Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Machine Learning-Driven Cost Prediction in Intermodal Logistics: A Case Study of Porto Romano

Eli Vyshka[1], Viola Bakiasi (Shtino)[2]
[1] *Faculty of Professional Studies, Department of Engineering and Marine Sciences, University 'Aleksander Moisiu', Durres, Albania*
[2] *Faculty of Information Technology, Department of Computer Science, University 'Aleksander Moisiu', Durres, Albania*
Email: elivyshka@uamd.edu.al, violashtino@uamd.edu.al
[1] https://orcid.org/0000-0002-8728-1057 , [2] https://orcid.org/0009-0003-5441-7717

ARTICLE INFO

Received: 24 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

As global supply chains continue to expand in complexity and scale, the integration of intelligent, data-driven solutions within logistics operations becomes increasingly essential. Ports are evolving from traditional gateways into dynamic, technology-enabled hubs that demand advanced predictive capabilities and operational flexibility. With Porto Romano poised to become a major logistics and energy platform for Albania, the early adoption of machine learning (ML) tools is a strategic advantage. This study explores the application of two widely recognized ML algorithms- Random Forest Regression and Support Vector Machine (SVM) Regression- to estimate intermodal transport costs based on critical factors such as distance, travel time, cargo weight, and transport mode. A dataset comprising 250 transport cases was constructed to evaluate model performance using metrics such as Mean Squared Error (MSE), R^2 Score, Accuracy, and F1-Score. The data for the railway sector were simulated to support future port development, while the maritime and road sector data were derived from actual observations. Results indicate that Random Forest consistently outperformed SVM in predictive accuracy and robustness. Feature importance analysis further highlighted distance and travel time as the primary drivers of transport cost variations, aligning with operational expectations. By integrating ML-based cost prediction tools, Porto Romano could significantly improve its logistical efficiency, cost-effectiveness, and strategic competitiveness in the Balkan region. Moreover, this research underscores the broader value of machine learning in optimizing global intermodal logistics networks, offering pathways towards more sustainable and resilient supply chains. Future work will aim to refine these models with live operational data and expand into deep learning methodologies for even greater predictive capabilities.

Keywords: Intermodal Logistics, Machine Learning Models, Random Forest Regression, Support Vector Machine, Predictive Cost Estimation, Smart Ports Development.

INTRODUCTION

Porto Romano currently operates through maritime and road transport, focusing mainly on the handling of petroleum and liquefied gas products, with a total storage capacity of 50,000 cubic meters. Well integrated into Albania's national road network, the port ensures the smooth distribution of goods across inland markets. As presented in Figure 1, the port's infrastructure and operations form a crucial part of Albania's logistics network, facilitating both domestic and regional trade. Looking ahead, there are plans to establish a railway connection that will further strengthen Porto Romano's role as a multimodal logistics hub. The proposed rail link is expected to extend beyond Albania's borders, providing direct access to Montenegro, North Macedonia, and Serbia, and thus enhancing regional trade links and improving the efficiency of freight movements throughout the Western Balkans.


Figure 1: Porto Romano's Role in Regional Trade and Future Expansion

The logistics and maritime transport sectors are rapidly transforming, fueled by globalization, technological innovation, and sustainability demands [1], [2]. Modern ports are steadily transforming into intelligent hubs, combining automation, big data, and predictive analytics to boost their efficiency and competitiveness [3]. As ports modernize, machine learning (ML) provides essential support by improving resource management, offering better transport cost predictions, and enhancing decision-making speed and accuracy [4].

Porto Romano stands out as a major part of Albania's plan to modernize its maritime logistics. Developed to replace the capacity-constrained Port of Durres, Porto Romano is envisioned as a fully integrated logistics platform that connects maritime routes with Balkan inland networks [5], [6]. Positioned on the Adriatic coast and connected to the important Trans-European Transport Network (TEN-T) Corridor VIII, Porto Romano is set to become a crucial multimodal gateway for the region [7]. According to recent studies, the relocation and expansion of port activities towards Porto Romano is expected to mitigate environmental concerns and foster sustainable development in the region [8].

