GOCE DELCEV UNIVERSITY - STIP
FACULTY OF COMPUTER SCIENCE

The journal is indexed in
EBSCO

ISSN 2545-4803 on line
DOI: 10.46763/BJAMI

BALKAN JOURNAL OF APPLIED MATHEMATICS AND INFORMATICS (BJAMI)

BALKAN JOURNAL
OF APPLIED MATHEMATICS AND INFORMATICS

YEAR 2025

VOLUME VIII, Number 1

AIMS AND SCOPE:
BJAMI publishes original research articles in the areas of applied mathematics and informatics.

Topics:
1. Computer science;
2. Computer and software engineering;
3. Information technology;
4. Computer security;
5. Electrical engineering;
6. Telecommunication;
7. Mathematics and its applications;
8. Articles of interdisciplinary of computer and information sciences with education, economics, environmental, health, and engineering.

BALKAN JOURNAL
OF APPLIED MATHEMATICS AND INFORMATICS
(BJAMI), Vol 8

ISSN 2545-4803 online
Vol. 8, No. 1, Year 2025

EDITORIAL BOARD

C O N T E N T

Balkan Journal of Applied Mathematics and Informatics
Volume VIII Number 1 Year 2025
Online ISSN 2545-4803
UDC: 004.85:004.932'1]:692.8-021.341/.342

AUTOMATED DOOR STATE DETECTION USING DEEP LEARNING: A COMPUTER VISION APPROACH WITH ROBOFLOW PLATFORM

ELENA JOVANOVSKA, MARJAN KOTEVSKI, BLAGOJ KOTEVSKI, SASO KOCESKI

Abstract. This study presents a deep learning-based approach for automated door state detection, capable of classifying doors as open, closed, or semi-open. The implementation leverages the Roboflow platform for comprehensive image processing and model development workflow. Our methodology encompasses data collection, annotation, augmentation, and model training using state-of-the-art deep learning architectures. The system demonstrates robust performance in real-world scenarios, offering potential applications in building automation, security systems, and smart home technologies. This work contributes to the growing field of automated building monitoring by providing a practical solution for door state recognition that can be integrated into existing surveillance and security infrastructures.

1. Introduction

The automation and monitoring of building elements have become increasingly important in modern infrastructure management, with doors being critical components that influence security, energy efficiency, and occupant comfort. Accurate and automated detection of door states (open, closed, and semi-open) present a significant challenge in computer vision and has various practical applications, from security surveillance to smart building management.

Traditional approaches to door state monitoring often rely on physical sensors, which require installation on each door and regular maintenance. These methods can be costly to implement at scale and may suffer from reliability issues over time. Recent developments in artificial intelligence have significantly influenced and reshaped numerous areas of society, including tourism [1], healthcare [2–4], biology [5], education [6–7], robotics [8–12], and the economy [13]. Computer vision-based solutions, particularly those utilizing deep learning, offer a promising alternative by leveraging existing camera infrastructure or integrated cameras on various mobile robots to monitor multiple doors simultaneously without additional hardware installations.

The significance of door state detection extends far beyond simple monitoring, encompassing crucial applications across multiple domains. In smart home environments, accurate door state detection forms a fundamental component of home automation systems, enabling intelligent climate control by preventing energy waste from doors left open, and facilitating automated lighting control based on room accessibility. These capabilities directly contribute to energy efficiency and resident comfort while potentially reducing utility costs.

In the context of security systems, door state monitoring plays a vital role in maintaining building safety. Commercial buildings, secure facilities and residential complexes can benefit from real-time alerts when doors are left open or accessed during unauthorized hours. This capability becomes particularly crucial in high-security areas where maintaining access control is paramount, such as data centers, research facilities, or restricted areas in healthcare institutions.

The healthcare sector, particularly in elderly care facilities, represents another crucial application domain for door state detection systems. These systems can help monitor patient movement, prevent wandering in dementia care units, and ensure that residents are safe while maintaining their independence. The ability to automatically detect if a patient's room door is open or closed can assist healthcare providers in monitoring patient activity patterns and responding quickly to potential safety concerns.

