FoodPAL 1.1: Novel Methods to Ensure Allergens Free Diet in Smart Healthcare Framework

Abdulrahman Alkinani, Laavanya Rachakonda, Saraju P. Mohanty, and Elias Kougianos

***Abstract*—The immune system plays a vital role in defending the body against pathogens and foreign substances. However, food allergies disrupt its normal functioning, leading to immune system related disorders. During early childhood (ages one to three), children begin exploring their environment by placing various objects, including food, into their mouths. While this exploratory behavior is essential for development, it also poses significant risks, especially for children with food allergies. Therefore, increased supervision is crucial during this stage of growth. In response to this challenge, FoodPAL, a smart surveillance device, is introduced to monitor toddlers' food consumption. A hybrid object detection approach is implemented to enhance performance efficiency and optimize resource utilization. A premium dataset was evaluated across four different object detection models, and the most accurate model was selected. The overarching goal of this research is to protect children's immune systems by preventing exposure to allergenic substances.**

***Index Terms*—Smart Healthcare, Diet Monitoring, Healthcare Cyber Physical System (HCPS), Machine Learning, YOLOv8, YOLOv12, RT DETR r18vd, RT DETR r50vd.**

I. INTRODUCTION

Children's natural curiosity supports early learning, but it can also increase exposure to hidden risks such as food allergies. Approximately 5% of children under the age of five experience food allergies, commonly triggered by foods such as eggs, wheat, and peanuts [1]–[3]. Allergic reactions may range from mild symptoms to fatal conditions requiring immediate medical attention [3], [4]. Fig. 1 illustrates common symptoms of food allergies. Unlike visible hazards, allergenic foods are difficult for young children to recognize, making continuous supervision essential during early development.

FoodPAL is a smart surveillance system designed to help protect toddlers from allergenic foods. The system employs a hybrid live object detection framework that combines edge and cloud processing to improve efficiency and reduce resource usage. The objective is to achieve an effective balance between detection accuracy and alert latency in a limited capacity environment. Four models YOLOv8, YOLOv12, RT DETR r18vd, and RT DETR r50vd were evaluated to select the most suitable cloud model, while SSD MobileNetV2 was deployed at the edge for lightweight local filtering. A curated dataset of six common allergenic food classes was prepared for training and evaluation.

Abdulrahman Alkinani, Saraju P. Mohanty, and Elias Kougianos are with the Department of Computer Science and Engineering, University of North Texas, Denton, TX 76203 USA. (e-mail: AbdulrahmanAlkinani@my.unt.edu; smohanty@ieee.org; elias.kougianos@unt.edu)

Laavanya Rachakonda is with the Department of Computer Science, University of North Carolina Wilmington, Wilmington, NC, USA. e-mail: rachakondal@uncw.edu

Corresponding author: Abdulrahman Alkinani.

Manuscript received April 19, 2021; revised August 16, 2021.

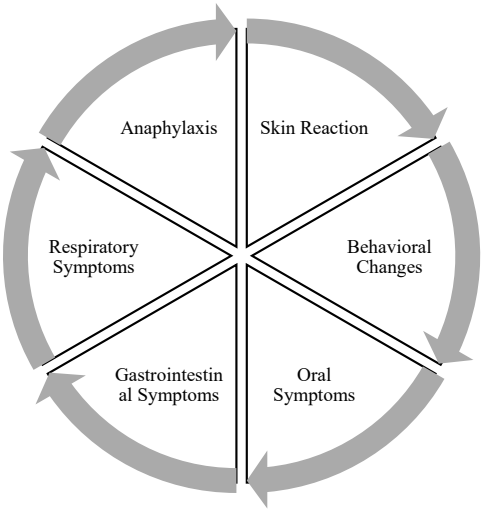


Fig. 1. Common Symptoms Associated With Food Allergies

The remainder of the manuscript is organized as follows. Section II presents the core contributions. Section III reviews related prior works. Section IV describes the proposed methodology. Section V details the experimental results. Section VI compares model performance. Finally, Section VII concludes the research and discusses future directions.

II. SYSTEM CONTRIBUTIONS

A. Problem Statement

Toddlers experience food allergies, requiring close and continuous monitoring to ensure their safety [1]. Potentially fatal allergic reactions can significantly restrict a child's natural exploration and learning processes. However, food allergies should not impede the daily development of new skills and abilities. As children grow and become more independent, effective supervision becomes increasingly challenging. Moreover, relying solely on human observation has limitations, as it is difficult to maintain continuous monitoring without technological support.

B. Proposed Surveillance Architecture

The proposed live surveillance system identifies allergenic foods using both edge and cloud processing. Unlike conventional edge and cloud architectures that merely pass raw data to the cloud for heavy processing, this framework introduces a specialized two tier filtering mechanism. A lightweight model analyzes images captured by a smart camera at the device level to immediately eliminate irrelevant data. This significantly

minimizes unnecessary cloud offloading, reducing both latency and bandwidth consumption compared to traditional methods. When a potential allergenic object is detected, the image is sent to the cloud, where a more powerful model performs verification and determines whether an alert should be issued. Unlike reactive systems that monitor food intake during or after eating, the proposed approach focuses on prevention before consumption occurs.

