Physical Reservoir Computing for Interactive Estimation of Weight from Food Texture in 3D-Printed Soft Matter in Picking Operations

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***Abstract*—This paper aims to improve the "Gel Biter," a device that can simultaneously acquire chewing texture data from three different parts (the upper jaw, tongue, and lower jaw) composed of oral mimic end effectors with different softness (Young's modulus), created using 3D printer technology, for use as a picking device. The Gel Biter utilizes physical reservoir computing, exploiting the deformation of the soft material in the oral model during chewing, to classify the texture of food materials with high accuracy. To apply this principle as a picking system, we examine whether it is possible to determine whether fried foods and fish roe have been cooked correctly and the extent of the weight being gripped based on texture. The results of the gripping object estimation experiments demonstrated that it is possible to distinguish between overcooked fried chicken and properly cooked fried chicken with 94.7% accuracy, and to identify the weight difference of artificial salmon roe in 5g, 10g, and 20g increments with 94.5% accuracy. These results suggest that the Gel Biter's piezoelectric sensors through a physical reservoir computing system can determine information on weight and cooking status based on texture information.**

***Index Terms*—physical reservoir computing, piezoelectric sensor, food texture detection, picking systems**

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I. Introduction

The challenge in the food picking process on production lines in factories lies in the development of gripping technologies that are both fast and non-damaging to the food items [1], [2]. Soft robotics has emerged as a promising technology to address this challenge [3], [4]. In particular, the automation of food handling using soft robotics includes high-speed picking solutions that combine 3D vision, artificial intelligence (AI), and soft gripping techniques [5]. These technologies aim to improve efficiency in food processing and reduce reliance on human labor.

Specifically, Soft Robotics Inc. has developed a solution called mGripAI [6], which integrates AI-driven 3D vision with soft gripping technology to enable high-speed picking, sorting, and packaging operations. This technology allows industrial robots to mimic human senses, cognition, and dexterity, thereby automating food and warehouse tasks. mGripAI operates at speeds allowing robots to handle up to 90 items per minute, reduces product damage, and can manage bulk products. Additionally, its food-grade design facilitates easy cleaning and hygienic operation.

In soft robotics, the development of pneumatically driven soft grippers and gripping mechanisms that do not damage food is being vigorously pursued, to the extent of holding competitions [7]. This has enabled the stable handling of items like breaded oysters (kaki fry) and raw fish without

