Automated Fruit Quality Testing using an Electrical Impedance Tomography-Enabled Soft Robotic Gripper

Elijah Almanzor[1], Thomas George Thuruthel[1], and Fumiya Iida[1]

***Abstract*— Soft robotic grippers are becoming increasingly popular for agricultural and logistics automation. Their passive conformability enables them to adapt to varying product shapes and sizes, providing stable large-area grasps. This work presents a novel methodology for combining soft robotic grippers with electrical impedance tomography-based sensors to infer intrinsic properties of grasped fruits. We use a Fin Ray soft robotic finger with embedded microspines to grab and obtain rich multi-direction electrical properties of the object. Learning-based techniques are then used to infer the desired fruit properties. The framework is extensively tested and validated on multiple fruit groups. Our results show that ripeness parameters and even weight of the grasped fruit can be estimated with reasonable accuracy autonomously using the proposed system.**

I. INTRODUCTION

Agri-food is one of the largest manufacturing sector in the world. However, the long-standing human operated field has been coming under pressure due to population growth, climate change and urban migration [1]. In the UK, the agri-fruit industry is worth approximately £1 billion [2] which have legal requirements for fruit ripeness. For example, citrus fruits that fall under the Specific Market Standards (SMS) class 1 require at least a 6-to-1 ratio of Brix to acidity levels [3]. However, up to 40% food-waste occurs, 3% of which is from the retail supply chain, costing approximately £360 million in economic loss due to agricultural produce not meeting the required market standards [4]. A report by the AMT Fruit company highlighted that 55% of their food waste comes from insufficiently ripe citrus fruits [5]. Currently, fruit quality testing is done manually using invasive techniques. These biological and biochemical analyses often require sample preparations of fruit extracts or supernatant which require the destruction of the fruits, expertise on the biological laboratory equipment and time [6]. Hence, the field is ripe for robotic automation [7], [8]. When it comes to crop manipulation, soft robotic technologies are identified as key facilitators [1]. Soft grippers utilize their compliance and underactuation to conform to the shape of an object, providing stable large-area grasps without active control [9]. This passive conformability not only provides stable grasps, but can also act as an avenue for surface measurements of the grasped object in a reliable and robust manner.

This work presents a Fin Ray inspired soft robotic gripper [10] embedded with passive microspines that serve a dual purpose, as electrodes and as frictional elements (see Fig. 1).

[1]The Bio-Inspired Robotics Lab, Department of Engineering, University of Cambridge, UK. email: `eda26@cam.ac.uk; tg444@cam.ac.uk; fi224@cam.ac.uk`

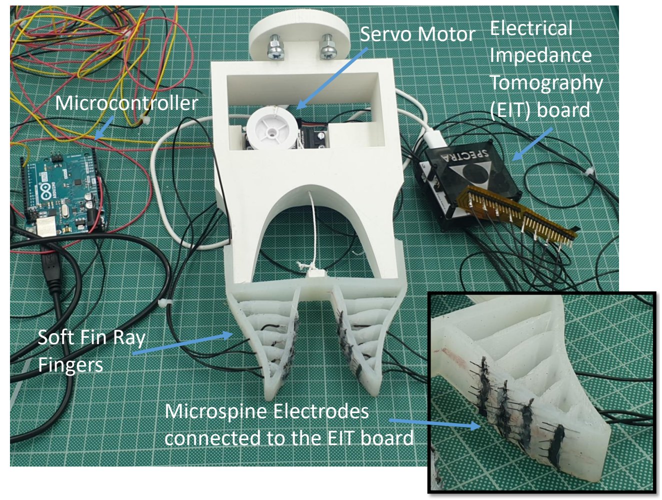

Fig. 1. Tendon driven gripper. Eight spine electrodes are embedded on the inner surface of the two Fin Ray fingers. Each row of spines is a single electrode.

Electrical Impedance Tomography-based technique is used to obtain electrical properties of the grabbed object. Electrical Impedance Tomography (EIT) is an imaging technique that applies alternating currents through some electrodes and the resulting equipotentials recorded from the other electrodes (see Fig. 2), similar to Computer Tomography (CT) scans which uses X-rays [11]. This process is repeated using different electrode configurations to obtain rich information about the electrical properties of the object in different directions.

Vision-based methods have proven capable of assessing fruit ripeness [12]. However, certain fruits such as mangoes, kiwis, and citruses do not provide useful visual cues as their colours are not indicative of their ripeness levels [13]. Scimeca et al. [14] proposed a non-destructive robotic gripper which uses capacitive tactile sensor arrays to determine mango ripeness levels based on stiffness. Similarly, other works have used spectrometer probes [15] and accelerometers [16] for mango ripeness identification. These approaches however, are limited to ripeness classification and are incapable of directly predicting intrinsic characteristic values such as weight, acidity, or sugar content due to the external form of sensing.