Four object detection models were trained and evaluated based on response time, accuracy, and computational efficiency. The system also monitors alert delivery status. If an alert is not acknowledged while the child remains at risk, the child's location and detection information are automatically sent to emergency services.

C. Key Contributions

- A hybrid object detection framework uses two models to improve detection accuracy and efficiency.
- The system operates autonomously, detecting allergenic foods and issuing alerts without human intervention.
- A lightweight edge model reduces latency by filtering irrelevant images before cloud transmission.
- Lower cloud workload reduces storage and processing costs.
- The cloud enables caregivers to remotely update the monitored allergenic food list.
- Alerts are delivered through a smartphone for convenient and immediate access.

III. RELATED PRIOR WORK

Diverse methodologies within smart healthcare have been utilized to care for children. Table I elucidates the several methodologies employed in smart healthcare for children. Assistive, entertainment, and monitoring devices have been adopted in previous frameworks. The developed architecture aims to predict risk in order to enhance the child's well-being.

In the domain of assistive technology, a humanoid robot was employed to support children with disabilities in interacting with their peers [5]. Neurological disorders that impair hand function were addressed in [6] through the development of a robotic hand. An Android based terminal was used to assist children with hearing impairments [7]. Additionally, a robot capable of reading QR codes on learning cards was introduced to aid children with intellectual disabilities [8]. While the deployment of assistive devices plays a critical role in supporting children with disabilities, it is equally important to anticipate and adapt to their evolving needs.

Regulating children's entertainment is essential for promoting their mental health. The Down children game was developed to improve their physical and cognitive abilities [9]. A library application designed to engage children's interest was discussed in [10]. Reprogramming the NAO robot to do dance routines and execute ball kicking actions provides a significant answer for children's amusement during the recent pandemic [11]. A two dimensional game was created particularly to educate children with dyslexia, including visually stimulating visuals and little text [12]. Children ought to modify physical exercise to enhance their creative abilities.

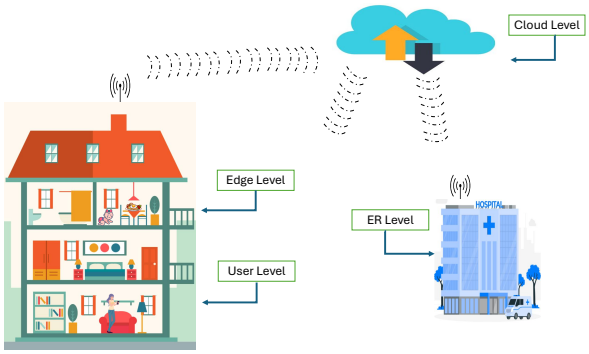


Fig. 2. Architectural Framework of the FoodPAL System

Previous research has utilized computer vision and voice recognition to track nutritional consumption. Monitoring food consumption was implemented to improve nutritional quality in [13], [14]. The correlation between food consumption and stress levels was elucidated and addressed in [15]. Fruit allergies were evaluated using a live gadget to assist caregivers in [4]. Two microphones were utilized to capture the sounds of mastication and consumption for the purpose of tracking dietary intake, as detailed in [16]. However, previous frameworks focused on tracking food consumption prior to or during the act of eating. FoodPAL is a cutting edge system that incorporates two rounds of object detection to assess the risk of food allergies before consumption.

IV. THE PROPOSED METHOD FOODPAL

A. Overview

The proposed system is a smart surveillance device designed for installation in home to monitor potential exposure to allergenic foods. The primary objective of the system is to ensure the child's safety while reducing the caregiver's stress associated with continuous monitoring. The system is fully autonomous, capable of tracking object locations and accurately identifying allergenic foods, followed by sending alerts to the caregiver.

FoodPAL is built with an efficient architecture designed to achieve its objectives with high accuracy and low cost. Fig. 2 presents the architecture of FoodPAL, which is composed of four levels: the Edge Level, Cloud Level, User Level, and Emergency Room (ER) Level. The number of required resources is reduced because each level operates sequentially, with each stage building on the output of the previous one. Algorithm 1 describes the step by step process and the interactions between the different system levels. The communication between each level is established wirelessly, enabling seamless data transfer throughout the system. Additionally, Fig. 3 illustrates the flow of data across these stages.

The cloud operated model must be characterized by high detection accuracy and fast response time. A comprehensive comparison among four different models was conducted to select the most effective one for deployment. Two members of the "You Only Look Once" (YOLO) family YOLOv8 [17]

TABLE I
DIFFERENT APPROACHES IN SMART HEALTHCARE FOR CHILDREN

Category	Device/Technology	Purpose
Assistive	Humanoid Robot [5]	Facilitates social interaction for children with disabilities.
	Robotic Hand [6]	Assists children with neurological disorders in improving hand functionality.
	Android Terminal [7]	Supports communication for children with hearing impairments.
	Reading Robot [8]	Enhances learning outcomes for children with intellectual disabilities.
Entertainment	Interactive Game [9]	Improves physical and cognitive skills through gameplay.
	Library Application [10]	Increases children's engagement and promotes learning interests.
	NAO Robot [11]	Provides entertainment and emotional support during the recent pandemic.
	Two dimensional Educational Game [12]	Supports the education of children with dyslexia.
Monitoring	Vision and Voice Systems [13], [14]	Tracks dietary intake and promotes overall wellness.
	Food Monitoring System [15]	Enhances health by monitoring food intake dynamically.
	Fruit Allergen Device [4]	Immediate detection of fruit allergens for caregivers.
	Acoustic Monitoring Device [16]	Analyzes chewing sounds to assess food intake.

