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Automatic food bio-hazard detection system

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ABSTRACT

This paper presents the design of a convolutional neural network architecture oriented to the detection of food waste, to generate a low, medium, or critical-level alarm. An architecture based on four convolution layers is used, for which a database of 100 samples is prepared. The database is used with the different hyperparameters that make up the final architecture, after the training process. By means of confusion matrix analysis, a 100% performance of the network is obtained, which delivers its output to a fuzzy system that, depending on the duration of the detection time, generates the different alarm levels associated with the risk.

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1. INTRODUCTION

Due to the recent isolation events in homes, originated by the coronavirus disease 2019 (COVID-19) pandemic, many side effects have emerged as support needs in residential environments, among these is the assistance in cleaning and/or disinfection tasks. Thus, several studies have been aimed to cover different fronts: developments of cleaning robots [1], [2], an Internet of things (IoT) application for a disinfection robot [3], which in the same way [4] exposes a robot for cleaning bathroom floors. The purpose of these robots can be varied, for example, grease removal in ventilation ducts [5], waste segregation [6], or recycling tasks [7], [8].

Machine vision systems are a fundamental part of robotic development [9], which can be employed in food sorting recognition [10]. A relevant aspect within the previously mentioned approachis the treatment of food waste [11], [12], where one of the techniques used are machine vision systems [13], among which convolutional neural networks [14], [15] stand out. Food waste in residential environments is a focus of future bacteria and diseases that must be treated [16], for which convolutional networks are currently used [17]–[19].

On the other hand, fuzzy inference systems are widely used in nonlinear and not very predictive models, even being recently used in research related to COVID-19 [20], bacterial analysis [21], and food adulteration [22], as well as their integration with neuro convolutional systems [23]. In turn, there are several applications of fuzzy models for alarm generation systems [24]–[26].

Given the relevance of the topic, the development of a neuro convolutional architecture for waste discrimination is presented below, to generate an alert, either for a robotic prototype that may have the ability to clean or an alarm system for notification of the risk that such waste presents. The alarm is generated by means of a fuzzy inference system that takes as inputs the waste detection and the detection duration time. The article is then divided into three sections, the first one corresponds to the methods and materials used, the second section corresponds to the analysis of results, and the third section to the conclusions obtained.

2. METHOD

The designed automatic system is oriented to the scheme shown in Figure 1. Initially, images of the environment are obtained, ideally from the top view of the table or the kitchen. The current image is input to a convolutional neural network [27], [28], which establishes whether there is food or food residue, this result is evaluated over time by a fuzzy inference system that determines an alarm level according to the duration of the residue. In the following, both the neuro convolutional architecture and the fuzzy inference system are explained.

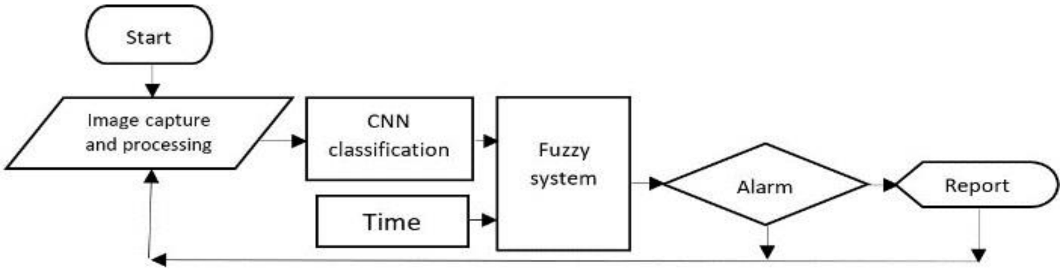


Figure 1. Classification scheme

It was established that the robot will generate inspection tours through the determined areas every 6 hours, which will be called an inspection cycle. Each time it detects the risk of paper waste, the count variable will be increased, which corresponds to an array of 4 elements, where each one associates with each of the inspection areas. To generate the biohazard alarm, a fuzzy inference algorithm is used based on the area where the waste is located employing ResNet-50 and the time spent in this area based on the number of cycles in which it was found. In the following, both parts of the algorithm, the training of the network and the fuzzy inference system, are presented.

