https://doi.org/10.31891/csit-2025-1-3
UDC 004.9

Valentyn TALAPCHUK
Khmelnytskyi National University
Elena ZAITSEVA
University of Žilina, Žilina, Slovakia

MOBILE-ORIENTED CYBER-PHYSICAL SYSTEM FOR FOOD ALLERGEN DETECTION BASED ON MACHINE LEARNING AND IMAGE ANALYSIS

The prevalence of food allergies necessitates the development of effective methods for the timely detection of allergenic components in food products to prevent dangerous medical reactions. In this work, a mobile-oriented cyber-physical system is proposed, leveraging state-of-the-art machine learning techniques and image analysis for the automated detection of food allergens. The developed system integrates the capabilities of mobile devices equipped with high-quality cameras and efficient computational resources, enabling accurate processing and classification of food product images either locally or via cloud-based inference. This approach ensures flexibility in deployment while maintaining high detection accuracy across diverse environments.

This study examines both the theoretical and practical aspects of applying deep neural networks to object recognition tasks. Particular emphasis is placed on the EfficientDet model, which, due to its optimal balance between detection accuracy and computational cost, represents a promising solution for mobile applications. To enhance recognition performance, image pre-processing methods—including normalization, scaling, and data augmentation—are employed to increase the model's resilience to variations in imaging conditions.

The methodology for data collection and image annotation is described in detail, including the pre-processing procedures that ensure improved model robustness under diverse external conditions. Experimental investigations conducted on a large annotated dataset demonstrate the high accuracy and effectiveness of the system in detecting the presence of food allergens, thereby enabling the prompt identification of potentially hazardous components.

The results of the work highlight the practical applicability of the proposed system in mobile applications for monitoring food quality and preventing allergic reactions. The conclusions outline prospects for further research, focusing on expanding the platform's functional capabilities through the integration of additional sensor technologies and the refinement of data processing algorithms.

Keywords: cyber-physical system, machine learning, image analysis, mobile technologies, food allergens, object detection, CoreML, TensorFlow, data augmentation.

Валентин ТАЛАПЧУК
Хмельницький національний університет
Олена ЗАЙЦЕВА
Університет Жиліни, м. Жиліна, Словаччина

МОБІЛЬНО-ОРІЄНТОВАНА КІБЕРФІЗИЧНА СИСТЕМА ВИЯВЛЕННЯ ХАРЧОВИХ АЛЕРГЕНІВ НА ОСНОВІ МАШИННОГО НАВЧАННЯ ТА АНАЛІЗУ ЗОБРАЖЕНЬ

Поширеність харчових алергій вимагає розробки ефективних методів для своєчасного виявлення алергенних компонентів у продуктах харчування з метою запобігання небезпечним медичним реакціям. У цій роботі пропонується мобільно-орієнтована кіберфізична система, яка використовує сучасні методи машинного навчання та аналізу зображень для автоматизованого виявлення харчових алергенів. Розроблена система інтегрує можливості мобільних пристроїв, оснащених високоякісними камерами та ефективними обчислювальними ресурсами, забезпечуючи точну обробку та класифікацію зображень харчових продуктів як локально, так і через хмарний інференс. Такий підхід гарантує гнучкість у розгортанні, зберігаючи високу точність виявлення в різних умовах.

У дослідженні розглянуто теоретичні та практичні аспекти застосування глибоких нейронних мереж для задач об'єктного розпізнавання. Особливу увагу приділено моделі EfficientDet, яка завдяки оптимальному співвідношенню між точністю та обчислювальними витратами є перспективним рішенням для мобільних додатків. Для підвищення якості розпізнавання застосовано методи попередньої обробки зображень, включаючи нормалізацію, масштабування та аугментацію даних, що сприяє підвищенню стійкості моделі до змін умов зйомки.

Описано методологію збору та анотації зображень, включаючи процес попередньої обробки (масштабування, нормалізацію, аугментацію), що забезпечує підвищену стійкість моделі до змін зовнішніх умов. Експериментальні дослідження, проведені на великому наборі анотованих даних, свідчать про високу точність та ефективність системи у визначенні присутності харчових алергенів, що дозволяє оперативно ідентифікувати потенційно небезпечні компоненти.