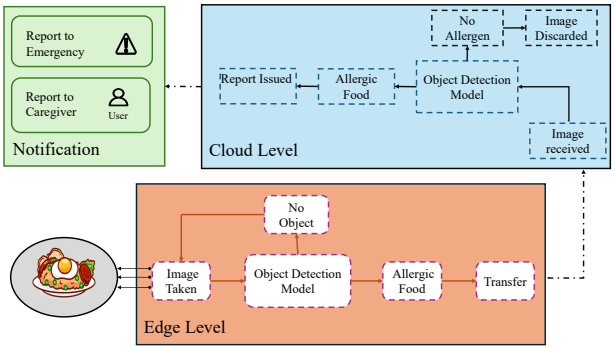


Fig. 3. Operational Pipeline for the FoodPAL Architecture

and YOLOv12 [18] were compared with two models from the "Real Time DEtection TRansformer" (RT DETR) family [19], specifically RT DETR r18vd and RT DETR r50vd. All models were evaluated on a premium dataset.

B. Edge Level

The primary objective of the Edge Level is to capture live images from the child's environment and transmit them to the cloud for further analysis. At this level, the lightweight SSD MobileNetV2 model functions as a filter, processing incoming images to identify potential allergenic content before transmission. This model classifies each object within the captured images immediately. If a food item potentially associated with an allergic reaction is identified, the corresponding image is transmitted to the cloud via an internet connection. Images that do not contain allergenic content are discarded locally, thereby optimizing system efficiency and minimizing unnecessary data transmission.

C. FoodPAL Cloud

The cloud hosts a powerful object detection model capable of both localizing and identifying allergenic foods. Leveraging the computational capabilities of the cloud enables high detection accuracy and fast response times. To determine the most suitable model for FoodPAL, four object detection models were compared, and the most accurate model was selected for deployment at the Cloud Level.

As described in Section IV-B, premium images suspected of containing allergenic foods are transmitted from the Edge Level to the cloud. These images are then analyzed to determine whether allergenic content is present. Images classified as negative (i.e., not containing allergenic foods) are discarded and removed from cloud storage to conserve resources. In contrast, positive detections trigger immediate notifications sent directly to the caregiver's smartphone.

In the event of a notification failure or missed alert, the system automatically escalates the situation by sending an emergency message along with the child's location to the nearest emergency response unit. Additionally, the Cloud Level allows caregivers to personalize the system by selecting specific allergenic foods that may pose a risk to the child.

1) YOLO Architecture for Object Detection and Localization: YOLO differs from two phase detectors such as Faster Region CNN by performing object classification and localization in a single step [20]. This single step design enables instantaneous performance, making YOLO suitable for time critical applications such as healthcare and agriculture [21]. Fig. 4 compares the architectures of YOLOv8 and YOLOv12. The main components are summarized as follows [22]:

- **Backbone:** YOLOv8 uses CSP Darknet with C2F, while YOLOv12 uses R ELAN with Area Attention for feature extraction.
- **Neck:** YOLOv8 applies PAN FPN with SPP F, whereas YOLOv12 uses Flash Accelerated Area Attention for varied scale feature fusion.
- **Head:** Both models use anchorless heads, while YOLOv12 adds attention and dual assignment strategies for improved detection.
- **NMS:** YOLOv8 requires Non Maximum Suppression to remove duplicate boxes, while YOLOv12 can operate without NMS.

2) RT DETR Architecture for Object Detection and Localization: Most object detection models, such as YOLO, rely on

Algorithm 1: FoodPAL sequential operation

Input: Live image stream from smart camera
Output: Notification to caregiver or escalation to emergency services

begin

```
/* --- EDGE LEVEL ---                                  */
Capture image from smart camera;
Run lightweight model on image;
if allergenic food detected then
    Send image to Cloud Level;
else
    Return to image capture and continue monitoring;
/* --- CLOUD LEVEL ---                                 */
Receive image from Edge Level;
Run powerful object detection model on image;
if allergenic food confirmed then
    Send alert notification to caregiver;
else
    Return to Edge Level ;
/* --- USER LEVEL ---                                  */
Wait for caregiver response (acknowledge or ignore);
if caregiver acknowledges within TIME_LIMIT then
    Return to Edge Level;
else
    Proceed to ER Level;
/* --- EMERGENCY ROOM LEVEL ---                        */
Automatically escalate alert to emergency services;
Provide emergency services with location and alert details;
Return to Edge Level ;
```

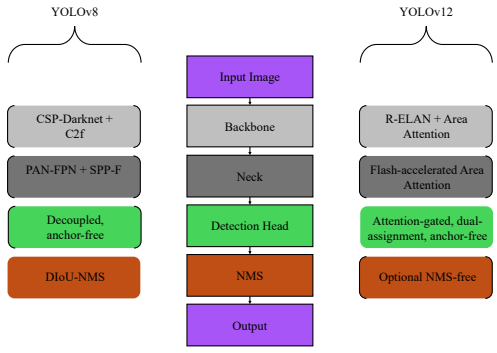


Fig. 4. Structural Comparison of YOLOv8 and YOLOv12 Object Identification Pipelines

convolutional neural networks (CNNs). In contrast, RT DETR combines CNNs and Transformers to leverage the strengths of both. This design removes the need for Non Maximum Suppression (NMS), which can improve speed and accuracy. CNNs are used for feature extraction, while Transformer enhanced modules improve attention and varied scale feature