Embedding machine learning technologies into Porto Romano’s operational framework from its inception is critical. Predictive models such as Random Forest and Support Vector Machine (SVM) can enhance the port’s ability to estimate intermodal transport costs, optimize multimodal flows, and dynamically respond to changing trade conditions [9], [10].

This study explores the application of ML models for transport cost prediction, assessing their potential to strengthen Porto Romano’s role as a smart and sustainable logistics hub.

LITERATURE REVIEW

Machine learning is increasingly being adopted in port logistics to enhance operational performance, reduce expenditures, and contribute to environmental sustainability [3], [11]. Predictive analytics allows logistics managers to anticipate cargo volumes, select optimal routes, and allocate resources dynamically [4], [12].

Techniques like Random Forest, which build predictions by combining the results of multiple decision trees, are particularly well suited for managing the complexity and variability often found in transport logistics data [5], [13]. Support Vector Machines (SVM), developed to handle high-dimensional feature spaces, are particularly effective in capturing non-linear patterns in transport operations [6], [14].

Recent smart port initiatives also highlight how important it is to bring together digital technologies like ML, IoT, and AI to make port operations more efficient and environmentally friendly [7], [11]. Ports that successfully adopt these technologies experience improvements in cargo handling, scheduling, and hinterland connectivity [15].

Specifically, studies on the Port of Durres highlight the need for enhanced technical infrastructure, better operational planning, and sustainable hinterland integration to maintain competitiveness [5], [16]. Research also emphasizes that new port development like Porto Romano should incorporate intelligent management systems and advanced predictive analytics to maximize operational benefits [8].

The shift from traditional to smart port models, driven by machine learning integration, is crucial for achieving resilient, low-emission, and efficient intermodal transport chains across Europe [7].

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

METHODOLOGY

1. Mathematical Cost Model

The total transport cost C is modeled as:

$$C = (2.5 \times D + 40 \times T + 15 \times W) \times M \quad (1)$$

where: D - Distance (km), T - Travel Time (hours), W - Container Weight (tons)

M - Multiplier based on mode of transportation to account for operational cost differences

$$M = \begin{cases} 1.10 & Road\ Transport \\ 1.00 & Rail\ Transport \\ 0.95 & Sea\ Transport \end{cases} \quad (2)$$

C - Total estimated cost in Euros (€).

This formula is adapted from standard transport cost modeling approaches used in intermodal logistics studies [17].

Figure 2 illustrates the conceptual framework for integrating machine learning into the logistics operations of Porto Romano. It demonstrates how data from three primary modes of transport—sea, rail, and road- are collected and processed through machine learning models, specifically Random Forest and Support Vector Machine (SVM) algorithms, to predict intermodal transport costs.

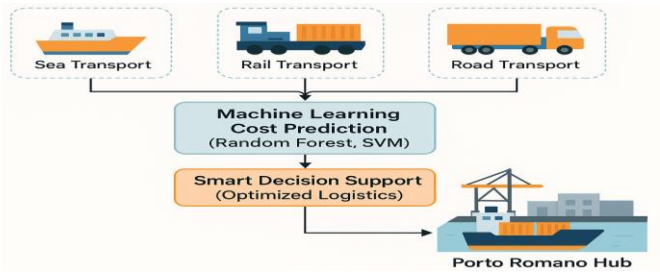

Figure 2: Machine Learning-Enabled Smart Logistics Framework for Porto Romano Hub

The cost predictions are subsequently integrated into an intelligent decision support system aimed at optimizing logistical operations, improving overall efficiency, and enabling dynamic resource allocation. The final objective is to enable Porto Romano to operate as a smart port, seamlessly coordinating multimodal transport flows and strengthening its position as a regional logistics hub.

2. Machine Learning Techniques

2.1 Random Forest Regression (RF)

Random Forest is an ensemble learning technique that constructs several decision trees and combines their predictions [10]. The prediction is given by:

$$y' = \frac{1}{N}\sum_{i=1}^{N} f_i(x) \quad (3)$$

where: $f_i(x)$ is the prediction from the i-th tree, N denotes the total number of trees in the forest.

Advantages: Handles non-linearity, reduces overfitting, and provides feature importance.