When alternating current is applied to organic matter, the bio-impedance of the biological tissue impedes its passage. The bioimpedance is a function of the anisotropic composition of the material, as well as the frequency of the

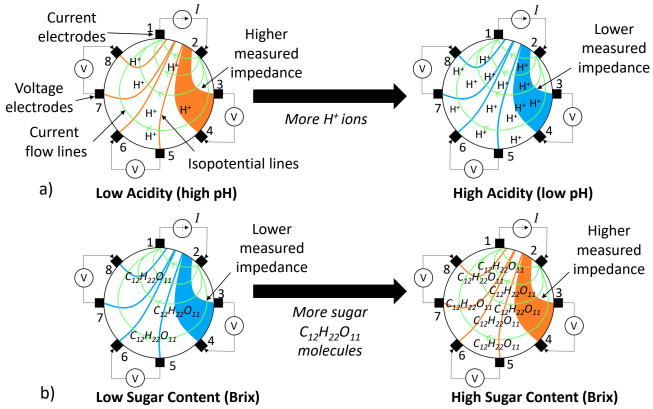

Fig. 2. Opposite effects of higher sugar and acid content on measured impedance values. a) Acidity increases with more free H^+ ions. Conductivity of a solution increases with ionic molecules. Therefore, in general, the impedance should increase with higher acidity. b) Sugar molecules are non-conductive, therefore higher sugar content will lead to higher impedance.

applied current. Thus, it can be used to obtain knowledge of the material properties [17], [18]. Bio-impedance is a complex number consisting of the resistance (real part), and the phase angle reactance (imaginary component) [19], [20], [21]. Each cell within the medium can then be treated as part of a circuit. Where the cell membranes behave like capacitors, with the resistive properties coming from the intracellular and extracellular fluids (see Fig. 4). Hence, the frequency of the AC source also decides the path of the least resistance. At low frequencies, biological cells introduce high impedance, hence the current pass around the cells through the extracellular fluids. However, at higher frequencies, the current can easily pass through the cells due to the local ionic conductivity [22], [23].

Fruits undergo physiological changes during the ripening period [24]. Ripening can occur when the fruits are still attached to the tree [25], or after picking, where the climacteric fruits seed contain ethylene, a fruit ripening hormone. Examples of climacteric fruits include apples, bananas, and kiwis. Examples of non-climacteric fruits include citrus fruits, strawberries, and watermelons. In general, sugar content increases, whilst acidity decreases during the ripening stage [26]. It is widely known that sugar in water impedes conductivity. Sugar molecules are held by covalent bonds that do not dissociate free ions in water (see Fig. 2b).

Chowdhury et al. [27] studied the bioimpedance of bananas during ripening. They found that impedance increases with ripening across a range of applied excitation frequencies. They suggested that the increase in sugar levels along with the reduction of water and acidic biochemicals contributed to this behaviour. They also found that there is a decreasing relationship between bioimpedance and the applied AC frequency. The same behaviour was also found in another investigation for bananas [28]. Work by Xingshu et al. [29] found that the impedance magnitudes decreased with kiwi ripening at low frequencies. In general, there is a proportional relationship between acidity and conductivity. Higher concentration of mobile hydrogen ions in an arbitrary solution allows for higher conductivity (lower impedance) on an applied AC current [30], [31] (see Fig. 2a). Juansah et. al. [32] found that the real resistance of Garut citrus fruits actually decreased during ripening (lower acidity), with an increase in the imaginary capacitance component. Both relationships were non-linear. They suggested that the changes in internal structure such as the cell wall, membranes, and composition of the fruit during ripening dominates the bioimpedance behaviour. A similar effect was found for nectarines [33]. The application of bioimpedance measurements for ripeness classification using learning-based methods was demonstrated by Islam et. al. [34].

The bioimpedance of fruits is a function of multiple variables; the mobility of hydrogen ions, presence of other chemicals such as sugars, the species and the internal structure of the fruit itself, and the applied signal frequency. However, these relationships are often intertwined in the ripening process, which makes their electrochemical relations highly non-linear. All previous works have observed this effect using fixed electrodes on a fruit and observing the effects over time, hence limiting their application. We extend the applicability of the approach by embedding the electrical probes onto the microspines of a soft robotic gripper, thereby giving the system the ability to probe the desired fruit autonomously. Now the modelling challenge is to estimate the low-dimensional physical parameters of the grasped object using the high-dimensional impedance value, without any prior knowledge about the shape of the fruit and location of grasp. In this work, we use machine learning techniques to solve this complex inference problem. We show how the spined soft grippers can provide both higher holding forces and a way to measure intrinsic electrical properties of the grasped object, which can be used to estimate desired physical properties of the fruit. We validate the applicability of our methodology on three fruits groups: predicting the ripeness of bananas; weight, sugar and acid content of oranges and kiwis. Our results show that the proposed methodology is highly promising for automated and fast quality testing of produce in the least invasive manner, compared to existing methods available in the market.

II. METHODOLOGY

A. EIT-enabled Soft Gripper

1) Gripper Design: The gripper consists of a pair of soft silicone Fin Ray [10] fingers attached to a 3D printed PLA gripper base (see Fig. 1). Actuation is achieved by a tendon attached to a servo motor. The gripper itself was mounted to a UR5 robot. Fin Ray fingers are based on the mechanism of fish fins. The structure bends in the opposite direction to the force applied. This allows for passive shape adaptation to the geometry of the object applying the force. The fingers' passive shape compliance makes it very suitable for grasping agricultural produce, which vary significantly in size and geometry.