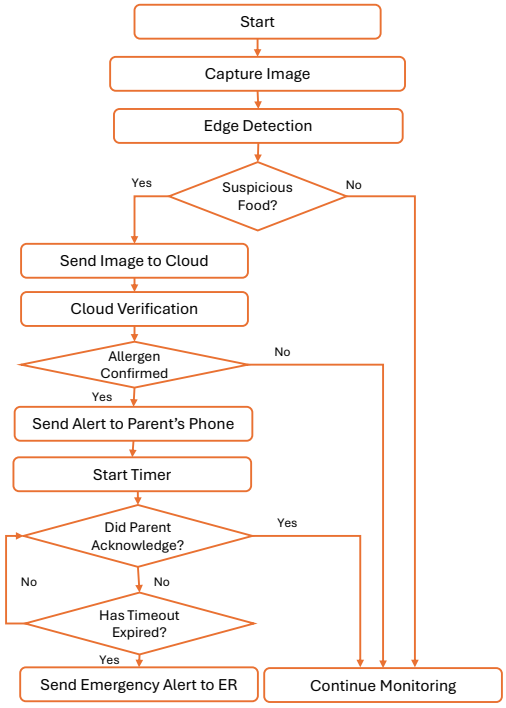


Fig. 5. Logic Flow for Notifications and Escalations at User and Emergency Response Levels

fusion [23], [24]. However, the added Transformer components increase computational cost, which may affect live deployment on restricted systems.

D. User Level and ER Level

Fig. 5 details notification and timeout escalation logic of FoodPAL at the User Level. The primary purpose of the User Level is to promptly notify caregivers when a child may come into contact with allergenic foods. After confirmed allergen detection, the system transmits an alert to the caregiver's smartphone and initiates a predefined response timer. Upon receiving the alert, caregivers are expected to respond immediately to ensure the child's safety. If acknowledgment is received within the allowed timeframe, the system returns to normal monitoring. However, if no response is recorded before timeout expiration, an emergency report, including critical information and the child's location, is automatically sent to the nearest Emergency Room to safeguard the child's life against allergenic exposure.

E. Mathematical Framework for System Optimization

To evaluate the efficiency of FoodPAL, the total safety latency is defined as the sum of processing and communication delays:

$$L_{total} = L_{edge} + L_{network} + L_{cloud} \tag{1}$$

where L_{edge} is the edge processing time, $L_{network}$ is the transmission delay, and L_{cloud} is the cloud inference time. If notification delay is considered, the model becomes:

$$L_{total} = L_{edge} + L_{network} + L_{cloud} + L_{alert} \tag{2}$$

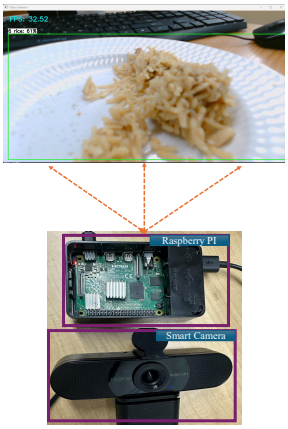


Fig. 6. Hardware Configuration for Object Detection at the Edge Level

To reduce bandwidth usage, the edge device filters unnecessary frames before transmission. The discarded images per second are:

$$IPS_{discard} = IPS_{in} - IPS_{tx} \tag{3}$$

The edge filtering efficiency is calculated as:

$$\eta = \frac{IPS_{discard}}{IPS_{in}} \times 100 \tag{4}$$

where IPS_{in} is the captured frames per second, IPS_{tx} is the transmitted frames per second, and η is the filtering efficiency (%).

V. EXPERIMENTAL VERIFICATION

A. Hardware at Edge

Fig. 6 illustrates the hardware configuration, which includes an EMEET HD 1080P camera and a Raspberry Pi. The Raspberry Pi features a multiple core processor capable of interfacing with the connected camera module to capture and forward images to the cloud. The attached EMEET HD 1080P camera captures high definition images at 1080p resolution with a ninety degree field of view. These high resolution images contribute to improved object detection accuracy by producing sharper and more detailed visual input for the cloud operated model. However, premium image quality leads to increased data volume, which may raise cloud storage costs and internet server fees. To balance visual quality with reduced cloud costs, a lightweight object detection model is employed at the Edge Level.

An example calculation of image volume for continuous capture at 30 frames per second (FPS) over a 24 hour period is shown below:

$$\text{Total frames per day} = 30 \times 60 \times 60 \times 24 = 2,592,000 \text{ frames} \tag{5}$$

B. Model at Edge

FoodPAL was developed using an integrated approach to detect allergenic foods across multiple processing levels. At the Edge Level, a lightweight model is deployed on a Raspberry Pi to perform initial object detection. Specifically, SSD MobileNetV2 a lightweight object detection architecture is utilized due to its high efficiency and suitability for limited capacity environments such as embedded systems. To enhance detection accuracy, a more powerful model is implemented at the Cloud Level for further analysis and verification.