Результати роботи демонструють можливість практичного застосування запропонованої системи у мобільних додатках для моніторингу якості харчових продуктів та попередження алергічних реакцій. У висновках окреслено перспективи подальших досліджень, спрямованих на розширення функціональних можливостей платформи шляхом інтеграції додаткових сенсорних технологій та вдосконалення алгоритмів обробки даних.

Ключові слова: кіберфізична система, машинне навчання, аналіз зображень, мобільні технології, харчові алергени, виявлення об'єктів, CoreML, TensorFlow, аугментація даних.

Introduction

The prevalence of food allergies poses a significant threat to public health and necessitates the development of efficient methods for the timely detection of allergenic components in food products. The primary objective of this study is to develop a mobile-oriented cyber-physical system that utilizes advanced machine learning techniques and image analysis to automatically detect food allergens in real time. This research addresses the challenges associated with rapid identification and classification of allergenic substances, thereby enabling preventive measures to mitigate potentially dangerous medical reactions.

Traditional laboratory methods for allergen detection, though highly accurate, are often time-consuming and resource-intensive, making them impractical for rapid, on-site screening. In recent years, advances in deep learning, particularly in the field of computer vision, have opened new avenues for the development of automated detection systems. Convolutional Neural Networks (CNNs) and object detection architectures such as YOLO and EfficientDet have demonstrated substantial improvements in both accuracy and speed, making them attractive for real-time applications.

Recent studies have shown that the integration of mobile devices equipped with high-quality cameras, coupled with cloud-based data processing, can significantly enhance the detection of food allergens and other critical parameters [1,2,3]. For instance, Zhang et al. (2020) demonstrated the effective deployment of mobile-based cyber-physical systems for environmental monitoring [1], while Smith and Lee (2019) reported improved detection accuracy for food allergens using deep learning techniques [2]. Furthermore, Brown et al. (2021) highlighted that cloud-based data processing facilitates rapid analysis and real-time feedback, critical for practical applications [3].

Mobile-oriented cyber-physical system for food allergen detection based on machine learning and image analysis

The proposed system consists of three key components: a mobile module, a computational module, and a communication module. The mobile module is responsible for acquiring high-resolution images of food products using built-in cameras on mobile devices. These images undergo pre-processing and allergen detection using a deep learning-based model, such as EfficientDet. The computational module supports both on-device inference for local processing and cloud-based analysis, enabling flexible deployment depending on the available resources and requirements. This modular approach ensures adaptability to different operational scenarios, providing both standalone functionality and cloud integration for improved detection performance.