The microspine electrodes have two main functionalities. The first is to increase the frictional forces. The second

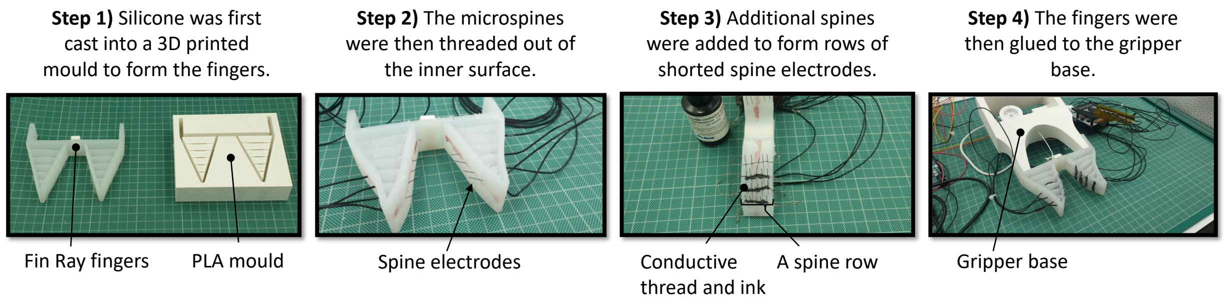

Fig. 3. Fabrication of the spine-embedded soft Fin Ray gripper.

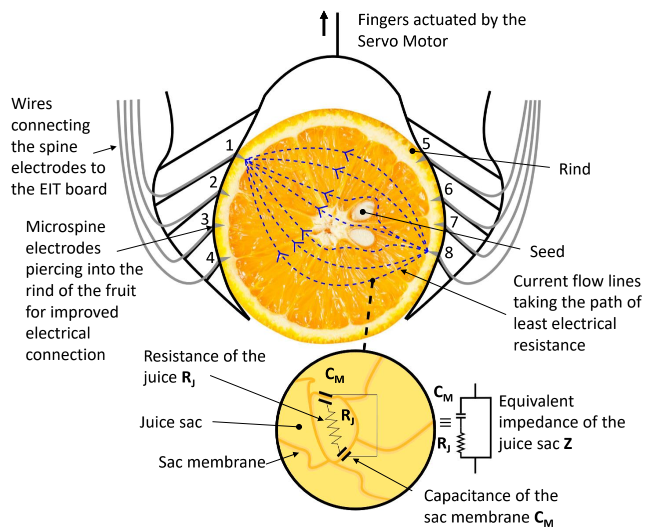

Fig. 4. Diagram showing the working principle of EIT-enabled microspine sensors. Characteristics of the fruit cells influence the measured impedance. The current flow lines between driving electrodes 1 and 8 take the path of the least electrical resistance.

purpose is to act as electrical impedance electrodes for the Minds Eye Biomedical Spectra EIT board [1]. The spines themselves are 300μm in diameter. Through preliminary testing, it was found that better conductivity was achieved when the spines were slightly piercing into the skin of the fruits. As such, the spines were deliberately designed to penetrate the fruits. Due to this, only fruits with thick epicarps were used; bananas, oranges and kiwis, as to not damage the edible tissue.

The Spectra EIT board is configurable up to 32 electrodes with 896 combinations of impedance measurements. However, to reduce the complexity of wiring the sensors to the soft fingers, only 8 electrodes are used, which provides 32 impedance measurements (see Fig. 4). The board was configured using the pre-packaged open source Python software. There are two protocols for impedance measurements: two and four electrode methods [17]. Two-electrode methods uses the same pair of electrodes as the driver to supply current, and to measure the voltage. However, this method suffers from voltage drop due to the contact impedance. In the four-electrode method, the driver and the sensor are two separate pairs of electrodes. The potential difference between the sensing electrodes equipotentials is then used to measure the impedance. One pair is used as the driver, and the remaining electrode pairs are successively measured for the mediums' impedance (see Fig. 2). Through multiplexing, the remaining electrode pairs are cycled through. The impedance measurements were made using an AC signal of 50KHz.

2) Gripper Fabrication: Fig. 3 shows the fabrication steps for the gripper. The initial step was the 3D printing of the custom Fin Ray finger mould. Dragon Skin 20 with a shore hardness of 20A was then cast to create the connected fingers. A separate component was 3D printed to allow the attachment of the string tendon to the soft fingers. The second step was the soldering of 8 steel spines, 300μm in diameter, to jumper cables connected to the multiplex pins of the EIT Spectra board. These were then threaded from the outer to the inner surface such that they protruded out at an angle. The third step was to include 4 additional spines to form 8 rows of spines, with the active electrode at the centre. Conductive thread was then wound around each spine to short each row to the centre spine, followed by gluing them down using conductive ink. A last layer of silicone glue was used to increase stability of the spines. The rows were implemented

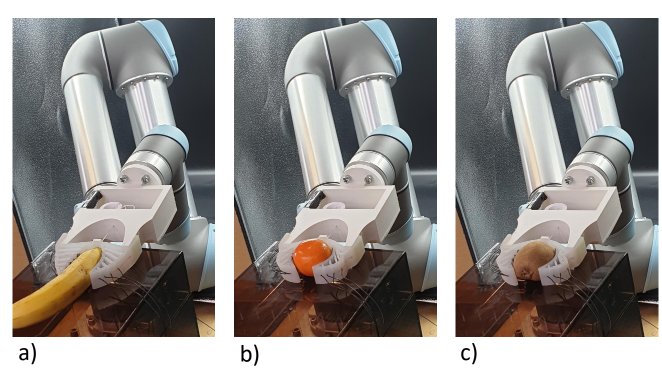

Fig. 5. Experimental setup for measuring the impedance of various fruits: a) banana, b) orange, and c) kiwi. The gripper was oriented parallel to the ground.