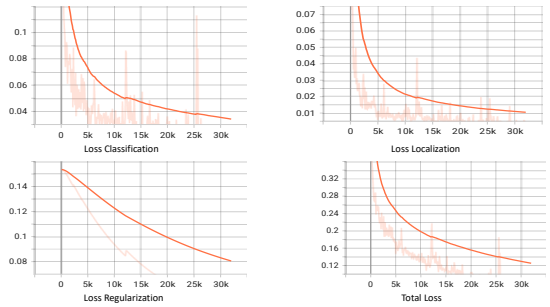


Fig. 7. Training Loss Curves for the Edge Model

The lightweight model was deployed on an embedded system and serves as the initial step in filtering images before transmitting them to the Cloud Level. SSD MobileNetV2 was selected due to its efficiency in low energy environments and was trained using a GPU on Google Colab. The training process spanned approximately six hours and included a total of 40,000 iterations, with each batch consisting of 16 images. Fig. 7 illustrates the loss curves for classification, localization, regularization, and total loss during the training process. Additionally, Fig. 6 shows the model's ability to detect rice at a confidence threshold of 61%, demonstrating its effectiveness in allergen identification at the edge level.

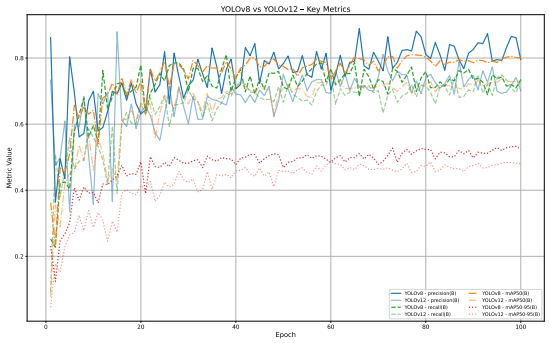
C. Dataset

The dataset used in this evaluation includes six common types of allergenic foods known to trigger allergic reactions: milk, seafood, egg, wheat (including rice and bread), and peanut butter. The curated dataset consists of 1,236 images [25], which were sourced from multiple datasets [26]–[29]. The dataset contains 2,149 annotated instances across six classes milk (878), seafood (586), omelette (253), rice (224), bread (135), and peanut butter (73). All images are square with a resolution of 640×640 pixels. To enhance dataset diversity and improve model generalization, data augmentation techniques were applied, including horizontal and vertical flipping, as well as noise injection affecting up to 0.22% of pixels. These augmentations expanded the dataset to a total of 4,139 images. The dataset was then divided into three subsets: training (70%), validation (20%), and testing (10%).

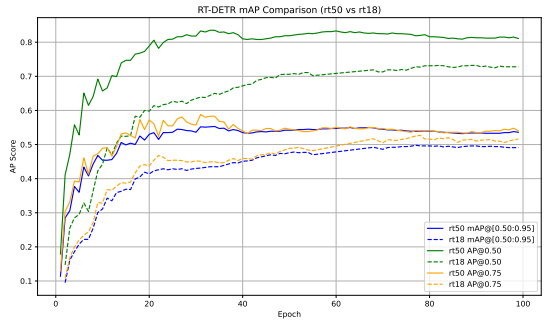
VI. PERFORMANCE COMPARISON: YOLO VERSUS RT DETR ARCHITECTURES

A. Results

1) YOLO Architecture: Two models from the YOLO family YOLOv8 and YOLOv12 were evaluated to determine the most suitable option. The models were trained on a local machine equipped with an NVIDIA GeForce RTX 2080 Super GPU and 32 GB of RAM. Fig. 8 presents the performance metrics of both models across training iterations, including



(a) YOLOv8 versus YOLOv12



(b) RT DETR r50 versus r18

Fig. 8. Comparison of Performance Metrics Across Training Epochs

mAP50, mAP50 to 90, precision, and recall. Overall, YOLOv8 outperformed YOLOv12, exhibiting higher mAP scores and greater precision. However, YOLOv12 achieved superior recall compared to YOLOv8.

2) RT DETR Architecture: To select the most accurate model from the RT DETR family, both RT DETR R18 and RT DETR R50 were trained and evaluated on an NVIDIA GeForce RTX 2080 Super GPU and 32 GB of RAM. Fig. 8b presents the mAP trends for RT DETR R18 and RT DETR R50 throughout the training process. RT DETR R50 consistently outperformed RT DETR R18 across all evaluation metrics throughout the training epochs.

B. Detection Performance Comparison

Two key metrics were used to determine the most accurate model for the FoodPAL objective: mAP 50 and mAP 50 to 95. Mean Average Precision (mAP) evaluates a model's ability to detect and classify objects within an image by integrating both precision (the proportion of accurate positive predictions) and recall (the proportion of actual positive instances correctly identified) [30]. Fig. 9 presents the mAP 50 and mAP 50 to 95 values for the four evaluated models. Among them, RT DETR R50 achieved the highest scores, outperforming the others in overall detection accuracy.