2.1. Convolutional neuronal network

The first step consists of establishing the database with which the classification system is trained. In this case, two classes, food and residue, are used. A database of 100 images is used with a distribution of 70% for training and 30% for testing. Figure 2 shows some samples of each class used, Figure 2(a) waste and Figure 2(b) food.

(a) (b)

Figure 2. Training database (a) waste and (b) food

These images are acquired using a conventional webcam with an image resolution of 640×480 pixels, which are resized inside the algorithm to 180×180 pixels to reduce the computational cost of training. For this case, the network architecture illustrated in Table 1 is used. It consists of 4 convolution layers in the feature extraction stage and two fully connected with 50% dropout in the classification stage, and a fully connected final output. The kernel column presents the number of filters used and the size of each one.

Table 1. Network architecture used

LAYER	KERNEL	
Input	180×180×3	# F Filters
Convolution/ReLU	98	8
Convolution/ReLU	192	6
MaxPooling		3
Convolution/ReLU	192	3
MaxPooling	3	
Convolution/ReLU	320	3
MaxPooling	2	

Figure 3 illustrates the performance obtained in the training of the network. For the case it is observed that it reaches 100% classification accuracy after 1500 iterations, taking just over 29 minutes on a computer with an NVIDIA GPU 1050 with 8 GB of memory. The confusion matrix in Figure 4 illustrates the classification performance with the validation data, showing the correct identification of each of the two classes used. This indicates that there are no errors in the performance of the network, taking into account that the lighting conditions used should not vary considerably. In this case, average classification times of 0.4 seconds were obtained, which allows the use of the algorithm in machine vision applications, such as the one proposed, in real-time.

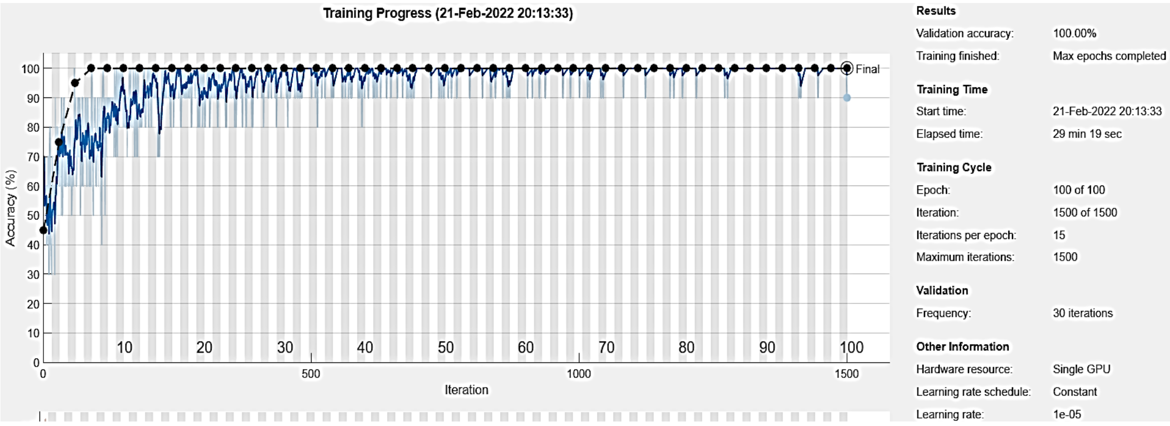


Figure 3. Final training performance

Figure 4. Confusion matrix

2.2. Fuzzy interference system

The alarm for possible biological risk due to food residues is established by means of a fuzzy inference system where once the food residue is recognized, the cycle in which it is found must be stored. Given the nonlinearity of the system, since it is not possible to predict precisely when a food residue will be found, fuzzy inference models are appropriate for this type of nonlinear and mathematically non-descriptive system. Two inputs are used, one associated with the time measured in cycles and the other associated with the detection of the residue, the output is determined by the percentage of the risk level that would imply leaving processed food for prolonged periods of time in the same space and the time it is kept in the residential environment. Figure 5 illustrates the fuzzy scheme implemented.