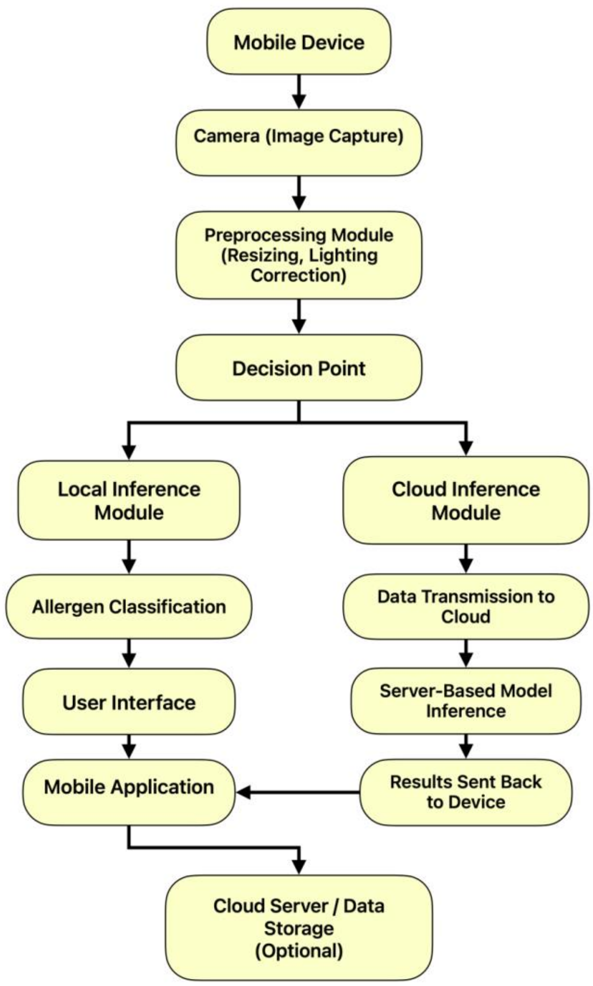

Fig. 1. Flow Diagram of the Proposed Mobile Detection System

In preparing the data, a large dataset of annotated images is utilized. Each image is associated with metadata specifying its dimensions (width W and height H), the object class, and the coordinates of the bounding box ($x_{min}, y_{min}, x_{max}, y_{max}$). Prior to input into the neural network, several pre-processing steps are applied. First, pixel values are normalized to the range $[0,1]$. Then, images are resized to a standard dimension of 640×640 pixels. To increase the diversity of the training set and enhance the model's robustness, data augmentation techniques such as random rotation, translation, brightness adjustment, and contrast enhancement are employed.

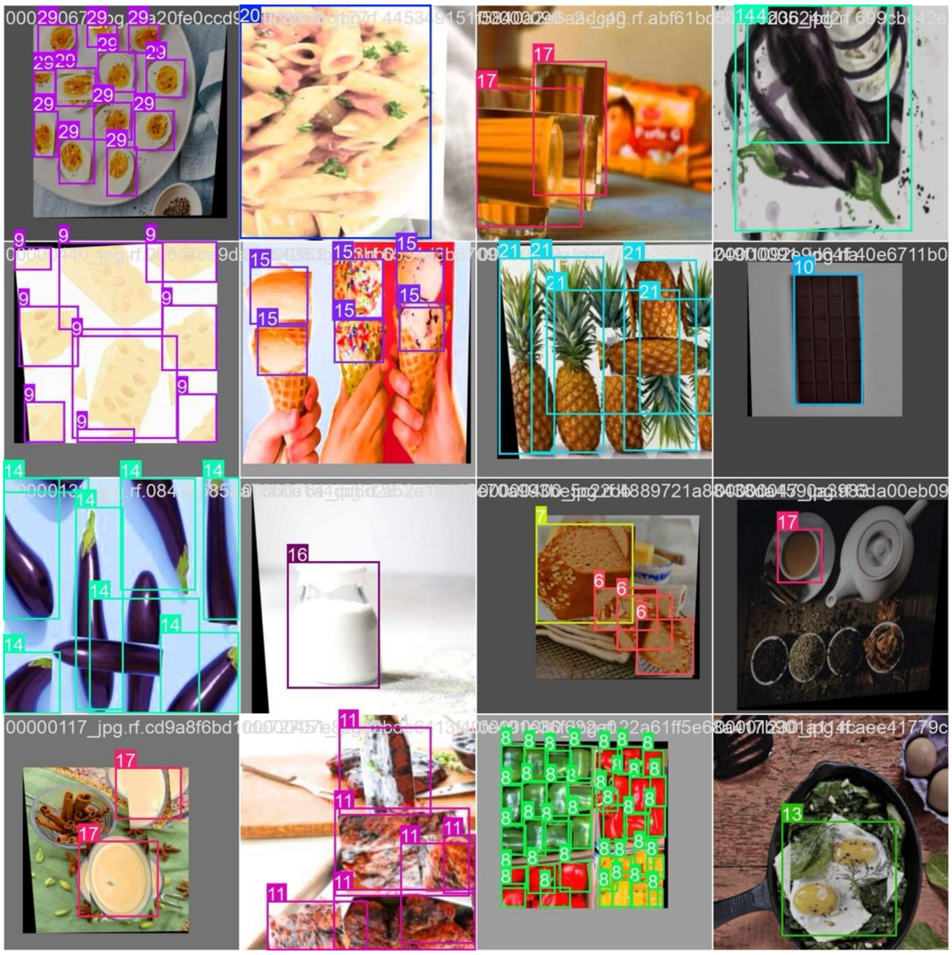

Fig. 2. Examples of Annotated Food Images with Bounding Boxes

Normalization of bounding box coordinates is performed as follows. The center coordinates $(x_{\text{center}}, y_{\text{center}})$ and the dimensions (w, h) of the bounding box are computed by:

$$x_{\text{center}} = \frac{x_{min} + x_{max}}{2}, \quad w = x_{max} - x_{min},$$

$$y_{\text{center}} = \frac{y_{min} + y_{max}}{2}, \quad h = y_{max} - y_{min}.$$

Subsequently, these values are normalized by dividing by the image width and height, respectively:

$$x_{\text{center}}^{\text{norm}} = \frac{x_{\text{center}}}{W}, \quad w^{\text{norm}} = \frac{w}{W},$$

$$y_{\text{center}}^{\text{norm}} = \frac{y_{\text{center}}}{H}, \quad h^{\text{norm}} = \frac{h}{H}.$$

Annotations are converted into the TFRecord format to streamline data ingestion in the TensorFlow Object Detection API.