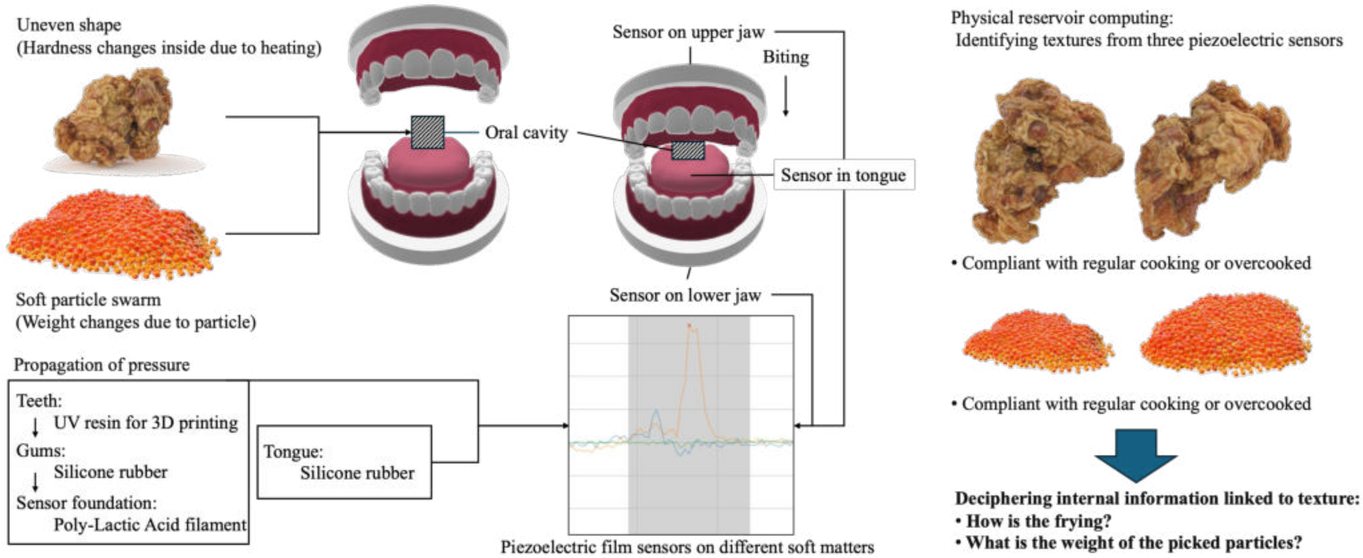


Fig. 1. Conceptual diagram illustrating the establishment of a picking function to identify indirect information contained in the texture information of each food product based on texture identification of fried foods and particulate foods

causing damage [8], [9]. One approach gaining traction involves constructing end effectors from soft matter, which has also drawn attention to the use of soft matter in information processing [10], [11]. A method called physical reservoir computing, which applies wave images generated by chemical reactions on a liquid surface, among other inputs, to machine learning methods like neural networks to solve predictive tasks, exemplifies this interest [12], [13]. The critical aspect of physical reservoir computing is its reliance on the complex computations of physical systems undergoing temporal changes, requiring only the adjustment of outputs to match the desired tasks [14]. Nakajima et al. have successfully applied this by attaching multiple bending sensors to a silicone arm modeled after an octopus's tentacle, using the inputs from these sensors in a neural network to solve nonlinear regression problems [15], [16]. Their work suggests that the sensing results of soft robots are already capable of intelligent processing. Hirose et al. developed an oral model with piezoelectric film sensors on the robot's end effector, simulating teeth with hard materials and gums and tongue with different soft materials, to function as a physical reservoir system for texture analysis [17]–[20]. They demonstrated that the piezoelectric signals obtained from different hardness levels could accurately distinguish the textures of five different food items. These technological innovations open new possibilities in automated food picking, improving productivity, operational efficiency, and reducing dependence on human labor. Moreover, they offer significant benefits in terms of quality control by minimizing food damage.

This study aims to apply soft robotics technologies to refine the "Gel Biter" texture analysis device as an end effector for picking and to develop a system that uses physical reservoir computing to accurately measure the hardness and weight of food items. This approach seeks to address challenges in the food service industry, such as rapid and accurate plating of ingredients and the avoidance of foreign object contamination and cooking errors. In particular, by exclusively using high-resolution and responsive piezoelectric sensors, we aim to execute more precise gripping actions and perform texture estimation through physical reservoir computing, thereby offering a new dimension of picking functionality to users. In this study, we focus on the handling and assessment of two distinct types of food items: fragile particle aggregates exemplified by fish roe, and foods with variable external textures such as fried foods. The aim is to deduce the tactile sensation of weight from the texture when grasping aggregates, providing insights into the material properties through tactile feedback. Additionally, we examine the capability of the system to evaluate the doneness of fried foods, which involves determining the extent of heat application and resultant softness. This involves a nuanced approach to texture and firmness analysis, critical for assessing the readiness and quality of such food items.The overview of the GelBiter system's enhanced picking functionality aimed in this paper is shown in Fig. 1.

II. METHOD

This section details the Gel Biter's design and operational framework. Illustrated in Fig. 1, this paper presents the strategy for leveraging the Gel Biter as an advanced tool for food selection tasks. Fig. 2 shows the appearance of the Gel Biter. The oral model developed by Hirose et al [17]. conformed to the shape of a human oral model, but its dimensions were 1.5 times that of a human's. In this device, the dimensions have been readjusted to 1.0 times (the same as a human's). The objective centers on utilizing the Gel Biter's capacity for texture recognition to accurately determine the doneness of

Fig. 2. The appearance of the Gel Biter developed in this study: a model designed to match the dimensions of the human oral structure, with piezoelectric film sensors placed on the upper surface center of the upper jaw, the center of the interior of the tongue, and the lower surface center of the lower jaw

fried chicken by assessing meat firmness and to measure the handling weight of Ikura (salmon roe), thereby ensuring their suitability for picking operations.