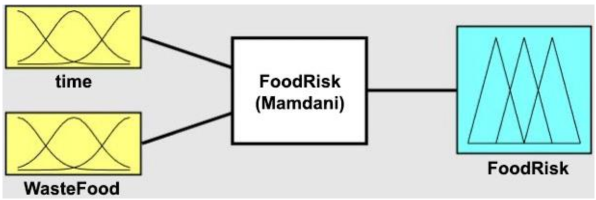


Figure 5. Fuzzy system implemented

The time input refers to finding the same or new residues in different spaces of time, these spaces are determined in 6-hour periods, which corresponds to an average time between meals for the three basic food cycles in human activity (breakfast, lunch, and dinner). For this purpose, a fuzzy input is established with three membership functions, each with linguistic labels of low, medium, and high to denote the temporal perception of the waste food in the site. For the time input, the universe of discourse is established in 10 cycles, where after the 6th cycle (36 hours) a high risk predominates.

This scheme is determined given that at a residential level, with a family nucleus (2 or more people), a daily cleaning cycle is predominant (approximately every 24 hours). Which implies waste collection at least once a day. For a standard case with three meals a day, waste generation would be close to every 18 hours on average (3 cycles), which delimits the transition from low to medium alarm, as shown in Figure 6(a). For the waste food entry, as shown in Figure 6(b), two membership functions are established, each with linguistic labels of food and waste, in relation to how much waste accumulates, where the longer the food becomes waste. The universe of discourse is set from 0% food to 100% waste.

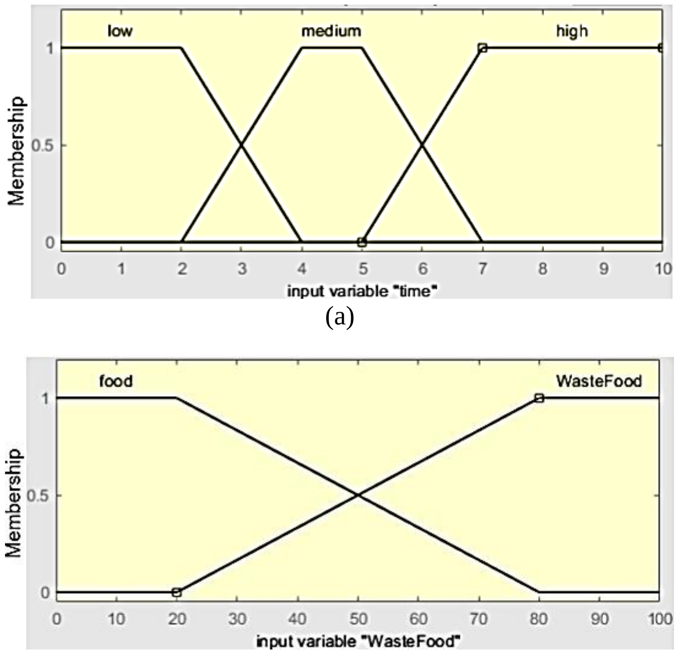


Figure 6. Time and waste food inputs of the fuzzy system: input variable (a) time and (b) waste food

The output of the fuzzy system corresponds to the level of biological risk determined in percentage, so it is framed in a universe of discourse from 0 to 100%, Given the nonlinearity inthe degradation of food [29], the medium level presents less coverage in the system, and the rule base plays a fundamental role in the output by relating this to the inputs, as seen on Figure 7.

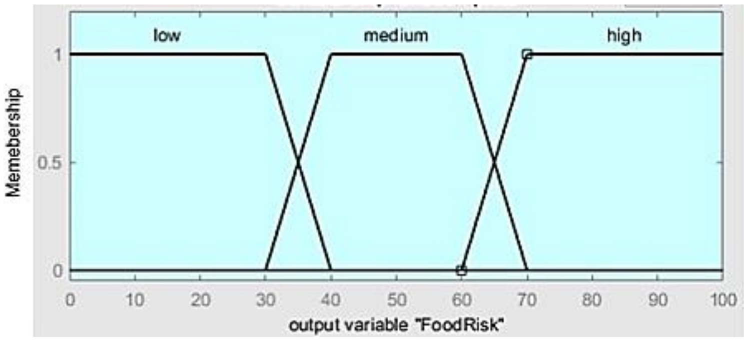
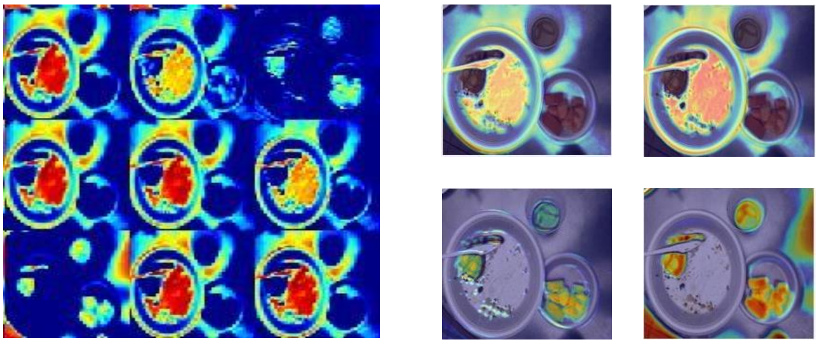