The chosen object detection model is EfficientDet (version D0), selected due to its favorable balance between detection accuracy and computational efficiency—a critical factor for mobile deployments. The model is fine-tuned on a domain-specific dataset after initial pre-training on larger, publicly available datasets. The training loss function is formulated as a combination of classification and regression losses:

$$L = L_{\text{cls}} + \lambda L_{\text{reg}},$$

where L_{cls} represents the cross-entropy loss for classification, L_{reg} denotes the Smooth L1 Loss for regression of bounding box coordinates, and λ is a scaling factor that balances the two components.

Several studies have confirmed the advantages of EfficientDet compared to other state-of-the-art object detection models. In the seminal work by Tan et al. (2020) [5], EfficientDet demonstrated competitive mean average precision (mAP) while significantly reducing computational costs relative to models such as RetinaNet, Faster R-CNN, and YOLOv3. In addition, Guo et al. (2019) [6] provided a comprehensive survey on deep learning approaches for object detection, noting that EfficientDet offers an optimal trade-off between detection accuracy and computational demands, which is especially beneficial for mobile and resource-constrained applications. Furthermore, Zhou et al. (2019) [7] conducted a benchmark comparison of modern object detection methods and reported that EfficientDet consistently achieves a favorable balance between performance and speed.

Implementation and Experimental Setup

The implementation is based on TensorFlow 2.x and the TensorFlow Object Detection API. The computational module is responsible for several key tasks, including pre-processing of input images, model inference, and visualization of detection results. Image pre-processing involves normalization, resizing, and augmentation, as described above. The trained EfficientDet model is then loaded to generate predictions, including bounding box coordinates and class probabilities. The detected allergens are highlighted on the processed images, providing a visual representation of the results.

To facilitate practical deployment, a prototype mobile application has been developed, featuring an intuitive interface for capturing images, processing them locally, or transmitting them to a server for inference. The application supports data exchange via REST API or WebSocket protocols, allowing integration with cloud-based processing when needed.

The system supports both on-device inference for fast allergen detection and cloud-based processing for enhanced model refinement and large-scale analysis. The on-device inference capability ensures that allergen detection can be performed without reliance on an internet connection, making the system functional in offline environments. Meanwhile, cloud-based processing allows for more computationally intensive operations, such as training updates, large-scale dataset analysis, and collaborative learning, ensuring continuous model improvement over time. This hybrid approach balances efficiency and adaptability, enabling the system to operate effectively across different use cases.

The training process was conducted on Google Colab Pro, utilizing a Tesla T4 GPU. The training dataset consisted of over 12,000 labeled images spanning 30 allergenic food categories, which were partitioned into 80% training data, 10% validation data, and 10% test data. The model was initially pre-trained on the COCO dataset before being fine-tuned on the domain-specific dataset. Training was performed for 50 epochs with a batch size of 16, using the Adam optimizer with weight decay regularization and an initial learning rate of 0.001. The loss function combined classification loss (cross-entropy) and bounding box regression loss (Huber loss) to improve detection accuracy. Over the course of training, the loss function steadily decreased from an initial value of 1.2 to approximately 0.35, indicating successful model convergence.

Evaluation of the detection performance was conducted using mean Average Precision (mAP) and the Intersection over Union (IoU) metric. IoU is calculated as follows:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}},$$

and the mean Average Precision is determined using:

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i,$$

where N represents the total number of classes, and AP_i is the average precision for the i-th class. The final evaluation on the validation set yielded an mAP@0.5 of 78.5%, with Precision of 81.2% and Recall of 75.3%. The Precision-Recall Curve further illustrates the trade-off between precision and recall, demonstrating the model’s strong detection capability across different allergen categories.