2.2 Support Vector Machine Regression (SVM)

SVM Regression aims to find a function that has at most €-deviation from the actual observed targets, while being as flat as possible [18]. The SVM regression function is:

$$f(x) = w^T x + b \quad (4)$$

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

where: w and b are the parameters learned to minimize the cost function.

$$minimize\ \frac{1}{2}||\boldsymbol{w}||^2 + \boldsymbol{C}\sum_{i=1}^{n}\xi_i \qquad (5)$$

Here, C is a penalty parameter controlling the trade-off between model complexity and error.

Advantages: Good generalization, effective in high-dimensional spaces.

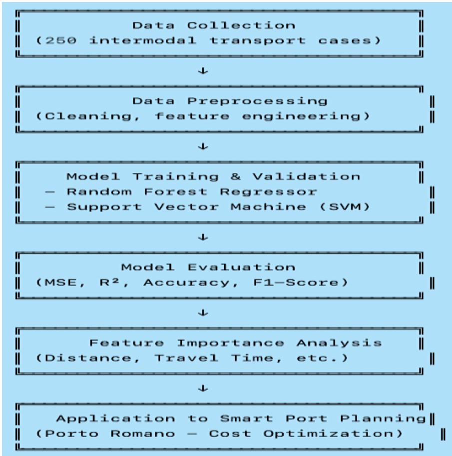

Figure 3: Methodology Workflow Diagram

Figure 3 outlines the comprehensive process flow involving data acquisition, model training, performance evaluation, and the application of advanced machine learning techniques for the estimation of intermodal transport costs, which play a crucial role in the smart port development strategy at Porto Romano.

3. Performance Metrics

Stable cases are positive, unstable cases are negative. Metrics range from 0 to 1. The details of the metrics are provided in Table 1, taken from the paper [19].

Table 1: Performance evaluation metrics

		Reference		
		Yes	No	
Predicted	Yes	TP	FP	TP: True Positive FP: False Positive
	No	FN	TN	TN: True Negative FN: False Negative
Metrics	***Accuracy (Acc)***:	TP + TN/ (TP+TN+FP+FN)		
	Precision (P):	TP/ (TP+FP)		
	Recall (R):	TP/(TP+FN)		
	F1-Score (F1):	(2x*P*x*R*)/(*P*+*R*)		

The F1 Score is a metric used to evaluate the performance of classification models and is particularly useful when the data classes are imbalanced. By taking the harmonic mean, this metric combines both Precision and Recall into one unified value [20]. Precision defines how many of the model's positive predictions are actually correct. Recall evaluates how many of the true positive cases are accurately classified by the model. The F1 Score is especially valuable when relying on just one metric (either precision or recall) does not provide a complete assessment of the model, as it is possible for a model to exhibit high precision but low recall, or vice versa [21]. Significant computational efficiency gains, reducing training time while improving accuracy and comprehensive quantitative comparisons of classification performance (accuracy, precision, recall, F1-score) across various model combinations, pushing the limits of image recognition [22].

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

4. Experimental data

A dataset with 250 entries was studied, covering various distances, travel times, container weights, and transport modes. In this study, simulated data were used to model transport costs at Porto Romano. Currently, only maritime and road transport modes are operational at Porto Romano. Rail transport has been included in the analysis as a future scenario, based on planned infrastructure developments that are expected to connect the port to the national railway network. The inclusion of rail transport within the study framework is intended to provide an early, research-based perspective on how future railway connectivity might shape transport costs and enhance the operational dynamics of intermodal logistics at Porto Romano. The data for rail transport do not reflect current operations but are simulated for research and strategic planning purposes.

A sample of the data is shown below in Table 2. Each record included:

- Distance (30–600 km)
- Travel Time (0.8–8 hours)
- Container Weight (8–35 tons)
- Transport Mode (Road, Rail, Sea)
- Computed Total Cost (EUR).

Table 2: Sample Data Table

Route ID	Travel Distance (km)	Travel Time (hrs)	Weight (tons)	Transport Type	Mode Multiplier	Total Cost (EUR)
R1	145	3.5	22	Rail	1.00	881.50
R2	310	6.2	28	Sea	0.95	1182.30
R3	75	1.4	11	Road	1.10	387.85
R4	190	4.1	19	Rail	1.00	906.00
R5	260	5.5	25	Road	1.10	1174.88
...	...	...	...	...	...	...