Figure 7. Fuzzy food risk output

3. RESULTS AND DISCUSSION

Figure 8(a) shows some of the activations of the filter bank resulting from the first convolution layer of the trained network. Where the learning of the filters is evident, as it clearly identifies the plate with food and what is associated with the background of the image. Figure 8(b) shows in detail the activations in the identification of food for both classes in a specific way. In Figure 8(b), the upper part is the full plate, and the lower part corresponds to food waste. The heat map shows the concentration of learning, which resulted in a high level of accuracy.

Figure 9 shows the level of confidence obtained by the classification category. This output is the one that enters the fuzzy system. Figure 10 illustrates the output of the fuzzy inference system with incremental time variations so that the three risk levels are generated, in Figure 10(a) low, Figure 10(b) medium, and Figure 10(c) high. Through simulations of the algorithm in the environment shown in Figure 11, using a video of the food area at 30 fps, the performance was evaluated, and the results shown in Table 2 were obtained.



(a) (b)

Figure 8. Activations of (a) learning process and (b) food and residue testing

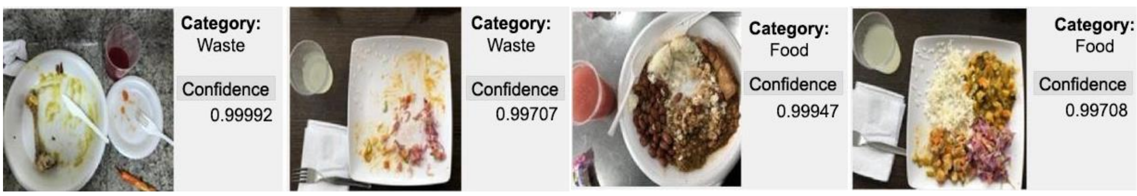
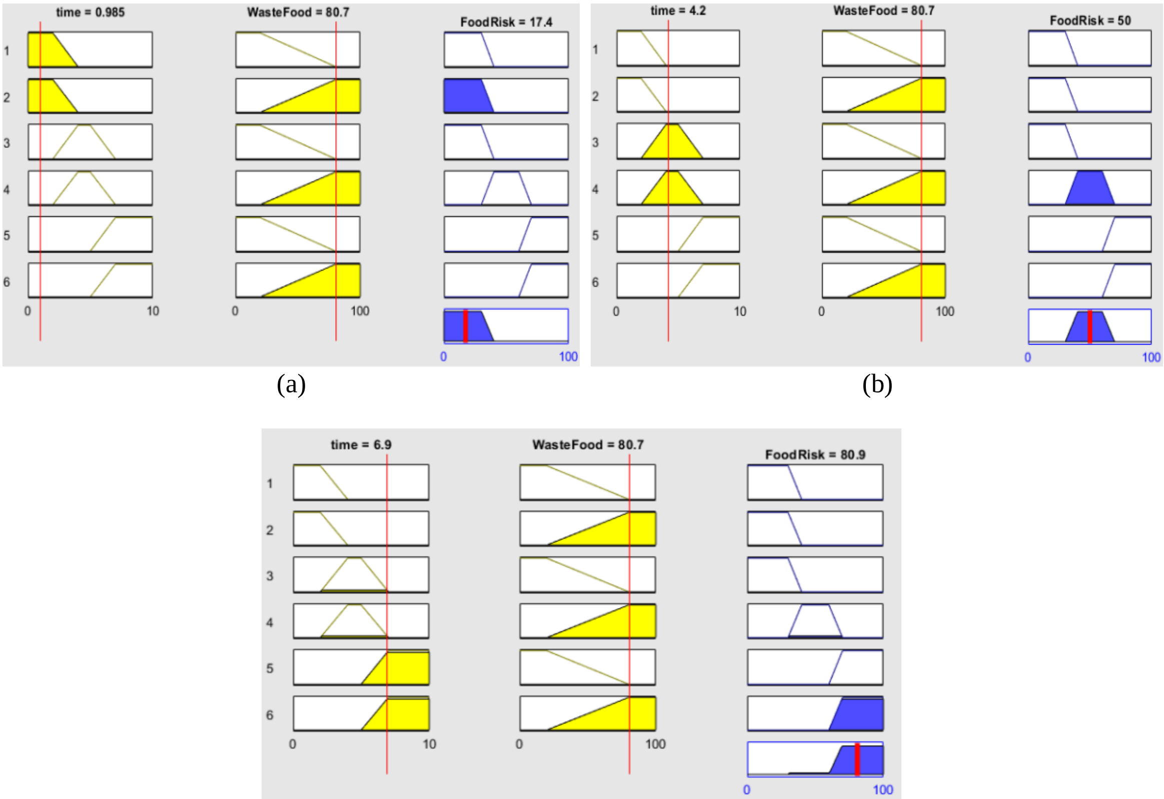