[1] https://shop.openbci.com/products/spectra-openeit-kit?variant=34541328400542

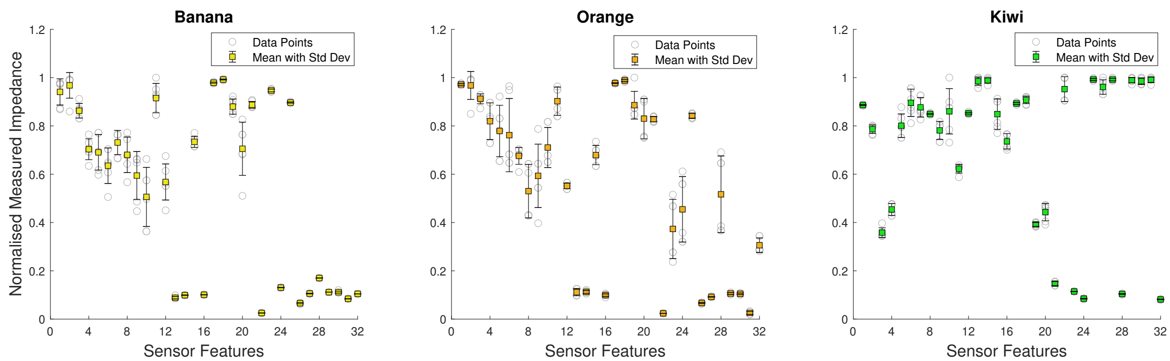

Fig. 6. For each plot, a singular fruit was grasped 5 times at the same pose, with the 32 impedance sensor readings recorded. The kiwi had the lowest standard deviation error bars, followed by the banana, then the orange.

to increase the likelihood of the electrode engaging with the fruits. The final step was to trim down each spine to 3 mm in length, followed by the gluing of the fingers to the gripper base. Two near identical grippers were created for the project; one with the sensorised spines, and one without.

B. Experimental Setup

As discussed previously, a fruits' bioimpendance has non-linear relations to the sugar content, acidity, the excitation frequency of the AC signal, and its structure. Fig. 4 illustrates the working principle of the EIT-enabled soft gripper, with a cross-section of an orange as an example. Due to the adaptive nature of the Fin Ray fingers, traditional EIT techniques for image reconstruction such as Graz Consensus, Gauss-Newton Method, and Back Projection are not analytically feasible as they require complete knowledge of the electrode placement. However, we only require low-dimensional scalar information about the fruit. Supervised learning methods are therefore employed to obtain the relationship between the day ripeness of bananas, and the weight, acidity and the sugar content of oranges and kiwis to the measured impedance pattern.

Here the methodology of the two main ripeness experiments are explained. The first experiment type is the learning of the fruit ripeness characteristics using Quadratic Support Vector Machines for banana-ripeness classification. The second is the use of simple Feed-Forward Neural Networks for weight, acidity, and sugar prediction.

1) Data Collection: The 32 sensor impedance readings are used as the feature training data for the banana day ripeness classification, and the orange and kiwi weight, acidity and sugar content regression. For all fruits, the robot arm was posed such that the gripper was parallel to the ground, as seen from Fig. 5.

For the banana day classification, a single bunch with 5 bananas was used for obtaining the training data. Each banana was grasped 10 times, with the corresponding sensor data recorded. Training data was recorded at the same time of day for 5 consecutive days, resulting in 250 data instances. To ease the process of data collection, the pose of the banana as seen in Fig. 5c, was kept the same throughout. Bananas, being climacteric fruits, ripen over time when left at room temperature. Day ripeness was therefore induced by waiting a day between each sensor reading. No dates were given on the packaging, hence the day labels are with respect to the day the bananas were bought.

For the orange data collection, 12 mandarins were used. Each orange was grasped 20 times, with 3 sensor recordings for each grasp. Oranges and citrus fruits are not climacteric. Hence, to obtain training data for varying levels of weight, acidity and sugar content, they were injected with the sugar and citric acid solutions. 400ml of water was mixed with 100g of sugar. 400ml was mixed with 50g of citric acid. Arbitrary amounts were added to each orange to induce variability in the data. After each injection, each fruit were left for an hour to allow the solutions to diffuse within the fruit. Impedance sensor measurements were first recorded for the unadulterated oranges. Another sensor measurement was recorded after the first sugar water injection. A final sensor measurement was recorded after the second citric acid solution injection. This resulted in 2160 data samples for the orange dataset.