The performance difference between RT DETR R50 and YOLOv8 is relatively small. Nevertheless, FoodPAL requires high accuracy detection, making model performance a critical factor. In comparison, YOLOv12 and RT DETR R18 exhibited lower accuracy and are considered less suitable for deployment

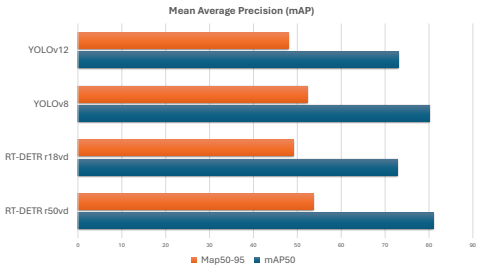


Fig. 9. Comparison of Mean Average Precision Across Evaluated Models

TABLE II
TRAINING TIME COMPARISON FOR OBJECT DETECTION MODELS

Model	Epochs	Batch	Time/Ep (min)	Total (h)
YOLOv8m	100	8	30	50.0
YOLOv12m	100	8	22.38	37.3
RT DETR r18	100	8	5.44	9.06
RT DETR r50	100	8	34	56.6

in the system. Furthermore, in the context of a smart healthcare framework, the implications of detection errors must be carefully weighed. A false positive may cause a temporary inconvenience by issuing an unnecessary alert to the caregiver. However, a false negative failing to detect an allergen poses a severe, potentially fatal risk to the child. Therefore, the selected model must prioritize high recall and robust mAP to guarantee the highest safety standards.

C. Training Time Comparison

The comparison of object detection model architectures based on training time highlights the relationship between the selected model and the computational resources required during training. Table II presents the training differences among the models. All models were trained on the same dataset with comparable epoch counts and batch sizes. Among them, RT DETR R18 demonstrated the shortest training time, completing 100 epochs in approximately 9.06 hours. In contrast, RT DETR R50 required the longest duration, totaling 56.6 hours. YOLOv8 and YOLOv12 exhibited nearly identical training times.

D. Speed and Resource Efficiency Comparison

As FoodPAL is a live detection system, response time is a critical factor in model selection. Three metrics were used to evaluate processing speed: FPS, latency, and parameter count. These experiments were conducted on a machine with an NVIDIA GeForce RTX 2080 Super GPU and 32 GB RAM.

Fig. 10 compares all four models. YOLOv8 achieved the highest FPS and lowest latency, making it the fastest model for live deployment. RT DETR r50vd showed the lowest FPS and highest latency, indicating the heaviest computational cost. YOLOv12 and RT DETR r18vd achieved intermediate results.

Parameter count also affects accuracy and storage requirements. RT DETR r50vd had the largest number of parameters, while YOLOv8 provided the best balance between accuracy,

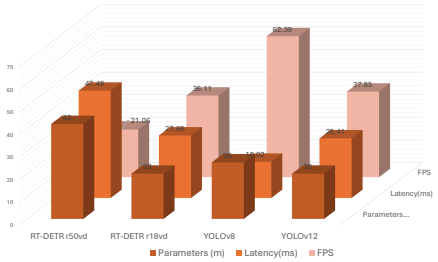


Fig. 10. Comparison of Processing Speed Latency and Parameter Count



(a) Ground Truths



(b) Predictions

Fig. 11. Visual Comparison of Ground Truth Annotations and Model Predictions

speed, and model size. YOLOv12 and RT DETR r18vd required less storage but showed lower overall performance.

Although RT DETR r50vd achieved the highest mAP, YOLOv8 was selected for FoodPAL due to its better balance between accuracy and processing speed. YOLOv8 provides fast inference with competitive accuracy, making it suitable for live allergen detection. Fig. 11 shows YOLOv8 predictions compared with the ground truth. In addition, its lower storage requirement helps reduce cloud computing costs. YOLOv12 and RT DETR r18vd were less suitable due to lower accuracy.

VII. CONCLUSION AND FUTURE WORK

FoodPAL is a hybrid smart surveillance system designed to protect children from allergen containing foods through live monitoring. The framework integrates an edge device and cloud processing to achieve high detection accuracy, low latency, flexibility, and reduced operational cost. SSD MobileNetV2 is deployed at the Edge Level for lightweight filtering and reduced cloud load, while YOLOv8 was selected for cloud deployment due to its strong balance between accuracy and speed compared with YOLOv12, RT DETR r50vd, and RT DETR r18vd. Table III shows the comparison between FoodPAL and other works.

TABLE III
COMPARISON OF FRUITPAL, FRUITPAL 2.0, AND FOODPAL

Feature	FruitPAL	FruitPAL 2.0	FoodPAL
Processing Method	Single phase	Single phase	Two phase
Edge Device Support	Yes	Yes	Yes
Cloud Intelligence	No	No	Yes

Future work will focus on expanding the number of allergenic food classes, further optimizing the hybrid framework, and providing a more detailed evaluation of the communication protocol and edge model. The system will also be tested under live deployment conditions to assess latency, reliability, accuracy, and overall efficiency across different hardware platforms.

VIII. ACKNOWLEDGMENT

An earlier version of this work was presented in [31]. This extended study provides a comprehensive comparison of YOLOv8, YOLOv12, RT DETR r18vd, and RT DETR r50vd using metrics such as mAP, precision, recall, training time, FPS, and latency. Based on the results, YOLOv8 was selected as the most suitable model for real deployment.