In industrial settings, door state detection contributes to workplace safety and efficiency. Manufacturing facilities can use this technology to ensure that sensitive areas remain properly sealed, maintaining clean room conditions or preventing contamination in food processing facilities. Additionally, loading dock doors can be monitored to optimize logistics operations and maintain appropriate environmental conditions within storage facilities.

Recent advances in deep learning architecture, coupled with the availability of sophisticated development platforms like Roboflow [14], have made it possible to create more accurate and robust door state detection systems. These platforms provide comprehensive tools for data preprocessing, augmentation and model training, streamlining the development process and improving model performance.

This paper presents a novel approach to door state detection using deep learning, implemented through the Roboflow platform. Our solution transcends traditional methods by offering a comprehensive end-to-end system that effectively handles the complexities of real-world door monitoring. Through the integration of advanced preprocessing techniques and the powerful YOLOv11 architecture [15], our system achieves robust detection across varying environmental conditions and door types. The Roboflow platform enables rapid model development and deployment, while our custom-designed data augmentation pipeline ensures the system's resilience to different lighting conditions, viewing angles, and door designs. This approach not only simplifies the implementation process but also delivers superior accuracy in distinguishing between different door states, making it particularly valuable for applications in building automation, security systems, and smart infrastructure monitoring.

The remainder of this paper is organized as follows: Section 2 reviews related work indoor state detection and deep learning applications in building automation. Section 3 describes our methodology, including data collection, preprocessing and model architecture. Section 4 presents our experimental results and performance analysis. Section 5 discusses the implications of our findings and potential applications. Finally, Section 6 concludes the paper and suggests directions for future research.

2. **Related work**

The development of door state detection systems has evolved significantly over the past decade, with approaches ranging from sensor-based solutions to advanced computer vision techniques. This section reviews relevant literature across several key areas:

traditional detection methods, deep learning approaches, and applications in smart environments.

Early approaches to door state detection primarily relied on hardware sensors. In [16], the authors presented a comprehensive review of door monitoring systems, comparing various sensor types including magnetic switches, infrared sensors, and accelerometers. Their findings highlighted the limitations of hardware-based approaches, particularly in terms of installation costs and maintenance requirements.

Chen and Birchfield [17] proposed one of the early vision-based approaches using traditional image processing techniques, employing edge detection and geometric feature extraction to identify door states. Their method achieved reasonable accuracy but struggled with varying lighting conditions and complex backgrounds.

The advent of deep learning has revolutionized door state detection capabilities. Zhang et al. [18] introduced a DSPP-YOLO (DenseNet SPP) algorithm. The algorithm is based on YOLO v3 model. Their work demonstrated the detection accuracy of 77.4% for doors.

Authors in [19] developed a door recognition and deep learning algorithm for visual based robot navigation. They used convolutional neural network (CNN) to identify the position of the doors and facilitate the navigation of mobile robots.

A real-time deep learning-based door detection model was introduced in [20], utilizing a pre-trained MobileNet-SSD through transfer learning. The computational approach operates on a portable device and employs a miniaturized camera. In real-time testing with the wearable device, the developed model showed to be temporally efficient for context-awareness recognition of patients with Parkinson's disease.

Recent research has focused on optimizing deep learning models for real-time processing on edge devices. In [21] a novel approach to implementing a deep learning neural network-based door open and close monitoring system using an STM32 microcontroller. Experimental results confirm the system's robustness, accuracy, and suitability for low-power embedded applications in a variety of real-world scenarios.

The emergence of platforms like Roboflow has also influenced recent research directions. In [22] the authors demonstrated how automated data augmentation and model optimization techniques could improve door state detection accuracy compared to manually tuned approaches.