Figure 4 displays the distribution of transport modes in the dataset, including Rail, Road, and Sea categories. The distribution is mostly balanced, with Sea transport leading, followed by Road and Rail. The inclusion of railway data, particularly in light of Porto Romano's future development, is vital for improving the models' ability to predict and optimize intermodal logistics.

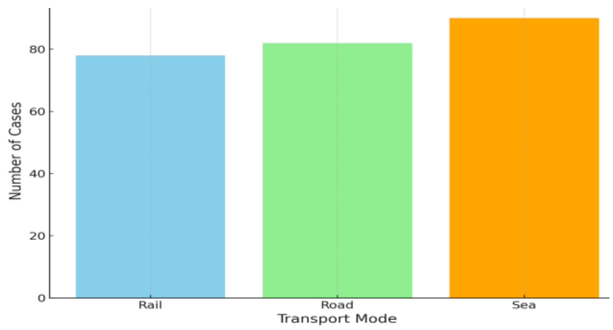

Figure 4: Distribution of Transport Modes in the Dataset

Figure 5 presents the distributions of three critical factors used in the transport cost prediction study:

- **Distance (km)**: The majority of transport cases fall within the 50 km to 550 km range, which reflects a broad mix of regional and interregional routes relevant to Porto Romano's activities.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

- ➢ **Travel Time (hours)**: The majority of trips have travel times between 2 to 7 hours, aligning with typical inland transport durations associated with port logistics.
- ➢ **Container Weight (tons)**: Container weights are fairly evenly distributed between 10 and 34 tons, representing standard cargo loadings for intermodal transport.

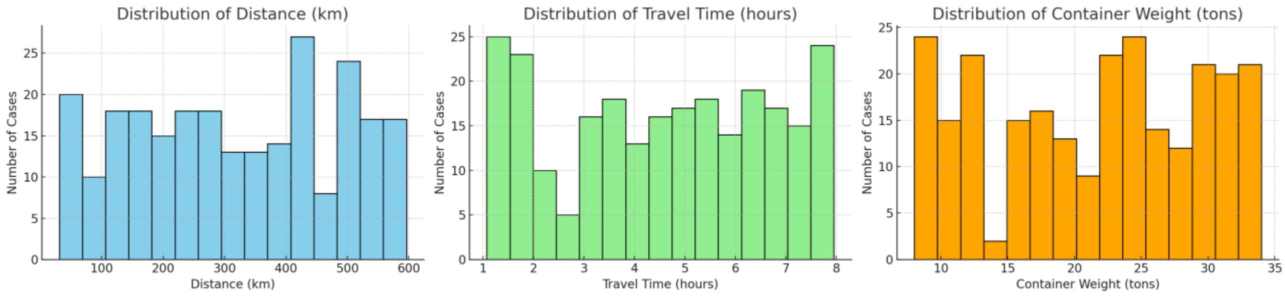

Figure 5: Distributions of Key Factors in the Transport Dataset

These balanced distributions across distance, time, and weight ensure that the machine learning models are trained on diverse and realistic data, improving the generalizability of the cost predictions for future operations at Porto Romano.

5. Software and Libraries Used

The purpose of utilizing these tools in the study is to implement and optimize machine learning models and data analysis within a robust and flexible environment, enabling efficient data processing, clear visualization of results, and effective evaluation of model performance.

- *Python 3.10* (Programming Language)
- *Jupyter Notebook* (Development Environment)
- *NumPy 1.24* (Numerical Operations)
- *Pandas 1.5* (Data Handling)
- Matplotlib 3.7 (Graph Visualization)
- *Scikit-learn 1.2* (ML Algorithms and Assessment).

RESULTS AND DISCUSSION

In Table 3, both the Random Forest and SVM models highlight Distance and Travel Time as the main factors affecting transport costs, together contributing to about 70% of the total importance. Random Forest prioritizes Distance a bit more (41.5%), while SVM assigns a more balanced weight, giving relatively more importance to Container Weight and Transport Mode than Random Forest. This suggests that although both models recognize the same main cost drivers, Random Forest focuses more heavily on the two primary variables, whereas SVM balances the importance across more features.