REFERENCES

[1] H. Medicines, "Food Allergies in Children," accessed on 2024 Aug 12. [Online]. Available: https://www.hopkinsmedicine.org/health/conditions-and-diseases/food-allergies-in-children

[2] A. Ng, A. Giri, and L. Bottoms-McClain, "Diagnosed Allergic Conditions Among Children Ages 0–17 Years: United States, 2024," *National Center for Health Statistics (U.S.)*, 2026.

[3] R. S. Gupta, C. M. Warren, B. M. Smith, J. Jiang, J. A. Blumenstock, and M. M. Davis, "Prevalence and Severity of Food Allergies Among US Children," *JAMA Pediatrics*, vol. 172, no. 1, pp. 39–46, 2018.

[4] A. Alkinani, A. Mitra, S. P. Mohanty, and E. Kougianos, "Fruitpal: A smart healthcare framework for automatic detection of fruit allergens," in *Proceedings of IEEE International Symposium on Smart Electronic Systems (iSES)*, 2023, pp. 369–372.

[5] S. Alves, I. N. Silva, C. Ranieri, H. F. Filho, M. Caldeira, and R. Pegoraro, "A friendly mobile entertainment robot for disabled children," in *Proceedings of ISSNIP Biosignals and Biorobotics Conference: Biosignals and Robotics for Better and Safer Living (BRC)*, 2013, pp. 1–6.

[6] J. Dittli, G. Goikoetxea-Sotelo, J. Lieber, R. Gassert, A. Meyer-Heim, H. J. A. Van Hedel, and O. Lambercy, "A tailorable robotic hand orthosis to support children with neurological hand impairments: a case study in a child's home," in *Proceedings of International Conference on Rehabilitation Robotics (ICORR)*, 2023, pp. 1–6.

[7] X. Fan, W. Chen, Q. Fan, and T. Sun, "The application design of hearing aid parameters auto adaptive system for hearing impaired children based on android terminal," in *Proceedings of International Conference on Information Science and Education (ICISE-IE)*, 2020, pp. 241–245.

[8] A. H. Fathaniard, A. Arifin, M. H. Fatoni, and M. Nuh, "Development of knowledge based assistive technology using robot to enhance cognitive ability for intellectual disability," in *Proceedings of International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, 2022, pp. 20–25.

[9] W. M. Shalash, S. AlTamimi, E. Abdu, and A. Barom, "No limit: A down syndrome children educational game," in *Proceedings of IEEE Games, Entertainment, Media Conference (GEM)*, 2018, pp. 352–358.
[10] C. Fang and K. Wu, "Development of a children's library application with gamification elements to enhance the intrinsic motivation," in *Proceedings of IEEE International Conference on Consumer Electronics - Taiwan*, 2022, pp. 235–236.
[11] R. C. Hsu, Y.-P. Lin, C.-J. Lin, and L.-s. Lai, "Humanoid robots for searching and kicking a ball and dancing," in *Proceedings of IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE)*, 2020, pp. 385–387.
[12] S. N. Sarah Abu Bakar, N. Hafizah Mahamarowi, and S. Mustapha, "Game-based learning as a teaching and learning tool for dyslexic children," in *Proceedings of IEEE 10th Conference on Systems, Process & Control (ICSPC)*, 2022, pp. 50–55.
[13] A. Mitra, S. Goel, S. P. Mohanty, E. Kougianos, and L. Rachakonda, "iLog 2.0: A novel method for food nutritional value automatic quantification in smart healthcare," in *Proceedings of IEEE International Symposium on Smart Electronic Systems (iSES)*, 2022, pp. 683–688.
[14] A. Alkinani, A. Mitra, S. P. Mohanty, and E. Kougianos, "Fruitpal 2.0: A smart healthcare framework for automatic monitoring of fruit consumption," in *Proceedings of OITS International Conference on Information Technology (OCIT)*, 2023, pp. 422–425.
[15] L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An intelligent device for automatic food intake monitoring and stress detection in the iomt," *IEEE Transactions on Consumer Electronics*, vol. 66, no. 2, pp. 115–124, 2020.
[16] S. Päßler and W.-J. Fischer, "Acoustical method for objective food intake monitoring using a wearable sensor system," *2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, pp. 266–269, 2011. [Online]. Available: https://api.semanticscholar.org/CorpusID:12300228
[17] G. Jocher, A. Chaurasia, J. Qiu *et al.*, "Yolov8: Ultralytics open-source object detection model," 2023, accessed: 2025-05-11. [Online]. Available: https://github.com/ultralytics/ultralytics
[18] Ultralytics, "Yolov12: State-of-the-art object detection by ultralytics," 2024, accessed: 2025-05-11. [Online]. Available: https://github.com/ultralytics/ultralytics
[19] L. Yao, J. Han, X. Liang, D. Xu, X. Zhang, J. Feng, H. Chen, C. Xu, Z. Li, and W. Liang, "Rt-detr: Real-time detection transformer," *arXiv preprint arXiv:2304.08069*, 2023. [Online]. Available: https://arxiv.org/abs/2304.08069
[20] A. Mitra, S. P. Mohanty, and E. Kougianos, "sgmodel 2.0: An automated real-time approach for multiclass plant disease detection," *SN Computer Science*, vol. 5, no. 5, p. 657, 2023. [Online]. Available: https://doi.org/10.1007/s42979-023-02076-6
[21] M. Shamsa, L. Rachakonda, S. P. Mohanty, and E. Kougianos, "qcrop: An iot-based framework to enhance crop productivity in smart agriculture," in *Proceedings of IFIP/IEEE 32nd International Conference on Very Large Scale Integration (VLSI-SoC)*. IEEE, 2024, pp. 1–6.
[22] R. Varghese and M. Sambath, "Yolov8: A novel object detection algorithm with enhanced performance and robustness," in *Proceedings of 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS)*. IEEE, 2024, pp. 1–6.
[23] N. Carion, F. Massa, G. Synnaeve, N. Usunier, A. Kirillov, and S. Zagoruyko, "End-to-end object detection with transformers," *arXiv preprint arXiv:2005.12872*, 2020. [Online]. Available: https://arxiv.org/abs/2005.12872
[24] Axinc AI, "Rt-detr: Hybrid object detection model combining convolution and transformer," 2023, accessed: 2024-08-27.
[25] Alkinani, "Allricge food dataset," https://universe.roboflow.com/alkinani/allrigce-food, accessed on 2024 Aug 27. [Online]. Available: https://universe.roboflow.com/alkinani/allrigce-food
[26] DFKI, "Shrimp clone dataset," https://universe.roboflow.com/dfki-djskn/shrimp_clone, accessed on 2024 Aug 27. [Online]. Available: https://universe.roboflow.com/dfki-djskn/shrimp_clone
[27] G. Project, "Peanut Butter Dataset," https://universe.roboflow.com/graduation-project-3v6ak/peanut-butter, jul, accessed on 2024 Aug 27. [Online]. Available: https://universe.roboflow.com/graduation-project-3v6ak/peanut-butter
[28] WillageNov, "11-5 dataset," https://universe.roboflow.com/willagenov/11-5, accessed on 2024 Feb 18. [Online]. Available: https://universe.roboflow.com/willagenov/11-5
[29] Project2982, "Milk products dataset," https://universe.roboflow.com/project2982/milk-products, accessed on 2024 Aug 27. [Online]. Available: https://universe.roboflow.com/project2982/milk-products
[30] S.-H. M. Ashtiani, G. Manafiazar, D. N. Do, G. Hu, P. Davoudi, and Y. Miar, "Fuzzy-augmented machine learning models for the prediction of feed efficiency and disease status in livestock: A mink case study," *Smart Agricultural Technology*, vol. 14, p. 102104, 2026. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772375526003254
[31] A. Alkinani, A. Mitra, S. P. Mohanty, and E. Kougianos, "Foodpal: A method to ensure food allergens free diet in smart healthcare framework," in *Synergies in Data Analytics and Cyber Security*, D. Puthal, B. K. Panigrahi, N. Ray, and Z. Ding, Eds. Singapore: Springer Nature Singapore, 2026, pp. 747–759.