A. Overview of the Gel Biter

The Gel Biter, an innovative soft-matter artificial oral device, demonstrates exceptional ability in detecting subtle differences in texture. Achieved through the assembly of polymer-based oral structures, each with unique physical properties, these components are attached to a robotic arm as end effectors. This oral model mimics a complex array of tactile sensors, incorporating a standardized piezoelectric film sensor within each element. Such an arrangement allows for the acquisition of tactile feedback from identical items, yielding significantly varied signal waveforms. Utilizing a suite of machine learning algorithms on the data collected from each soft matter element, the system significantly enhances food classification and improves accuracy in object recognition. The materials for the oral cavity model were carefully selected to closely replicate the human oral environment. The teeth were crafted from a state-of-the-art, durable UV-curable resin (Formlabs), and the tongue and gums were made from Ecoflex00-10™ (Smooth-On), renowned for its lifelike softness.

B. Physical Reservoir Computing

Physical reservoir computing constitutes a computational paradigm that exploits the complex temporal dynamics inherent in natural or physical systems. Situated within the expansive field of machine learning, specifically as a subtype of Recurrent Neural Networks (RNNs), it is characterized by the practical application of these dynamics within real-world systems. In this context, an oral model serves as the reservoir, utilizing the system's inherent dynamics, such as oscillatory behavior, as computational elements. This methodology significantly augments learning efficiency by enabling the straightforward interpretation of the reservoir's state and its oscillatory features. [21].

As shown in the lower left part of Fig. 1, the physical reservoir layer in the Gel Biter can be divided into two categories. The first category involves piezoelectric changes read by piezoelectric sensors installed in the jaw, where UV resin initially feels the pressure, which is then transferred to a softer material, silicone rubber Ecoflex00-10. The silicone rubber amplifies the pressure transmitted through the hard material. Finally, the pressure is passed from the silicone rubber to the base made of polylactic acid filament, where the sensors are mounted. This base is designed with a thickness of 1.0mm; while it is hard enough to dampen the amplified pressure changes in the silicone rubber, it can adequately transmit the pressure changes originating from the UV resin to the sensors. Since the shapes of the upper and lower jaws differ, the material transmission is the same, but the resulting signals are different time series data. Capturing this different time series data through the physical reservoir layer expands the feature set, making this aspect an important part of the design. Meanwhile, the tongue directly incorporates piezoelectric film sensors within the silicone rubber, capturing data directly from the significant deformation of the soft material. Thus, with each act of mastication, the Gel Biter is able to acquire sensor data through three distinct physical reservoir layers.

C. Data Acquisition Process

The methodology for data collection is outlined in Fig. 3. The process begins with the model mouth performing mastication, during which vibrations arise from the interaction among the teeth, tongue, and other contact surfaces, spreading through the oral cavity. These vibrations are captured by a piezoelectric film sensor, converting them into electrical signals represented as voltage waveforms. The waveform data are then forwarded to an Arduino board and subsequently transmitted to a Python script via serial communication for analysis on a computer. To ensure the integrity of the data, a low-pass filter, incorporating linear filtering and fast Fourier transform methods, is applied to remove noise, a critical step for enhancing the accuracy of further analysis. The extraction of data focuses on pinpointing and isolating prominent waveform characteristics, especially peaks, to frame the analysis and simplify data interpretation. For feature generation from these isolated peaks, the tsflesh library is utilized, enabling the automated generation of multidimensional features from time-series data. This final stage of data processing prepares the dataset for machine learning applications, marking an essential strategy for the efficient analysis of large datasets and the extraction of relevant information.