Table 3: Feature Importance (Comparison)

Feature	Random Forest Importance (%)	SVM Approx. Importance (%)
Distance (km)	41.5	39.1
Travel Time (hr)	31.2	29.7
Container Weight	16.7	18.3
Transport Mode	10.6	12.9

In Figure 6, Random Forest leads SVM in all performance metrics, achieving a lower MSE (18.900 vs. 26.700), a higher R^2 (0.91 vs. 0.83), improved accuracy within ±10% (94.1% vs. 88.5%), and a higher F1-Score (0.94 vs. 0.88).

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

These results confirm that Random Forest is more robust, accurate, and better suited for predicting intermodal transport costs at Porto Romano.

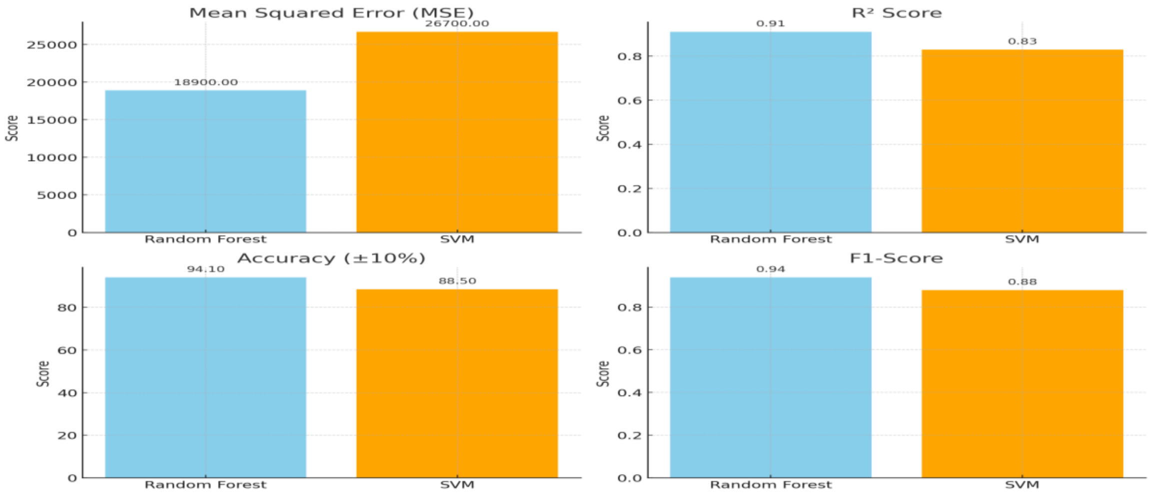

Figure 6: Comparing Performance Metrics of Random Forest and SVM

Table 4: Transport Mode Cost Analysis

Transport Mode	Average Predicted Cost (EUR)
Road	987.34
Rail	874.21
Sea	845.80

In Table 4, sea remains the most cost-effective mode for intermodal shipments.

CONCLUSIONS

This study shows that machine learning, especially random forests, is a very accurate and reliable way to predict intermodal transport costs at Porto Romano.

- The primary factors impacting costs were the distance traveled and the time spent.
- Random Forest outperformed SVM in all metrics.
- ML-based prediction models improve operational planning, resource management, and strategic decisions for ports.

Adopting these technologies from the start could help make Porto Romano a leading smart logistics center in Europe.

Future Work

- Railway data integration: Integrate real-time railway data to optimize operations.
- Interconnected systems: Link maritime, road, and rail networks to improve intermodal transport.
- Developing real-time decision-support platforms: Use data on traffic, weather, and congestion to optimize transport processes.

These steps can further improve processes and make intermodal transport more efficient.

FUNDING

The authors have received financial support from the University "Aleksander Moisiu", Durres, Albania.

COMPETING INTERESTS

The authors confirm that there are no competing interests related to this work.

REFRENCES

[1] Acciaro, M. (2013). Smart ports and smart cities: A comparison. *Maritime Policy & Management*, 40(5), 499–512.