The same methodology was done for the kiwi fruit. Ten kiwi fruits were used. This resulted in 1800 data instances. Kiwis are climacteric. However, to conduct a fair test between the kiwi and the orange, the same procedure was done. Multiple juice extraction points across each fruit were done to obtain an average distribution of the fluid content. The sugar content was measured in Brix using a pocket refractometer. Fluid was extracted until the refractometer sensor was fully filled, after which five readings were taken and averaged. An Extech pH meter was used on the extracted fluids to obtain the acidity labels in pH. Five readings were taken to get an average value. Acidity pH level is a function of temperature, hence all data were collected at room temperature. Both the kiwi and oranges were of class 1 under the UK Specific Market Standard. Bananas are generally imported to the UK, hence, they fall under the General Market Standard category [3]. The sensor data and its repeatability results is shown in Fig. 6. Here, a single fruit of each species was grasped 5 times in the same pose

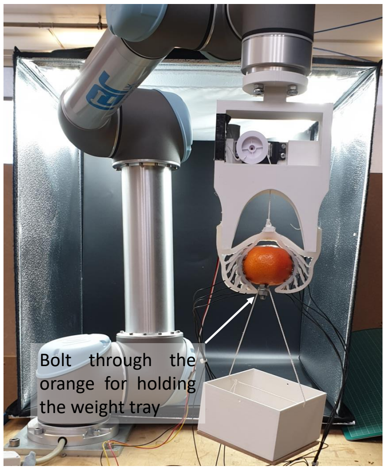

Fig. 7. Experimental setup for determining the maximum holding weight for the grippers. Comparison was done between two identical grippers; one with the microspines, and one without.

to analyse the repeatability. Note that even though the fruit is not moved between each grasp, there is still some variability, indicating that there will always be some variability in the placement of the electrodes.

C. Learning Methodology

The MATLAB Machine Learning Toolbox was used for learning the mapping between the labels and impedance features. A multi-class 1-to-1 Support Vector Machine using the Quadratic kernel function was used to classify the different day ripeness. For predicting the weight, acidity, and sugar content, a single hidden layer neural network with 60 neurons was used. The inputs to both the networks are 32 impedance values. For the classification task, 5-fold cross validation was used. For the regression task, the data were divided into train, validation, and test instances at ratios of 80%, 5%, and 15% respectively.

III. EXPERIMENTAL RESULTS

A. Maximum Gripper Holding Load

We first characterize the increase in gripping force achieved with the microspine addition. Maximum holding weight experiments using 5 oranges were done between two identical grippers: one with sensorised spines and one without (see Fig. 7). Each orange had an M6 bolt pierced through its centre to allow attachment of the weight tray. Weights were incrementally added until either the orange was dropped or the bolt was ripped out of the orange.

Results for the weight experiments are given in Table I. The average maximum graspable weight for the spined gripper is 74% higher than its non-spined counterpart. Note that three of the test oranges failed by being incapable of supporting the weight tray.

B. Banana Day Ripeness Classification

The objective of the ripeness classification task is to predict the age of the banana given the raw sensor data.

TABLE I
GRIP FORCE IMPROVEMENT WITH THE MICROSPINED GRIPPER.

	Normal Gripper		**Microspined Gripper**	
Test Orange	*Maximum Weight (g)*	*Failure Mode*	*Maximum Weight (g)*	*Failure Mode*
1	296	Dropped	496	Dropped
2	318	Dropped	544	Ripped
3	352	Dropped	580	Ripped
4	376	Dropped	716	Ripped
5	366	Dropped	654	Dropped
Average	342		596	

After training, the SVM achieved an 85.6% accuracy on the validation set. The confusion matrix is given in Fig. 8. From this figure, it can be seen that the majority of the incorrect classifications happen between consecutive days, indicating that there is a smooth relation between the sensor data and the day of ripeness. With the addition of more electrodes and more training data, the accuracy can be improved significantly.

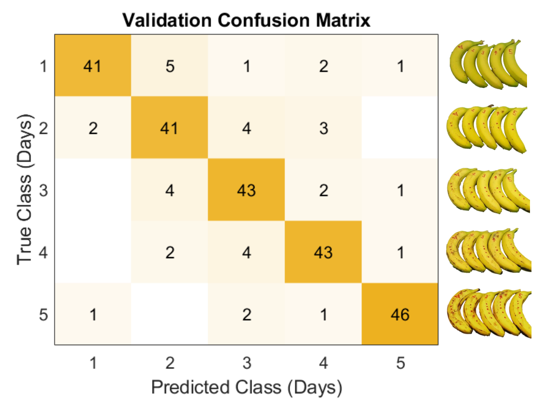

Fig. 8. Confusion matrix for the banana day ripeness classification using the SVM model.

C. Mandarin and Kiwi Ripeness Identification

In this task, we try to predict the weight, sugar, and acid content of a grasped fruit using the raw impedance value. The prediction errors for quality testing the oranges, and kiwis are given in Table II. From the table, it can be seen that the error and standard deviation for the kiwi is lower than the orange for the three ripeness characteristics. The pH precision observed with the Kiwi measurement even meet the standards of industrial devices [2]. The larger observed deviations in oranges could be because of our artificial ripening technique, which can lead to uniform material distribution in kiwis but not in a segment fruit like orange. Natural variants must be used for better evaluation of the technique. Fig. 9 plots the test predictions for each parameter

[2]https://www.awe-ltd.co.uk/products/ph/ph-meter/ph-tester-phtestr10.html

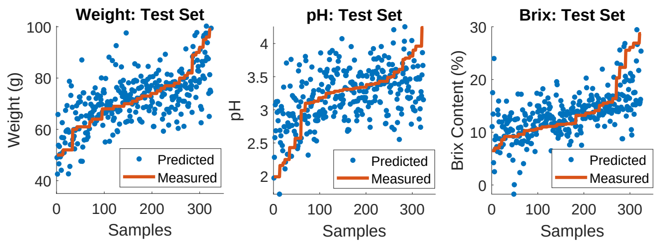

Fig. 9. Fruit quality predictions on the orange test data.