D. Machine Learning Framework within the Gel Biter System

Within the Gel Biter system, the integrated machine learning model utilizes training datasets to identify complex relationships between input features and their associated labels. This model further evaluates its predictive performance on test datasets, extracting insights from the established correlations between features and labels. Such methodology enhances the precision of predictions for new datasets by capitalizing on

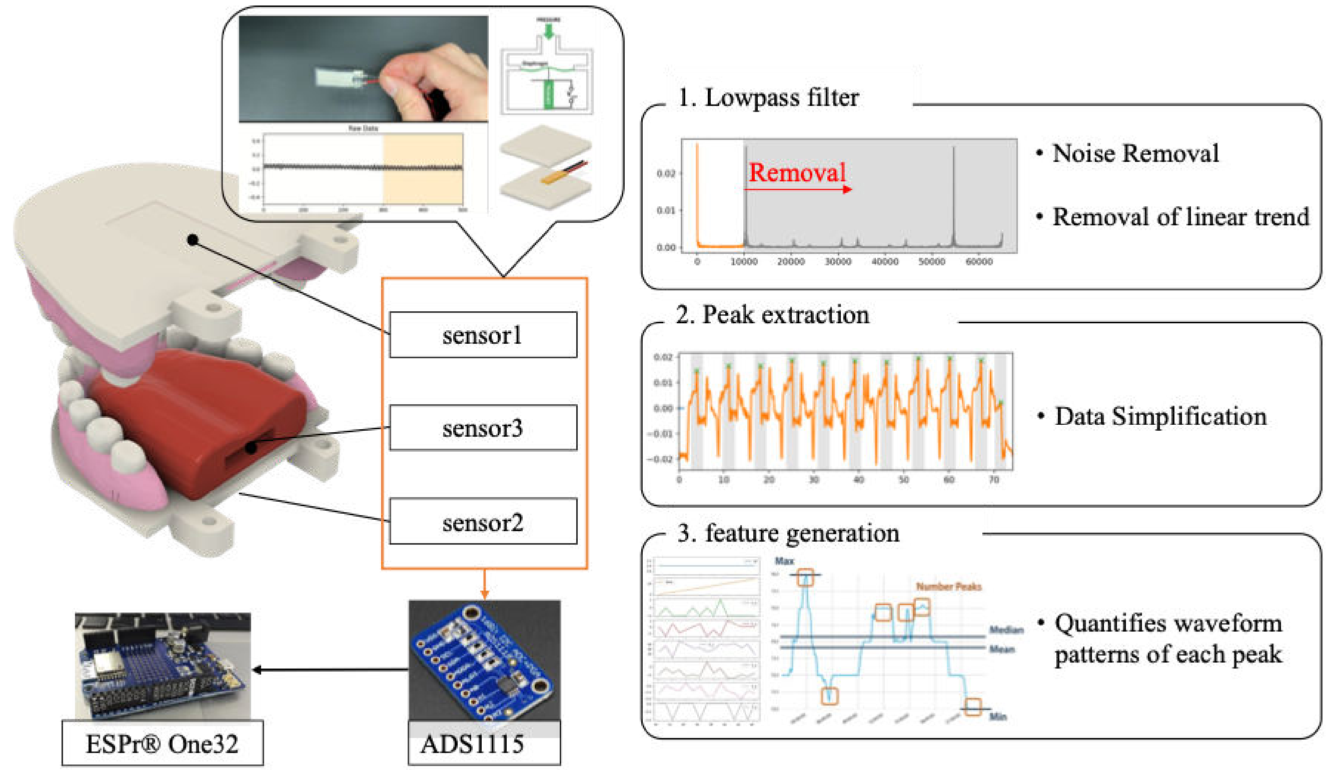
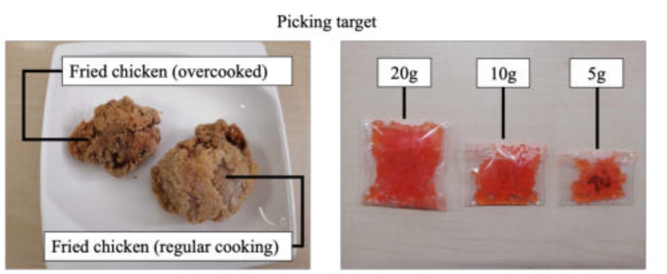


Fig. 3. Flow of processing piezoelectric data acquired from chewing motion for machine learning



(a) Uneven shape food (fried chicken)　(b) Soft particle swarm (artificial salmon roe)

Fig. 4. Picking targets include: (a) distinguishing between regularly cooked and overcooked fried chickens, and (b) identifying different weights of artificial salmon roe

the delineated relationships between features and labels. For classification tasks, logistic regression is employed as the foundational algorithm, enabling accurate prediction of label categories based on input features, informed by insights gained through the training process.