Abdulrahman Alkinani received the bachelor's degree (Excellent with Honors, Second Class) in computer engineering from Al Baha University in 2016, the master's degree in computer engineering from University of North Texas in 2023, and is currently pursuing the Ph.D. degree in computer science and engineering at University of North Texas, where his research focuses on hybrid AI and IoT based autonomous systems for enhancing child wellness in smart cities.

He is currently an Assistant Professor with University of Tabuk and has also served as a Teaching Assistant with the Department of Computer Science and Engineering, University of North Texas. His research interests include autonomous intelligent systems for smart healthcare, computer vision, IoMT, and live monitoring, detection, and decision making for vulnerable populations. He has authored multiple research publications in venues including IEEE and Springer, with contributions such as FoodPAL, AngelRide, and FruitPAL smart healthcare systems.



Laavanya Rachakonda is an Assistant Professor with the Department of Computer Science, University of North Carolina Wilmington, where she has served since 2021. She received the Ph.D. and M.S. degrees in computer science and engineering from the University of North Texas, and the B.Tech. degree in electronics and communication engineering from Jawaharlal Nehru Technological University Hyderabad.

She is the Founder and Director of the Smart and Intelligent Physical Systems Laboratory. Her research interests include machine learning, artificial intelligence, IoT, IoMT, smart healthcare, smart agriculture, intelligent transportation, and smart living systems.



Saraju P. Mohanty (Senior Member, IEEE) received the bachelor's degree (Hons.) in electrical engineering from the Orissa University of Agriculture and Technology, India, in 1995, the master's degree in systems science and automation from the Indian Institute of Science, India, in 1999, and the Ph.D. degree in computer science and engineering from the University of South Florida, USA, in 2003.

He is currently a Professor with the University of North Texas, Denton, TX, USA. His research focuses on Smart Electronic Systems. He has authored over 550 research articles, five books, and multiple patents. He is a recipient of several awards and has served as Editor-in-Chief of the IEEE Consumer Electronics Magazine.



Elias Kougianos (Senior Member, IEEE) received the B.S.E.E. degree from the University of Patras, Greece, in 1985, and the M.S.E.E., M.S. degree in physics, and Ph.D. degree in electrical engineering from Louisiana State University, USA, in 1987, 1988, and 1988, respectively.

He is currently a Professor with the Department of Electrical Engineering, University of North Texas, Denton, TX, USA. He previously worked with Texas Instruments, Avant! Corporation (now Synopsys), and Cadence Design Systems. He has authored more than 140 peer reviewed publications. His research interests include analog mixed signal RF IC design, simulation, and VLSI architectures for multimedia applications.