Figure 9. Levels of confidence



(a) (b) (c)

Figure 10. Alarm activations (a) low alarm (b) medium alarm, and (c) high alarm

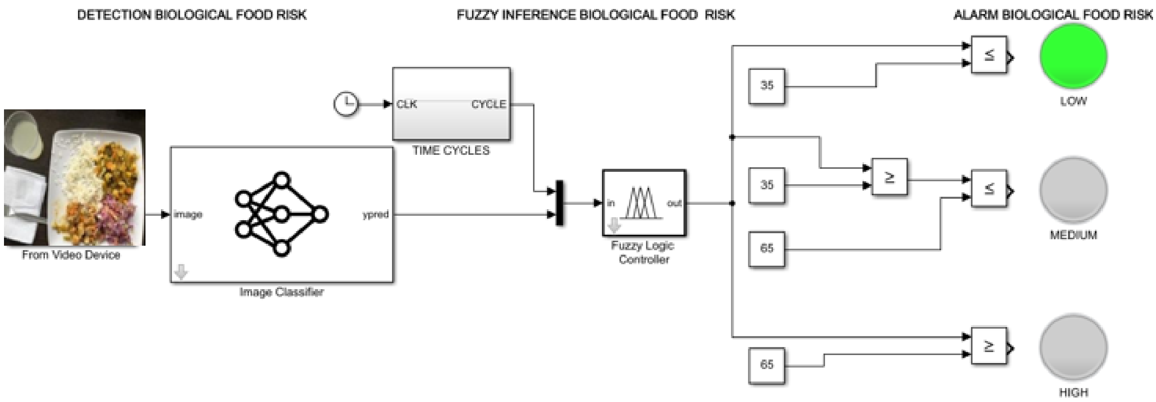


Figure 11. Simulation test

Table 2. Risk simulation

Risk	TP %
Low	97
Medium	92
High	100
Average	96.3

By means of the simulation, it was possible to validate the temporal relevance of the system, depending fundamentally on the time when food was found in the evaluation area. The losses of true positives are due to variations in the level of confidence with which each image in the video is classified since a threshold of 85% is used to discard those that give values below, which are usually subject to error. However, the average value obtained of 96.3% shows the effectiveness of the algorithm in generating the alarms.

4. CONCLUSION

Machine vision systems are an important complement to automation systems, which employ pattern recognition techniques to operate. Within these techniques, neuro convolutional networks demonstrated high efficiency in the recognition of the two established classes, with reduced classification times and high levels of confidence. It is concluded that the automation of risk levels by means of the exposed methodology allows the development of efficient automatic assistants for the prevention of biological risks due to bacterial growth as in the case presented by food residues.