Fig. 3 delineates the machine learning workflow in the Gel Biter system, from data collection to model training and subsequent predictive analysis.

III. Experiment

A. Enhancing the Gel Biter's Picking Capabilities: An Experiment with Artificial Salmon Roe and Fried Chicken

This section describes an experiment designed to evaluate the Gel Biter end effector's proficiency in handling both artificial salmon roe and fried chicken, highlighting its adaptability and precision in picking tasks. Picking and texture identification targets are illustrated in Fig. 4. Fig. 4(a) showcases food with an uneven shape, selecting fried chicken, which undergoes physical property changes during the cooking process, as the target. For the fried chicken, two pieces that were pre-fried at the same time are defined as ”regular cooking - CHICKEN1” when cooked for the specified regular heating time(1 minute and 10 seconds in a 500W microwave) as instructed by the provider, and ”overcooked - CHICKEN2” when further heated in the same microwave for an additional 2 minutes. Fig. 4(b) describes the creation of artificial salmon roe by adding a red dye (a suitable amount of food coloring) to a solution of sodium alginate (dissolving 5g of sodium alginate in 500ml of water) and then dropping droplets into a calcium chloride solution (20g of calcium chloride dissolved in 100ml of water). The learning targets for this artificial salmon roe are packaged in different weights of 5g, 10g, and 20g.

The experiment demonstrates the Gel Biter's successful grasp of artificial salmon roe, capturing between 19g and 21g in a single attempt, as illustrated in Fig. 5. This test illustrates the device's salmon roe to adjust to the volume of the Salmon roe, deepening its engagement with the material and marking a maximum capacity threshold at 21g. The analysis extends to assessing the Gel Biter's ability to securely pick up fried chicken, detailed in Fig. 5, using samples measuring 60mm $\times$ 40mm $\times$ 30mm. The device leverages its teeth for an effective grip on the fried chicken, with stability tests affirming that

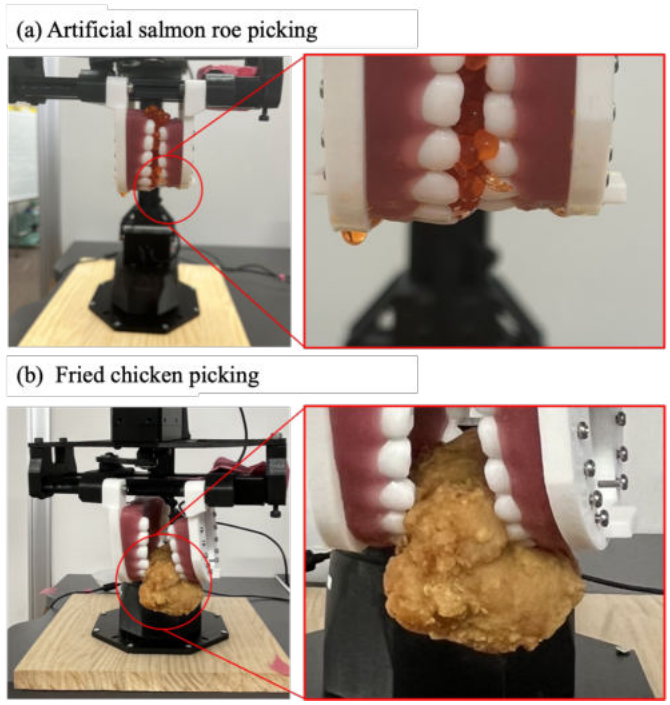


Fig. 5. Illustration of the Gel Biter in action, demonstrating its picking capabilities with artificial salmon roe and fried chicken

arm movements do not compromise the grip, thus ensuring the chicken remains securely held throughout the process. Notably, a post-release examination indicates that the Gel Biter's operation does not damage the chicken's coating, underscoring the device's gentle handling and the experiment's overall success.