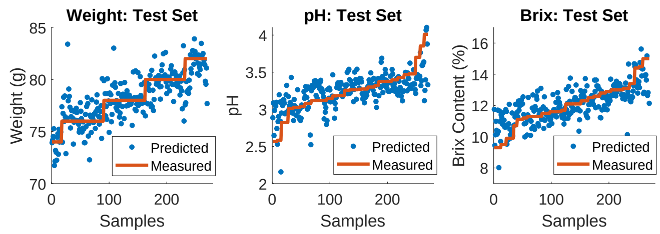

Fig. 10. Fruit quality predictions on the kiwi test data.

of orange. Similarly, for kiwi, the test predictions are shown in Fig. 10.

TABLE II
PERFORMANCE OF THE LEARNED MODEL ON THE TEST SET FOR ORANGES AND KIWIS.

	Oranges	**Kiwis**
Ripeness Property	*Average Error*	*Average Error*
Weight (g)	6.62 ± 5.95	1.12 ± 1.10
Acidity (pH)	0.37 ± 0.30	0.16 ± 0.14
Sugar Content (Brix %)	3.24 ± 3.28	0.72 ± 0.62

IV. DISCUSSION AND CONCLUSION

In this letter, we propose a proof-of-concept EIT-enabled microspined soft Fin Ray gripper for fruit quality testing. We integrated machine learning techniques with an EIT-based sensing method to gather features for learning the relation between a fruit's bio-impedance, and its ripeness characteristics. This is an advantage over external stiffness-based sensing approaches which are incapable of directly predicting ripeness characteristics [14], [15], [16]. Our EIT-based gripper was able to predict the day-ripeness of bananas with 85.6% accuracy. For oranges, we were able to achieve weight, acidity, and sugar content predictions with errors of 6.62 ± 5.95g, 0.37 ± 0.30pH, and 3.24 ± 3.28% respectively. Likewise for kiwis, it achieved errors of 1.12 ± 1.10g, 0.16 ± 0.14pH, and 0.72 ± 0.62% for mass, acidity and sugar content respectively. It has also been proven to increase the maximum holding weight of Fin Ray based grippers by at least 74%.

The EIT-enabled robotic gripper therefore has many potential uses in agri-fruit robotics. The gripper is far less destructive than industrial quality assessment techniques [6], [35]. This robotic gripper can therefore be used as a much faster method of routine inspections in processes such as quality control or artificial ripening. In the latter, the fruits are stimulated by chemical treatments to allow for production and marketing out of season, as well as for transport [36]. Control of these processes are therefore of vital importance in achieving optimum ripeness. As the sensors are integrated to the robot gripper, it also bypasses the need for manually attaching the sensors to the fruits as was done in all previous research that integrated Electrical Impedance Tomography or Spectroscopy based ripeness identification [27], [37], [29], [38].

Future work include usage of the EIT-enabled robotic gripper for the determination of the ripeness of fruits before harvesting. Thus, it has the potential to reduce food-waste by assessing the properties in situ such that fruits and vegetables are only harvested once they are sufficiently ripe and meet market standards.

Previous works using EIS and EIT based sensing have looked at adulteration, ageing or damage to fruits [38], milk [39], and meat [40]. In the same vein, future subjects of research will look at identification of fruits with internal rot, mould, and damage. Other potential uses of the EIT-based gripper outside the agri-fruit domain will also be explored. Such as quality assessments of meat, or in applications such as culinary robotics. The EIT technology uses low power AC frequencies [41], hence they are much safer than CT scans which use ionizing X-Rays [42] as well as being energy efficient and inexpensive.

The EIT-enabled spine gripper is far from being industry ready. There is much scope for improvement. The microspines does meet the UK market standards for class 1 fruits, where the minimum requirement are that the fruits must be free of extensive healed over cuts without rot, damage from pests or foreign matter [3]. Further research is required to minimise damage to fruits. One way of achieving this would be through the incorporation of smaller microspines, in both length and diameter, such that they would have a smaller contact area per spine, whilst ensuring the electrical contact is sturdy. The prediction errors of the method is also higher than industrial equipment, especially for the orange predictions. Thus, to achieve commercial viability, the accuracy must meet the tolerances of industrial weighing scales, refractomers and pH sensors with accuracy of around ± 2g [3], ± 0.2% [4], and ± 0.2pH [5]. Our initial results do however indicate that, at least for kiwis, the precision of the device is close to industrial standards. Possible ways to further improve accuracy would be by adding more electrodes to the gripper to obtain richer impedance data and by collecting more data from non-simulated fruits of varying ripeness. In conclusion, we have shown a high performing and non-destructive EIT-based soft gripper proof-of-concept that is capable of identifying fruit ripeness during grasping. With improvements, this has large potentials for industrial use, as well as high research prospects in other domains such

[3] https://www.oneweigh.co.uk/brecknell-405-bench-scale-181-p.asp
[4] https://www.atago.net/en/products-pal-top.php
[5] https://www.awe-ltd.co.uk/products/ph/ph-meter/ph-tester-phtestr10.html

as the robotic automation of the meat industry and robotic kitchen applications.