It is concluded on the importance of analyzing the activations, which allowed making adjustments in the hyperparameters of the network, facilitating the convergence in the selection of the final architecture. At the same time, the fuzzy inference system allows the generation of a natural system that alarms the health conditions for decision making, complementing the action of the convolutional network.

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REFERENCES

[1] K. Akila, B. Sabitha, and R. Saravanan, "Railway track cleaning robot," in *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, Oct. 2021, pp. 1–4. doi: 10.1109/ICAECA52838.2021.9675742.

[2] P. Veerajagadheswar, S. Yuyao, P. Kandasamy, M. R. Elara, and A. A. Hayat, "S-Sacrr: A staircase and slope accessing reconfigurable cleaning robot and its validation," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 4558–4565, Apr. 2022, doi: 10.1109/LRA.2022.3151572.

[3] C. McGinn, E. Bourke, and M. F. Cullinan, "An IoT approach for monitoring UV disinfection robots," in *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Oct. 2021, pp. 3056–3060. doi: 10.1109/SMC52423.2021.9659310.

[4] Y. Nishida, T. Ura, T. Hamatsu, K. Nagahashi, S. Inaba, and T. Nakatani, "Fish recognition method using vector quantization histogram for investigation of fishery resources," in *2014 Oceans - St. John's*, Sep. 2014, pp. 1–5. doi: 10.1109/OCEANS.2014.7003268.

[5] A. Yeshmukhametov, A. Baratova, A. Salemkhan, Z. Buribayev, K. Ozhikenov, and Y. Amirgaliyev, "Design and modeling of self-sustainable bathroom floor cleaning robot system," in *2021 21st International Conference on Control, Automation and Systems (ICCAS)*, Oct. 2021, pp. 1860–1865. doi: 10.23919/ICCAS52745.2021.9649969.

[6] T. Hitomi, Y. Yamanaka, F. Ito, and T. Nakamura, "Development of a rotary cleaning mechanism using planetary gears for removing grease deposited in kitchen ventilation ducts," in *2022 IEEE/SICE International Symposium on System Integration (SII)*, Jan. 2022, pp. 473–478. doi: 10.1109/SII52469.2022.9708739.

[7] R. S. Nakandhrakumar, P. Rameshkumar, V. Parthasarathy, and B. Thirupathy Rao, "WITHDRAWN: Internet of things (IoT) based system development for robotic waste segregation management," *Materials Today: Proceedings*, Mar. 2021, doi: 10.1016/j.matpr.2021.02.473.

[8] A. C. Medina, J. F. Mora, C. Martinez, N. Barrero, and W. Hernandez, "Safety protocol for collaborative human-robot recycling tasks," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 2008–2013, 2019, doi: 10.1016/j.ifacol.2019.11.498.

[9] J. Li, M. Barwood, and S. Rahimifard, "A multi-criteria assessment of robotic disassembly to support recycling and recovery," *Resources, Conservation and Recycling*, vol. 140, pp. 158–165, Jan. 2019, doi: 10.1016/j.resconrec.2018.09.019.

[10] Z. Wang, H. Li, and X. Yang, "Vision-based robotic system for on-site construction and demolition waste sorting and recycling," *Journal of Building Engineering*, vol. 32, Nov. 2020, doi: 10.1016/j.jobe.2020.101769.

[11] W. Song, N. Jiang, H. Wang, and J. Vincent, "Use of smartphone videos and pattern recognition for food authentication," *Sensors and Actuators B: Chemical*, vol. 304, Feb. 2020, doi: 10.1016/j.snb.2019.127247.

[12] K. Xu, M. M. Zheng, and X. Liu, "A two-stage robust model for urban food waste collection network under uncertainty," in *2021 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Dec. 2021, pp. 824–828. doi: 10.1109/IEEM50564.2021.9672895.

[13] E. L. Cosbuc, E.-D. Ungureanu-Comanita, and M. Gavrilescu, "Identification of the risks generated in the environment by food waste," in *2021 International Conference on e-Health and Bioengineering (EHB)*, Nov. 2021, pp. 1–4. doi: 10.1109/EHB52898.2021.9657709.