Fig. 6 shows the time series changes of piezoelectric sensors at the moment of picking various foods. In the case of fried chicken, the material is compressed, and it is observed that the amplitude of the sensor on the lower jaw in particular is amplified compared to other sensors. On the other hand, in the case of salmon roe, it seems that the movement of the particle groups within the cavity has more of an effect than the compression caused by chewing, resulting in the sensor data read by the tongue being the most amplified.

B. Mechanical Characterization of Food Textures through Fracture Experiments

This section is dedicated to the exploration of mechanical characteristics of food textures, specifically focusing on the fracture strength of fried chicken and artificial salmon roe, employing the Gel Biter's end effector. The experiments aim to establish a correlation between mastication speeds and the mechanical properties indicative of food texture, such as hardness, through detailed fracture analysis.

A creep meter, specifically the "CREEP METER RE2-33005C" by YAMADEN, was utilized to evaluate the deformation, fracture occurrences, and stress values of foods under constant compression speeds, as illustrated in Fig. 7. The analysis measured the physical properties of conventional fried chicken, directly correlating with the objectives of the picking challenge. Employing a wedge-shaped plunger with specific dimensions and compression rates, the experiments produced load-strain curves depicted in Fig. 8.

Fig. 8 juxtaposes the graphs for "CHICKEN1," indicative of ideally cooked fried chicken, against "CHICKEN2," representing overcooked and therefore harder fried chicken. The differences between these samples are highlighted, with "CHICKEN1" showing a distinct yield point, beyond which hardness diminishes, and "CHICKEN2" exhibiting uniform excessive hardness without a yield point. These distinctions are critical for the machine learning model within the Gel Biter system, which relies on objective data from the creep meter to discern between variations in hardness, thereby rejecting overly hard fried chicken.

Moreover, the experiment underlines the Gel Biter's potential in serving consistent amounts of food by substituting a piezoelectric sensor for a traditional weight sensor. This involves collecting training data from various quantities grasped by the robot, with subsequent machine learning analysis to predict the mass of items picked in real-time based on sensor feedback, aiming for precise portion control.

C. Applying Machine Learning to Distinguish Between Fried Chicken Textures and to Estimate Salmon Roe Weights

Leveraging the Gel Biter's machine learning capabilities enables distinguishing between normally cooked and overcooked fried chicken, employing data from simulated mastication cycles. To minimize noise, a low-pass filter with a cutoff frequency of 9,000Hz was utilized during data collection, which involved conducting ten sets of ten chewing cycles for both standard and overcooked chicken variants. The Gel Biter's mechanistic chewing simulation during the picking phase is depicted in Fig. 5(b).

Fig. 9 showcases the outcomes of applying machine learning to distinguish chewed samples, with "CHICKEN1" representing normally cooked and "CHICKEN2" indicating overcooked variants. A confusion matrix visualizes classification accuracy, where the X-axis denotes predicted, and the Y-axis actual labels, illustrating the method's effectiveness in categorizing fried chicken by its cooking degree through logistic regression.

Regarding the determination of salmon roe weights using machine learning, Fig. 10 delineates the model's precision in interpreting collected data.

The Gel Biter was trained to recognize various salmon roe quantities, targeting weights of 5g, 10g, and 20g, through simulations involving five sets of ten repetitions each. A cutoff frequency of 10,000Hz was applied to filter noise. The selection of 20g as the training weight cap is justified by the Gel Biter's maximum salmon roe picking capacity evaluation of 21g.