ACKNOWLEDGMENT

This work was supported by the SHERO project, a Future and Emerging Technologies (FET) programme of the European Commission (grant agreement ID 828818), Agri-FoRwArdS Centre for Doctoral Training programme under the UKRI grant [EP/S023917/1], and the Jersey Farmers Union.

REFERENCES

[1] T. Duckett, S. Pearson, S. Blackmore, B. Grieve, W.-H. Chen, G. Cielniak, J. Cleaversmith, J. Dai, S. Davis, C. Fox, *et al.*, "Agricultural robotics: the future of robotic agriculture," *arXiv preprint arXiv:1806.06762*, 2018.

[2] D. for Environment Food and R. Affairs, *Horticulture Statistics 2020*, 2021.

[3] [Online]. Available: https://www.gov.uk/guidance/comply-with-marketing-standards-for-fresh-fruit-and-vegetables

[4] G. F. S. Programme, *Food waste within global food systems*, 2013.

[5] AMT Fruit, *Food waste inventory*, 2018.

[6] M. A. Hossain, M. M. Rana, Y. Kimura, and H. A. Roslan, "Changes in biochemical characteristics and activities of ripening associated enzymes in mango fruit during the storage at different temperatures," *BioMed Research International*, vol. 2014, p. 232969, Jul 2014.

[7] S. Birrell, J. Hughes, J. Y. Cai, and F. Iida, "A field-tested robotic harvesting system for iceberg lettuce," *Journal of Field Robotics*, vol. 37, no. 2, pp. 225–245, 2020.

[8] J. Lowenberg-DeBoer, I. Y. Huang, V. Grigoriadis, and S. Blackmore, "Economics of robots and automation in field crop production," *Precision Agriculture*, vol. 21, no. 2, pp. 278–299, 2020.

[9] J. Shintake, V. Cacucciolo, D. Floreano, and H. Shea, "Soft robotic grippers," *Advanced materials*, vol. 30, no. 29, p. 1707035, 2018.

[10] R. B. Bannasch and L. Kniese, "Manipulator tool and holding and/or expanding tool with at least one manipulator tool," 2010.

[11] T. K. Bera and N. Jampana, "Electrical impedance tomography (eit): A harmless medical imaging modality," pp. 235–273, 01 2013.

[12] E. Vrochidou, C. Bazinas, M. Manios, G. A. Papakostas, T. P. Pachidis, and V. G. Kaburlasos, "Machine vision for ripeness estimation in viticulture automation," *Horticulturae*, vol. 7, no. 9, 2021.

[13] S. Z. Hussain, B. Naseer, T. Qadri, T. Fatima, and T. A. Bhat, *Citrus Fruits—Morphology, Taxonomy, Composition and Health Benefits*. Cham: Springer International Publishing, 2021, pp. 229–244.

[14] L. Scimeca, P. Maiolino, D. Cardin-Catalan, A. P. d. Pobil, A. Morales, and F. Iida, "Non-destructive robotic assessment of mango ripeness via multi-point soft haptics," in *2019 International Conference on Robotics and Automation (ICRA)*, 2019, pp. 1821–1826.

[15] V. Cortés, C. Blanes, J. Blasco, C. Ortíz, N. Aleixos, M. Mellado, S. Cubero, and P. Talens, "Integration of simultaneous tactile sensing and visible and near-infrared reflectance spectroscopy in a robot gripper for mango quality assessment," *Biosystems Engineering*, vol. 162, pp. 112–123, 2017.

[16] C. Blanes, V. Cortés, C. Ortiz, M. Mellado, and P. Talens, "Non-destructive assessment of mango firmness and ripeness using a robotic gripper," *Food and Bioprocess Technology*, vol. 8, no. 9, pp. 1914–1924, Sep 2015.

[17] T. K. Bera, "Bioelectrical impedance methods for noninvasive health monitoring: A review," *Journal of medical engineering*, vol. 2014, pp. 381 251–381 251, 2014, 27006932[pmid].

[18] P. Ibba, C. Tronstad, R. Moscetti, T. Mimmo, G. Cantarella, L. Petti, Ø. G. Martinsen, S. Cesco, and P. Lugli, "Supervised binary classification methods for strawberry ripeness discrimination from bioimpedance data," *Scientific reports*, vol. 11, no. 1, pp. 1–13, 2021.

[19] "Experimental comparison of integer/fractional-order electrical models of plant," *AEU - International Journal of Electronics and Communications*, vol. 80, pp. 1–9, 2017.

[20] M. I. N. ZHANG and J. H. M. WILLISON, "Electrical Impedance Analysis in Plant Tissues11," *Journal of Experimental Botany*, vol. 42, no. 11, pp. 1465–1475, 11 1991.