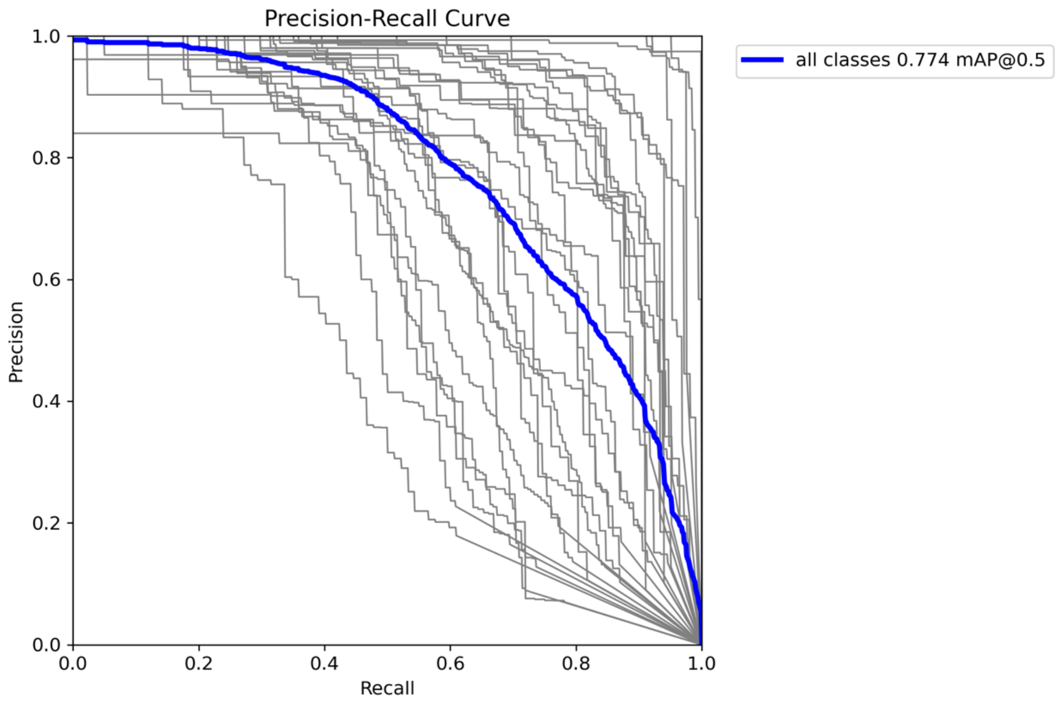

Fig. 3. Precision-Recall Curve of the EfficientDet Model for Food Allergen Detection