The machine learning results shown in Fig. 9 successfully classify "CHICKEN1" with 94.7% accuracy and "CHICKEN2" with 100% accuracy, affirming the system's efficacy in identifying overcooked chicken. Similarly, Fig. 10 demonstrates a 94.5% success rate in classifying the weight of

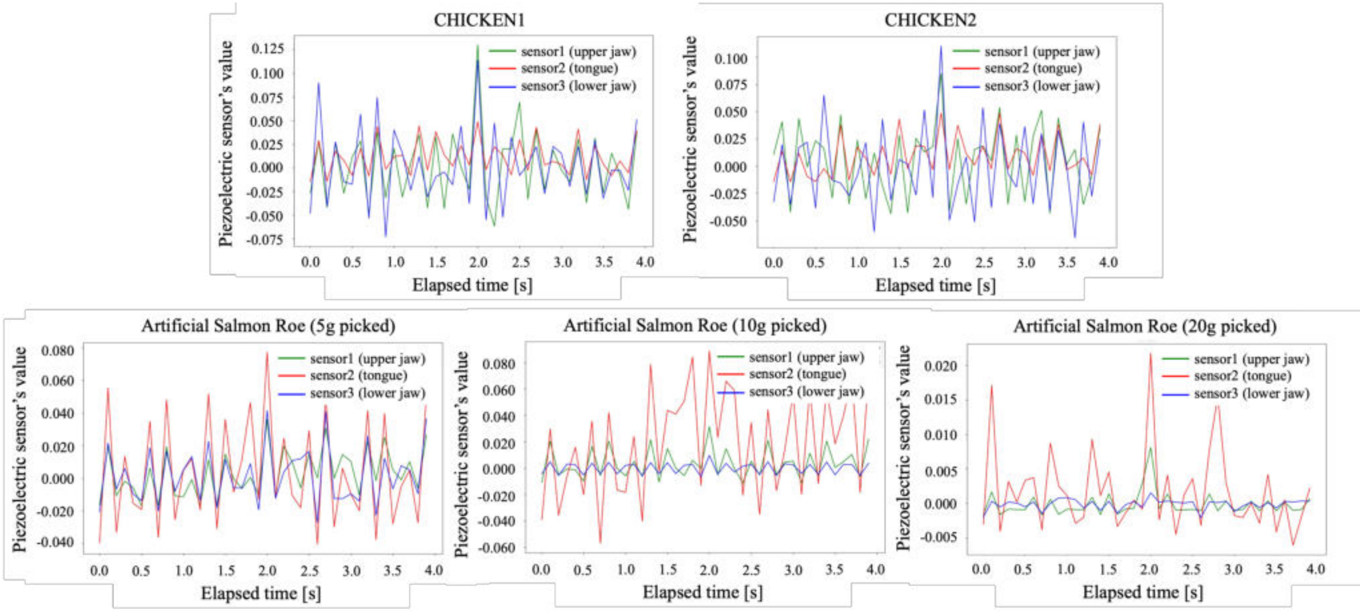


Fig. 6. Time series changes of three piezoelectric sensors when one picking various foods

Fig. 7. Representation of the creep meter used in the experiments

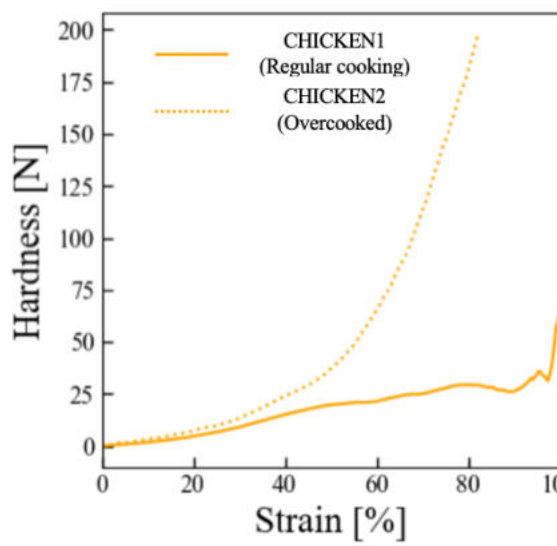


Fig. 8. Load-strain diagrams contrasting ideally cooked versus overcooked fried chicken

salmon roe, highlighting the advanced analytical capabilities of the Gel Biter.