[14] Z. Shen, A. Shehzad, S. Chen, H. Sun, and J. Liu, "Machine learning based approach on food recognition and nutrition estimation," *Procedia Computer Science*, vol. 174, pp. 448–453, 2020, doi: 10.1016/j.procs.2020.06.113.

[15] P. Furtado, M. Caldeira, and P. Martins, "Human visual system vs convolution neural networks in food recognition task: An empirical comparison," *Computer Vision and Image Understanding*, vol. 191, Feb. 2020, doi: 10.1016/j.cviu.2019.102878.

[16] L. Xiao, T. Lan, D. Xu, W. Gao, and C. Li, "A simplified CNNs visual perception learning network algorithm for foods recognition," *Computers & Electrical Engineering*, vol. 92, Jun. 2021, doi: 10.1016/j.compeleceng.2021.107152.

[17] A. Laila, M. von Massow, M. Bain, K. Parizeau, and J. Haines, "Impact of COVID-19 on food waste behaviour of families: Results from household waste composition audits," *Socio-Economic Planning Sciences*, vol. 82, Aug. 2022, doi: 10.1016/j.seps.2021.101188.

[18] Z. Qiuhao, "Kitchen waste classification based on deep residual network and transfer learning," in *2021 6th International Symposium on Computer and Information Processing Technology (ISCIPT)*, Jun. 2021, pp. 625–629. doi: 10.1109/ISCIPT53667.2021.00133.

[19] E. Aguilar and P. Radeva, "Uncertainty-aware integration of local and flat classifiers for food recognition," *Pattern Recognition Letters*, vol. 136, pp. 237–243, Aug. 2020, doi: 10.1016/j.patrec.2020.06.013.

[20] Z. B. Ozger and P. Cihan, "A novel ensemble fuzzy classification model in SARS-CoV-2 B-cell epitope identification for development of protein-based vaccine," *Applied Soft Computing*, vol. 116, Feb. 2022, doi: 10.1016/j.asoc.2021.108280.
[21] N. E. Dina, A. M. R. Gherman, A. Colniță, D. Marconi, and C. Sârbu, "Fuzzy characterization and classification of bacteria species detected at single-cell level by surface-enhanced Raman scattering," *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 247, Feb. 2021, doi: 10.1016/j.saa.2020.119149.
[22] P. P. Lal *et al.*, "IoT integrated fuzzy classification analysis for detecting adulterants in cow milk," *Sensing and Bio-Sensing Research*, vol. 36, Jun. 2022, doi: 10.1016/j.sbsr.2022.100486.
[23] S. Dey, R. Roychoudhury, S. Malakar, and R. Sarkar, "An optimized fuzzy ensemble of convolutional neural networks for detecting tuberculosis from Chest X-ray images," *Applied Soft Computing*, vol. 114, Jan. 2022, doi: 10.1016/j.asoc.2021.108094.
[24] G. Guo, J. Qiao, W. Wang, and T. Chai, "A fuzzy leakage alarm method of liquid steel," *IFAC Proceedings Volumes*, vol. 30, no. 13, pp. 43–47, Jul. 1997, doi: 10.1016/S1474-6670(17)44367-9.
[25] M. J. Jafari, M. Pouyakian, A. Khanteymoori, and S. M. Hanifi, "Reliability evaluation of fire alarm systems using dynamic Bayesian networks and fuzzy fault tree analysis," *Journal of Loss Prevention in the Process Industries*, vol. 67, Sep. 2020, doi: 10.1016/j.jlp.2020.104229.
[26] Q. Zheng, Y. Li, and J. Cao, "Application of data mining technology in alarm analysis of communication network," *Computer Communications*, vol. 163, pp. 84–90, Nov. 2020, doi: 10.1016/j.comcom.2020.08.012.
[27] T. Guo, J. Dong, H. Li, and Y. Gao, "Simple convolutional neural network on image classification," in *2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA)*, Mar. 2017, pp. 721–724. doi: 10.1109/ICBDA.2017.8078730.
[28] M. D. Zeiler and R. Fergus, "Visualizing and understanding convolutional networks," in *European conference on computer vision*, Springer, 2014, pp. 818–833. doi: 10.1007/978-3-319-10590-1_53.
[29] C. Anzueto, *Mathematical models for food shelf-life estimation*. San Salvador, Guatemala: Food and Beverage, 2012.

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