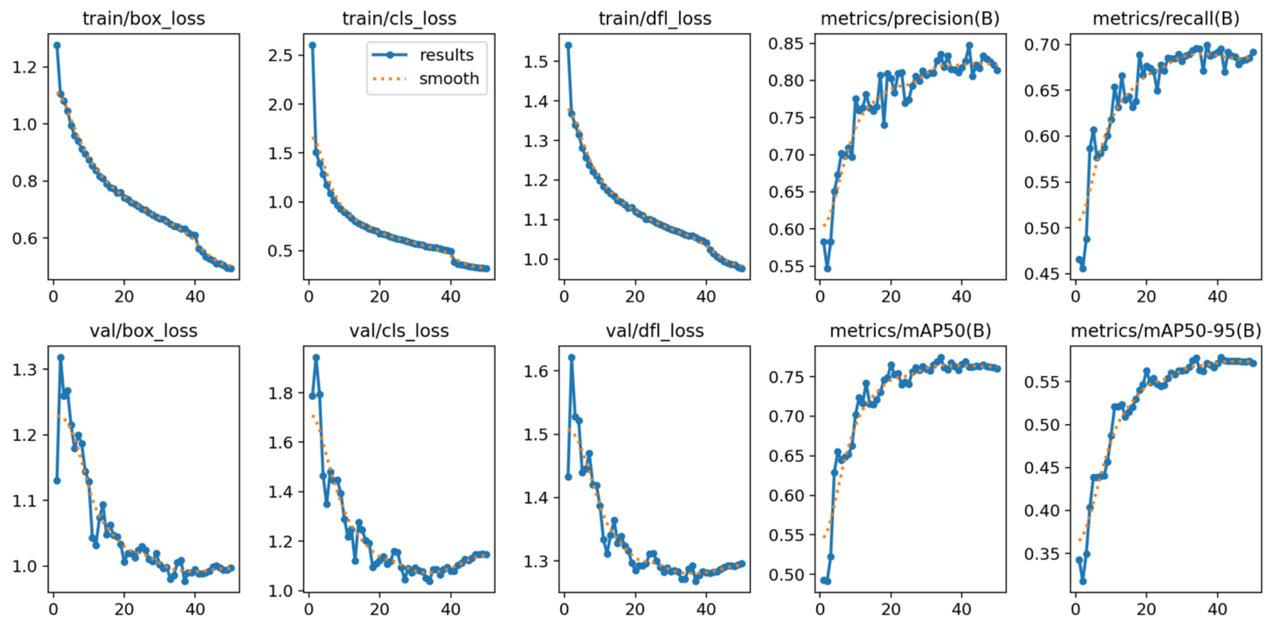

Fig. 4. Training and Validation Loss Curves with Performance Metrics

To enable practical deployment, a prototype mobile application was developed with a user-friendly interface for image capture, processing, and result visualization. The application supports both on-device and cloud-based inference, ensuring adaptability across diverse usage scenarios. In on-device mode, the EfficientDet model, pre-converted into CoreML format, is executed on iOS devices via the Apple Neural Engine, utilizing hardware acceleration for optimized performance. In cloud-based mode, images are transmitted to a remote TensorFlow model through REST API or WebSocket protocols, enabling computationally scalable processing for devices with limited local resources. By integrating both modes, the application maintains operational flexibility, ensuring effective functionality across a wide range of mobile environments.