Despite significant advances in deep learning-based door state detection, several important challenges persist in the field. Current systems still struggle with reliability under extreme lighting variations, particularly in scenarios involving strong backlighting or near-darkness conditions. Detecting accuracy is often compromised when dealing with reflective or glass doors, which create complex visual patterns that can confuse the existing models. Real-time performance remains another crucial challenge, especially when systems need to simultaneously monitor multiple doors across large facilities while maintaining high accuracy. Furthermore, the existing approaches often require substantial computational resources for deployment, limiting their practical implementation in edge devices and simpler monitoring systems. These challenges highlight the need for more robust, efficient, and adaptable door state detection solutions that can perform reliably across diverse real-world scenarios. Our work aims to address these gaps while building upon the successful approaches documented in the literature.

3. Door detection and state classification workflow

The workflow for developing and training a door detection and state classification model is illustrated in Figure 1.

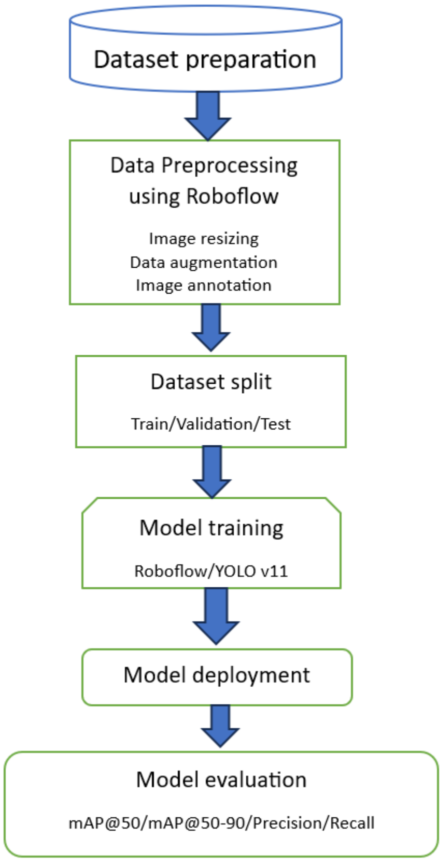

Figure 1. Door detection and state classification workflow based on YOLOv11 and Roboflow

It begins with an extensive data collection phase. This initial step involves gathering a diverse set of images depicting doors in various states (e.g., open, closed, partially open), environments, lighting conditions, and orientations. All the images were uploaded to the Roboflow platform. The platform supports common image formats such as JPG and PNG, ensuring compatibility with various data sources. To ensure robust model training, a dataset composed of 1515 images was constructed. The images in the dataset were balanced among the three classes (Figure 2). The images in the dataset were with different sizes and aspect ratios (Figure 3).