[21] M. I. N. ZHANG, D. G. STOUT, and J. H. M. WILLISON, "Plant Tissue 2," *Journal of Experimental Botany*, vol. 43, no. 2, pp. 263–266, 02 1992.

[22] Y. Ando, K. Mizutani, and N. Wakatsuki, "Electrical impedance analysis of potato tissues during drying," *Journal of Food Engineering*, vol. 121, pp. 24–31, 2014.

[23] R. Pethig and D. Kell, "The passive electrical properties of biological systems: Their significance in physiology, biophysics and biotechnology," *Physics in medicine and biology*, vol. 32, pp. 933–70, 09 1987.

[24] J.-M. Lelièvre, A. Latchè, B. Jones, M. Bouzayen, and J.-C. Pech, "Ethylene and fruit ripening," *Physiologia Plantarum*, vol. 101, no. 4, pp. 727–739, 1997.

[25] S. P. Burg and E. A. Burg, "Ethylene action and the ripening of fruits," *Science*, vol. 148, no. 3674, pp. 1190–1196, 1965.

[26] W. Batista-Silva, V. L. Nascimento, D. B. Medeiros, A. Nunes-Nesi, D. M. Ribeiro, A. Zsögön, and W. L. Araújo, "Modifications in organic acid profiles during fruit development and ripening: Correlation or causation?" *Frontiers in Plant Science*, vol. 9, 2018.

[27] A. Chowdhury, T. Kanti Bera, D. Ghoshal, and B. Chakraborty, "Electrical impedance variations in banana ripening: An analytical study with electrical impedance spectroscopy," *Journal of Food Process Engineering*, vol. 40, no. 2, p. e12387, 2017.

[28] P. Pushparaj and K. Athmaselvi, "Influence of sucrose concentration on electric conductivity of banana pulp during ohmic heating," *Food Science and Technology International*, vol. 24, p. 108201321878706, 07 2018.

[29] X. Li, G. Xu, L. Huang, Z. Zhang, and T. Yue, "Effect of plant growth regulator on electrical impedance spectroscopy during ripening process in kiwifruits," *Transactions of the Chinese Society of Agricultural Engineering*, vol. 31, pp. 288–293, 2015.

[30] P. Atkins and J. Paula, *Atkins' physical chemistry*. Oxford University press, 2008.

[31] K. Sugiyama, S. Fujita, H. Narita, S. Mae, T. Hondoh, K. Goto-Azuma, D. Fisher, and R. Koerner, "Measurement of electrical conductance in ice cores by ac-ecm method," 01 2000.

[32] J. Juansah, I. W. Budiastra, K. Dahlan, and K. Seminar, "Electrical behavior of garut citrus fruits during ripening: Changes in resistance and capacitance models of internal fruits," *International Journal for the History of Engineering Technology*, vol. 12, pp. 01–08, 08 2012.

[33] F. Harker and J. Dunlop, "Electrical impedance studies of nectarines during coolstorage and fruit ripening," *Postharvest Biology and Technology*, vol. 4, no. 1, pp. 125–134, 1994.

[34] M. Islam, K. Wahid, and A. Dinh, "Assessment of ripening degree of avocado by electrical impedance spectroscopy and support vector machine," *Journal of Food Quality*, vol. 2018, 2018.

[35] K. Miloski, K. Wallace, A. Fenger, E. Schneider, and K. Bendinskas, "Comparison of biochemical and chemical digestion and detection methods for carbohydrates," *Am. J. Undergrad. Res.*, vol. 7, 09 2008.

[36] M. Mursalat, A. H. Rony, A. Rahman, M. Islam, and M. S. Khan, "A critical analysis of artificial fruit ripening: Scientific, legislative and socio-economic aspects," vol. 04, pp. 6–12, 06 2013.

[37] P. Ibba, A. Falco, A. Rivadeneyra, and P. Lugli, "Low-cost bio-impedance analysis system for the evaluation of fruit ripeness," in *2018 IEEE SENSORS*, 2018, pp. 1–4.

[38] F. Zamora-Arellano, O. R. López-Bonilla, E. E. García-Guerrero, J. E. Olguín-Tiznado, E. Inzunza-González, D. López-Mancilla, and E. Tlelo-Cuautle, "Development of a portable, reliable and low-cost electrical impedance tomography system using an embedded system," *Electronics*, vol. 10, no. 1, 2021.

[39] S. Tripathy, A. R. Ghole, K. Deep, S. R. K. Vanjari, and S. G. Singh, "A comprehensive approach for milk adulteration detection using inherent bio-physical properties as 'universal markers': Towards a miniaturized adulteration detection platform," *Food Chemistry*, vol. 217, pp. 756–765, 2017.

[40] Y. He, X. Bai, Q. Xiao, F. Liu, L. Zhou, and C. Zhang, "Detection of adulteration in food based on nondestructive analysis techniques: a review," *Critical Reviews in Food Science and Nutrition*, vol. 61, no. 14, pp. 2351–2371, 2021, pMID: 32543218.

[41] 2022. [Online]. Available: https://www.crowdsupply.com/mindseye-biomedical/spectra

[42] E. C. Lin, "Radiation risk from medical imaging," *Mayo Clinic proceedings*, vol. 85, no. 12, pp. 1142–1146, Dec 2010, 21123642[pmid].