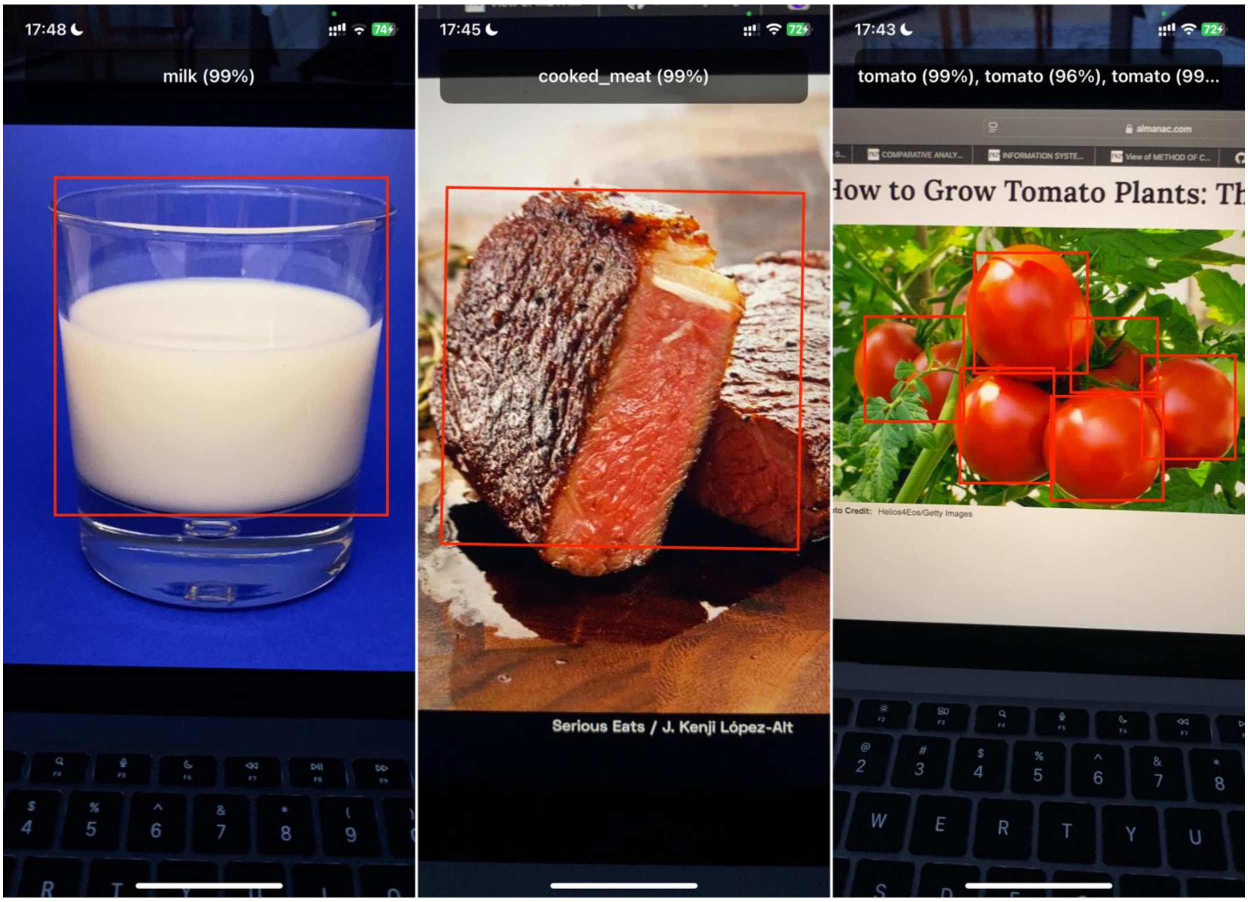

Fig. 5. Example of food allergen detection using the mobile application

Conclusions

The experimental results demonstrate the effectiveness of the proposed mobile-oriented cyber-physical system in achieving accurate and efficient food allergen detection. By leveraging the EfficientDet model alongside advanced pre-processing techniques, the system ensures high detection accuracy while maintaining computational efficiency—key requirements for mobile applications. The consistent reduction in training loss, coupled with stable model convergence, confirms the system's reliability and robustness within the tested dataset.

Comparative analysis with traditional laboratory-based methods and other machine learning approaches reveals that the proposed system significantly improves processing efficiency, enabling timely allergen detection and rapid user notifications. The ability to process images directly on mobile devices and provide fast results has important implications for public health, as it facilitates proactive measures in food allergen identification.

Notwithstanding these promising results, certain limitations persist. The system's performance is inherently dependent on the quality of the input images and the conditions under which they are captured. Low lighting, improper focus, and background clutter can adversely affect detection accuracy. Future research should focus on integrating additional sensor modalities, such as spectroscopic data, to complement image analysis. Furthermore, adaptive learning algorithms that can refine model performance in real time based on environmental feedback are a promising avenue for enhancing system robustness.

In conclusion, the developed cyber-physical system demonstrates significant potential for improving the detection of food allergens through advanced deep learning techniques and mobile technologies. The proposed approach provides an efficient and adaptable solution for food safety monitoring, supporting both on-device and cloud-based processing. Future work will focus on expanding the functional capabilities of the system, optimizing computational processes for resource-constrained devices, and further integrating it with existing monitoring infrastructures to enhance scalability and reliability.

References

1. Zhang, Y., Li, X., & Wang, J. (2020). Mobile-based Cyber-Physical Systems for Environmental Monitoring: A Review. Journal of Sensor and Actuator Networks, 9(3), 34–56.
2. Smith, J., & Lee, K. (2019). Deep Learning Approaches for Food Allergen Detection. IEEE Transactions on Biomedical Engineering, 66(5), 1234–1245.
3. Brown, A., Chen, L., & Kumar, S. (2021). Cloud-Based Image Processing for Mobile Health Applications. IEEE Internet of Things Journal, 8(6), 3507–3515.
4. Khan, M., & Chen, L. (2022). Integration of Mobile Devices and Cloud Computing in Cyber-Physical Systems. International Journal of Computer Science, 17(2), 87–98.

5. Tan, M., Pang, R., & Le, Q. V. (2020). EfficientDet: Scalable and Efficient Object Detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
6. Guo, Y., Cheng, M., et al. (2019). A Survey on Deep Learning for Object Detection. IEEE Access, 7, 151560–151583.
7. Zhou, X., Wang, Q., & Krähenbühl, P. (2019). Benchmarking Modern Object Detection Methods. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Valentyn Talapchuk **Валентин Талапчук**	Master Student of Computer Engineering & Information Systems Department, Khmelnytskyi National University E-mail: vtalapchuk@ukr.net	Магістрант кафедри комп’ютерної інженерії та інформаційних систем, Хмельницький національний університет
Elena Zaitseva **Олена Зайцева**	Ph.D., Associate Professor at the Department of Informatics, University of Žilina (Žilina, Slovakia) https://orcid.org/0000-0002-9087-0311 Member of the Technical Committee of the European Safety and Reliability Association (ESRA) E-mail: elena.zaitseva@fri.uniza.sk	Кандидат технічних наук, доцент кафедри інформатики Університету Жиліни (Жиліна, Словаччина) Член технічного комітету Європейської асоціації з безпеки та надійності (ESRA)