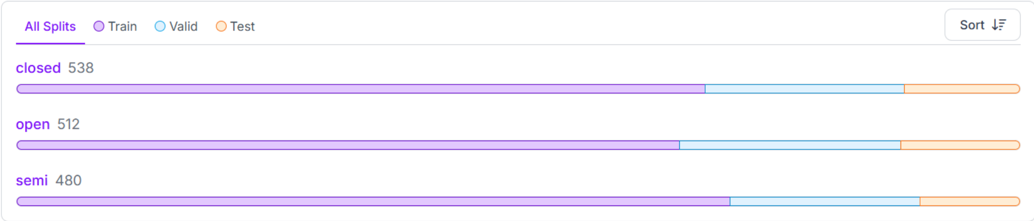

Figure 2. Overview of the number of annotations for each class in the dataset

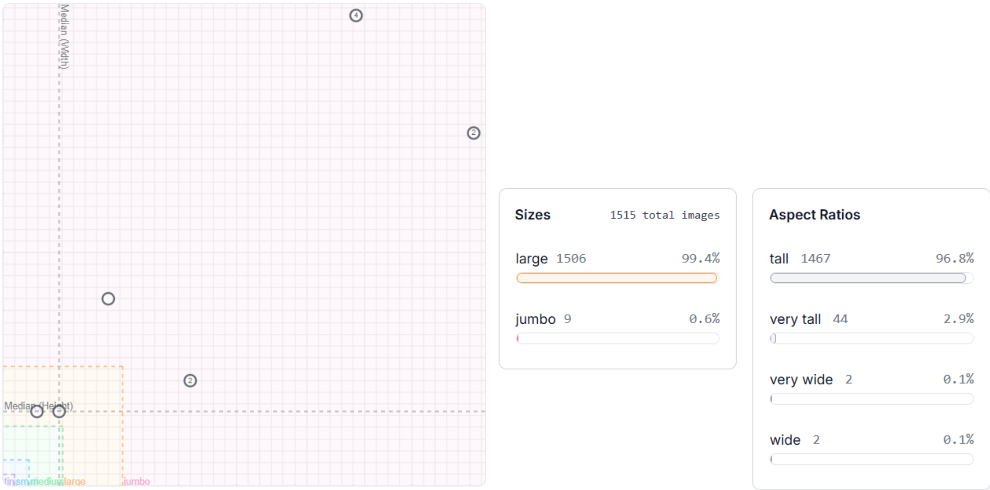

Figure 3. Overview of the sizes and aspect ratios of the images in the dataset

Following the upload phase, image preprocessing is performed. All images are resized to 640x640 pixels to meet the input requirements of YOLOv11. The platform automatically corrects image orientation and normalizes pixel values to ensure consistent input quality. During this stage, any corrupted images are identified and addressed to maintain dataset integrity. The annotation process is a critical step in the workflow. Using Roboflow's annotation tool, each image is meticulously labeled with bounding boxes for distinct door states, such as fully open, fully closed, and partially open. Consistency in annotation style and accuracy is maintained across the entire dataset to ensure reliable model training.

After annotation, the dataset is divided into three subsets: training (70% of the data), validation (20%), and testing (10%). This split ensures ample data for training while retaining independent sets for validation and final performance evaluation.

Data augmentation techniques are then applied to enhance the model's robustness. These techniques include rotating images within a ±15-degree range, adjusting brightness by ±20%, adding random noise, and applying slight blur effects of 0.5 pixels. These augmentations effectively triple the dataset size and help the model generalize better to various real-world conditions. After the augmentation process, the number of images in the dataset increased to 3607 images.

The training phase employs the YOLOv11 architecture with carefully tuned hyperparameters. The model is trained using a batch size of 64 over 120 epochs. Early stopping with a patience of 10 epochs is implemented to prevent overfitting. Model checkpoints are saved throughout training to preserve the best-performing iterations.

Model evaluation is conducted using key metrics such as mean Average Precision (mAP), precision, and recall. These metrics provide a comprehensive understanding of the model's detection and classification capabilities across all door states. A confusion matrix analysis is also performed to identify specific areas where the model may struggle with certain door states.

If the evaluation reveals suboptimal performance, the workflow enters an iteration phase. This may involve adjusting hyperparameters, expanding the training dataset, modifying augmentation strategies, or reviewing annotation quality. Once the model achieves satisfactory performance across all metrics, it proceeds to the deployment phase.

The final deployment phase involves exporting the model in the required format, setting up API endpoints for inference, and implementing the necessary pipeline for production use. This ensures the model is ready for real-world applications, such as monitoring door states in security systems or automated access control.

4. **Experimental evaluation**

YOLOv11 represents the latest advancement in the YOLO (You Only Look Once) series, a state-of-the-art architecture (Figure 4) designed for real-time object detection in computer vision.

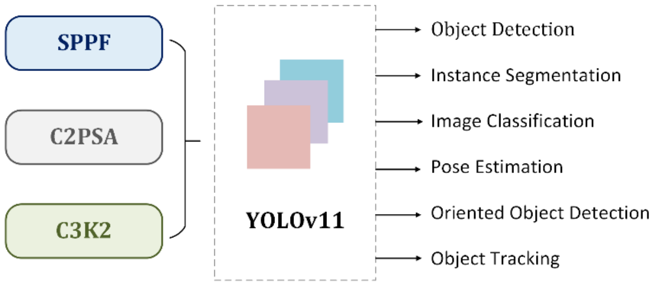

Figure 4. Key architectural modules in YOLO11[15].

