the time and resources required for seed viability testing could lower the costs associated with corn production. Ultimately, the developed method aligns with the principles of sustainable agriculture, which seeks to meet the current food needs and enhance environmental quality. If this method and technology are scaled up, detection of corn viability will be even much faster and greatly save time in checking seeds' viability the conventional method as it was and improve food production in general. Hence, the developed method is significantly useful for non-destructively detecting seeds that have been stored in longer time, making it stale seeds.

4. CONCLUSION

This study has demonstrated the first successful integration of EIS with ML for rapid, non-invasive classification of corn seed viability. Unlike image-based methods such as HSI, NIR spectroscopy, FT-NIR, and Raman spectroscopy, this study revealed that EIS is cost-effective and simpler to use while providing comparable accuracy. The impedance data revealed distinct trends: viable seeds showed impedance peaks around 990 kHz with minimum values near 440 kHz, whereas non-viable seeds peaked around 1 MHz. Various ML models were trained with features extracted from impedance data. The RTree+RO model achieved a 95% classification accuracy, while the deep learning models like SNN+RO and DRNN+RO achieved 51.25% and 70% accuracy, respectively. The developed model was successfully deployed, and the viability of another set of corn seeds was assessed. The practical implementation of this model reduced seed viability testing from 7-14 days to one day, leading to cost savings, reduced resource use, and alignment with green production goals. While currently applicable only to individual corn seeds using an evaluation board, future research could develop batch-measuring electrodes to enhance the method's scalability. Applying this integrated EIS-ML approach to other seed types and seed-borne disease detection could further extend its agricultural benefits.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to De La Salle University for providing an avenue for conducting this research. Acknowledgment is also expressed to the Department of Science and Technology–Engineering Research and Development Training (DOST-ERDT) program for the financial support provided to the authors.

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