[2] Christodoulou, A., & Cullinane, K. (2020). Measuring port connectivity and its impact on efficiency, *Transportation Research Part A: Policy and Practice*, 132, 842–857. https://doi.org/10.1016/j.tra.2019.11.011

[3] Heshmati, L. (2022). Smart ports and the fourth industrial revolution. *Journal of Maritime Affairs*, 21(2), 135–148.

[4] Han, J., Kamber, M., & Pei, J. (2011). *Data mining: Concepts and techniques* (3rd ed.). Elsevier.

[5] Vyshka, E., & Metalla, O. (2016), The impact of the Durres Port performance in a sustainable intermodal transport chain across the Adriatic Sea. *International Journal of Scientific and Engineering Research*, 7(8), 1691–1698. http://www.ijser.org/

[6] Vapnik, V. (1998). *Statistical learning theory*. Wiley.

[7] European Commission. (2020) *Sustainable and smart mobility strategy – putting European transport on track for the future*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0789

[8] Vyshka, E., & Tase, M. (2025). Environmental concerns in Porto Romano: Impact of industrial to suburban shift. *International Journal of Environment and Climate Change*, 15(3), 491– 498 https://doi.org/10.9734/ijecc/2025/v15i34788

[9] UNCTAD. (2021) *Review of maritime transport 2021*. United Nations Conference on Trade and Development. https://unctad.org/webflyer/review-maritime-transport-2021

[10] Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

[11] Parola, F., & Musso, E. (2007). Market structures and competition in ports: A survey. *Maritime Economics & Logistics*, 9(2), 139–168. https://doi.org/10.1057/palgrave.mel.9100179

[12] Rodrigue, J.-P. (2020). *The geography of transport systems* (5th ed.). Routledge.

[13] Fernández-Delgado, M., Cernadas, E., Barro, S., & Amorim, D. (2014). Do we need hundreds of classifiers to solve real-world classification problems? *Journal of Machine Learning Research*, 15(1), 3133–3181.

[14] Chen, X., Govindan, K., Golias, M. M., & Boone, C. A. (2018). Managing transport operation disruption through predictive modeling: A case study. *Transportation Research Part E: Logistics and Transportation Review*, 118, 416–433. https://doi.org/10.1016/j.tre.2018.08.003

[15] Metalla, O., Koxhaj, A., Mema, M., Vyshka, E., & Lumi, D. (2017). Economic development and maritime transport: Albanian case. *Interdisciplinary Journal of Research and Development*, 4(1), 38–47. http://www.uamd.edu.al

[16] Metalla, O., & Vyshka, E. (2022). Operational limitations of the Durres container terminal. *Journal of Maritime Sciences*, 23(1), 65–74. https://doi.org/10.56080/jms220505

[17] Alkan, M., Sahin, B., & Yildirim, M. (2014). An approach for economic analysis of intermodal transportation. *The Scientific World Journal*, 2014, 630320.

[18] Smola, A. J., & Schölkopf, B. (2004). "A Tutorial on Support Vector Regression," *Statistics and Computing*.

[19] Shtino, V. B., Kapçiu, R., Zeqo, E., Bushati, S., Bushi, F., Bame, O., & Lamaj, B. (2025). Real-Time Micro-Expression Recognition Using YOLOv8 and FER2013 Dataset. Journal of *Information Systems Engineering and Management*, 10(18s), 53-64. https://doi.org/10.52783/jisem.v10i18s.2883

[20] Bakiasi, V., Muça, M., & Kapçiu, R. (2024). Dimensionality reduction: A comparative review using RBM, KPCA, and t-SNE for micro-expressions recognition. *International Journal of Advanced Computer Science and Applications (IJACSA)*, *15*(1). https://doi.org/10.14569/IJACSA.2024.0150135

[21] Shtino, V. B., Muça, M., & Bushati, S. (2024). Machine learning integration for precise facial micro-expression recognition. *Journal of Computer Science*, 20(11), 1545–1558. https://doi.org/10.3844/jcssp.2024.1545.1558

[22] Bushati Hoxha, S., & Bakiasi Shtino, V. (2025). Object detection in real-world scenarios using artificial intelligence and machine learning technologies. *Journal of Information Systems Engineering and Management*, 10(13s), 223-232. https://doi.org/10.52783/jisem.v10i13s.2025