Building on the strengths of its predecessors, YOLOv11 introduces several innovative features to improve detection accuracy, speed, and computational efficiency. At its core, YOLOv11 processes entire images in a single forward pass through a neural network, enabling it to predict bounding boxes and class probabilities simultaneously. This approach eliminates the need for multi-stage processing, making it significantly faster than traditional object detection methods while maintaining high precision.

One of the key enhancements in YOLOv11 is the introduction of the C3K2 block, which replaces the earlier Cross Stage Partial (CSP) mechanism. The C3K2 block optimizes information flow within the network by dividing feature maps and applying a sequence of 3x3 convolutions. This design reduces computational complexity and improves feature representation, resulting in faster inference times and lower parameter counts compared to previous versions like YOLOv8.

YOLOv11 also retains the Spatial Pyramid Pooling Fast (SPFF) module, which aggregates multi-scale features from different regions of an image. This allows the model to detect objects of varying sizes more effectively. Additionally, YOLOv11 incorporates the Cross Stage Partial with Spatial Attention (C2PSA) block, a novel component that leverages attention mechanisms to focus on critical areas within an image. This is particularly useful for detecting small or partially obscured objects, enhancing the model's robustness in complex scenarios.

The architecture is designed to handle real-time applications with high efficiency, making it suitable for tasks such as surveillance, autonomous driving, and industrial automation. YOLOv11 achieves this by balancing speed and accuracy, ensuring reliable performance even in environments with limited computational resources. Its ability to process images quickly and accurately makes it a powerful tool for modern computer vision challenges.

The model was trained with a batch size of 64 over 120 epochs. After training the model on the curated dataset, its performance was assessed using the Roboflow platform. The real-time detection engine was tested on custom images, with some results illustrated in Figure 5.

Figure 5. Real-time detection of doors in a sample image.

5. Results and discussion

The training and validation metrics are illustrated in Figure 6. The training graphs reveal consistent improvement across key performance indicators. Both the box loss and classification loss curves show a steady decrease for both training and validation, reflecting enhanced accuracy in bounding box localization and object classification.

Likewise, the focal loss distribution indicates continuous refinement in predicting box boundaries.

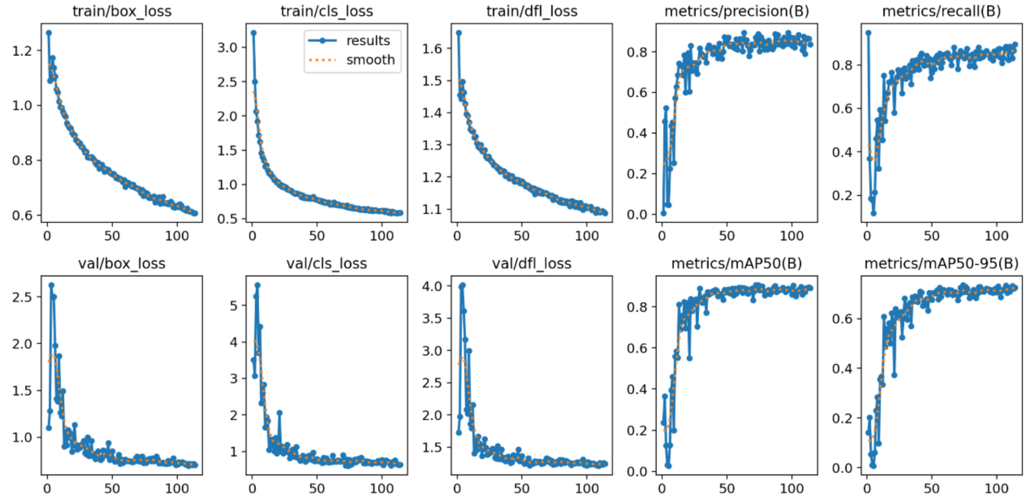

Figure 6. Training and validation performance graphs.