IV. Discussion

The primary reason for fried chicken becoming tough due to overheating is attributed to the loss of moisture during the cooking process and the denaturation and contraction of proteins contained in the meat when exposed to high temperatures. The ability to identify this state implies that, when applied as a picking system, the system can discern whether the meat retains its juiciness and moist softness merely by grasping, thus ensuring the provision of high-quality products to consumers. The results demonstrate the capability to distinguish between ideally cooked fried chicken and otherwise with 94.7% accuracy, where the conducted action merely involves sandwiching the meat between the upper and lower jaws without biting hard enough to leave teeth marks, suggesting that the cooking state can be non-destructively read from the surface texture and slight elastic deformation alone. As an end effector, it is composed of durable materials that can withstand conditions except for

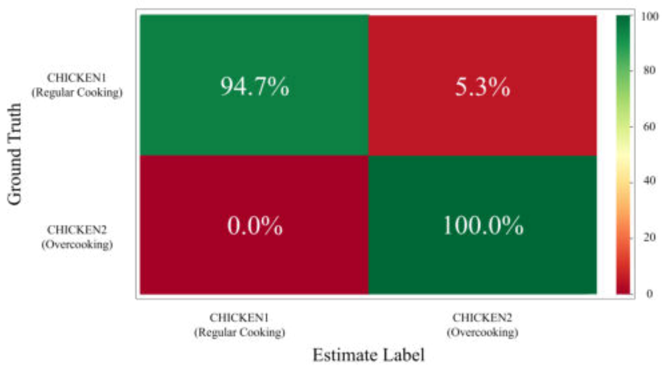


Fig. 9. Machine learning classification results for fried chicken with varying degrees of doneness

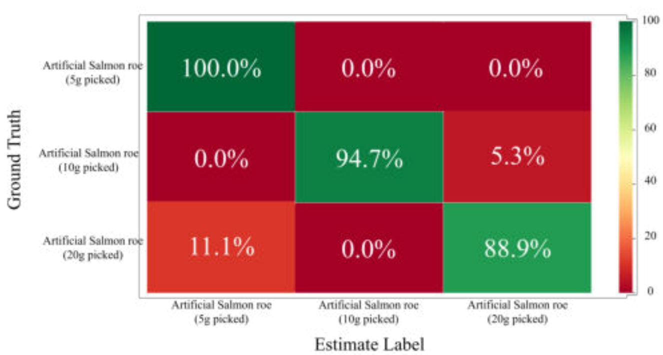


Fig. 10. Machine learning outcomes for salmon roe weight classification

extreme situations (such as directly removing from a tank of olive oil), making it applicable in picking environments like those found on factory conveyor belts.

Regarding artificial salmon roe, the system has identified the weight of a cluster of gripped salmon roe particles with 94.5% accuracy. This indicates that the Gel Biter captures the movement of the particle cluster within the oral cavity during mastication. The difference in weight corresponds to the difference in the number of particles; fewer particles mean less intense movement of the cluster, while more particles result in more vigorous movement with each chew, implying that the piezoelectric sensors through soft matter adequately contain the features necessary for reading these differences. As for particle damage, it is mostly negligible; however, there is a risk of causing particle loss if a particle perfectly fits and gets trapped by the molar teeth, which have a surface area sufficient for one or two particles. Nonetheless, the end effector is designed to be less prone to damage, as the gums are soft and any misalignment in the bite due to the gums' elastic deformation allows the movement to escape the cavity or exit the oral region, preventing particle damage.

Overall, it can be understood that the piezoelectric physical reservoir computing through soft matter as a function of the picking system is capable of setting information on factors determining texture as identifiable targets.

V. Conclusion

This study introduces an innovative application of the Gel Biter system in food production facilities, leveraging machine learning to analyze the vibrational signatures of food for identification purposes. The Gel Biter system demonstrates proficiency in differentiating between optimally cooked and overcooked fried chicken by assessing hardness and in accurately gauging the weight of salmon roe in the picking process.

Experimental results highlight Gel Biter's precision in recognizing fried chicken and salmon roe, with a notable 5.3% misclassification rate of standard fried chicken as overcooked. However, its ability to flawlessly identify and exclude 100% of overcooked chicken underscores its potential as a pioneering robot for the efficient removal of defective products.

Considering the critical role of food safety and the challenge of detecting defects invisible to the human eye, the technology presented in this paper is deemed vital for the elimination of such imperfections, thereby contributing to improved food quality and safety standards.

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