After training, the model achieved the following evaluation metrics: mAP: 90.6%, Precision: 88.8%, and Recall: 84.1%. The gradual increase in precision and recall highlights a reduction in false positives and a higher rate of correctly detected objects. Furthermore, the mAP50 and mAP50-95 values demonstrate consistent improvement, emphasizing the model's strong performance even under rigorous evaluation standards. These trends suggest effective learning without overfitting, achieving a balanced performance between training and validation, as shown in Figure 7.

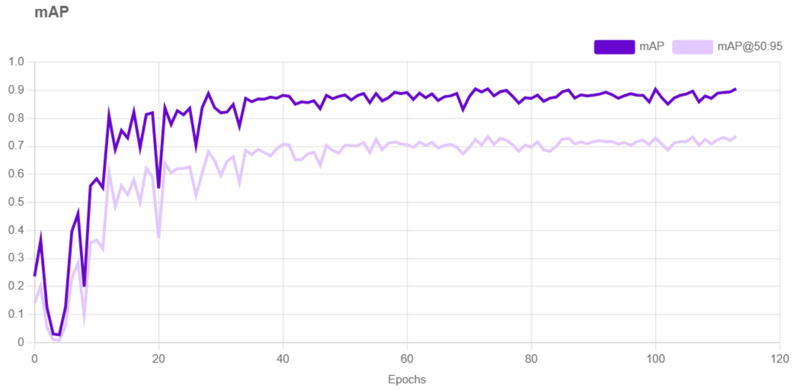

Figure 7. Training and validation performance graphs.

6. **Conclusion**

In this paper, we have presented a robust and efficient deep learning-based solution for door state detection, addressing a critical need in modern infrastructure management. By leveraging the YOLOv11 architecture and the comprehensive capabilities of the Roboflow platform, our approach overcomes the limitations of traditional sensor-based methods, offering a scalable, cost-effective, and maintenance-free alternative for monitoring door states in real-time. The system demonstrates exceptional accuracy in distinguishing between open, closed, and semi-open-door states, even under varying environmental conditions and door designs.

Future research directions could explore the integration of additional contextual information, such as time of day or occupancy patterns, to further enhance the system's capabilities. Additionally, extending the model to detect other building elements or integrating it with IoT platforms could unlock new possibilities for comprehensive smart infrastructure management. As deep learning technologies continue to evolve, we anticipate further improvements in accuracy, efficiency, and adaptability, paving the way for even more innovative applications in the field of automated building monitoring.

References

[1] Koceski, S. and Petrevska, B., 2012. Empirical evidence of contribution to e-tourism by application of personalized tourism recommendation system. Scientific Annals of the "Alexandru Ioan Cuza" University of Iasi–Economic Sciences Section, (1), pp.371-383.

[2] Trajkovik, V., Vlahu-Gjorgievska, E., Koceski, S. and Kulev, I., 2015. General assisted living system architecture model. In Mobile Networks and Management: 6th International Conference, MONAMI 2014, Würzburg, Germany, September 22-26, 2014, Revised Selected Papers 6 (pp. 329-343). Springer International Publishing.

[3] Stojanov, D. and Koceski, S., 2014, September. Topological MRI prostate segmentation method. In 2014 Federated Conference on Computer Science and Information Systems (pp. 219-225). IEEE.

[4] Koceska, N., Komadina, R., Simjanoska, M., Koteska, B., Strahovnik, A., Jošt, A., ... & Trontelj, J. (2020). Mobile wireless monitoring system for prehospital emergency care. European Journal of Trauma and Emergency Surgery, 46, 1301-1308.

[5] Stojanov, D., Mileva, A. and Koceski, S., 2012. A new, space-efficient local pairwise alignment methodology. Advanced Studies in Biology, 4(2), pp.85-93.

[6] Koceski, S., Koceska, N., Lazarova, L. K., Miteva, M., & Zlatanovska, B. (2025). Exploring the performance of ChatGPT for numerical solution of ordinary differential equations. Journal of Technology and Science Education, 15(1), 18-34.

[7] Velinov, A., Koceska, N., & Koceski, S. (2024). Virtual Tour Using Telepresence Robot and MQTT Protocol. TEM Journal, 13(1), 750-756.

[8] Koceski, S., Koceska, N. and Kocev, I., 2012. Design and evaluation of cell phone pointing interface for robot control. International Journal of Advanced Robotic Systems, 9(4), p.135.

[9] Koceski, S., Panov, S., Koceska, N., Zobel, P.B. and Durante, F., 2014. A novel quad harmony search algorithm for grid-based path finding. International Journal of Advanced Robotic Systems, 11(9), p.144.

[10] Koceska, N., Koceski, S., Durante, F., Zobel, P.B. and Raparelli, T., 2013. Control architecture of a 10 DOF lower limbs exoskeleton for gait rehabilitation. International Journal of Advanced Robotic Systems, 10(1), p.68.

[11] Koceska, N., & Koceski, S. (2022). Supporting elderly's independent living with a mobile robot platform. The Journal of Universal Computer Science-JUCS, 28(5), 475-498.

[12] Koceska, N., Koceski, S., Beomonte Zobel, P., Trajkovik, V., & Garcia, N. (2019). A telemedicine robot system for assisted and independent living. Sensors, 19(4), 834.

[13] Koceska, N. and Koceski, S., 2014. Financial-Economic Time Series Modeling and Prediction Techniques–Review. Journal of Applied Economics and Business, 2(4), pp.28-33.

[14] Dwyer, B., Nelson, J., Hansen, T., et. al. (2024). Roboflow (Version 1.0) [Software]. Available from https://roboflow.com. computer vision.

[15] Khanam, R., & Hussain, M. (2024). Yolov11: An overview of the key architectural enhancements. arXiv preprint arXiv:2410.17725.

[16] De Geyter, S., Bassier, M., De Winter, H., & Vergauwen, M. (2022, January). Review of Window and Door Type Detection Approaches. In *7TH INTERNATIONAL WORKSHOP LOWCOST 3D-SENSORS, ALGORITHMS, APPLICATIONS* (Vol. 48, No. W1, pp. 65-72). Copernicus Publications.

[17] Chen, Z., & Birchfield, S. T. (2008, June). Visual detection of lintel-occluded doors from a single image. In *2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops* (pp. 1-8). IEEE.

[18] Zhang, T., Li, J., Jiang, Y., Zeng, M., & Pang, M. (2022). Position detection of doors and windows based on dspp-yolo. *Applied Sciences*, *12*(21), 10770.

[19] Chen, W., Qu, T., Zhou, Y., Weng, K., Wang, G., & Fu, G. (2014, December). Door recognition and deep learning algorithm for visual based robot navigation. In *2014 ieee international conference on robotics and biomimetics (robio 2014)* (pp. 1793-1798). IEEE.

[20] Gonçalves, H. R., & Santos, C. P. (2023). Deep learning model for doors detection: A contribution for context-awareness recognition of patients with Parkinson's disease. *Expert Systems with Applications*, *212*, 118712.

[21] Devaki, M. (2024). A Deep Learning Approach to Door Open and Close Monitoring Systems. *Journal of Microprocessor and Microcontroller Research*, 13-20.

[22] Rebuffi, S. A., Gowal, S., Calian, D. A., Stimberg, F., Wiles, O., & Mann, T. A. (2021). Data augmentation can improve robustness. *Advances in neural information processing systems*, *34*, 29935-29948.

Elena Jovanovska
Goce Delcev University,
Faculty of Computer Science
Stip, North Macedonia
E-mail address: elena.210224@student.ugd.edu.mk

Marjan Kotevski
Goce Delcev University,
Faculty of Computer Science
Stip, North Macedonia
E-mail address: marjan.210223@student.ugd.edu.mk

Blagoj Kotevski
Goce Delcev University,
Faculty of Computer Science
Stip, North Macedonia
E-mail address: blagoj.210209@student.ugd.edu.mk

Saso Koceski
Goce Delcev University,
Faculty of Computer Science
Stip, North Macedonia
E-mail address: saso.koceski@ugd.edu.mk