International Journal of Innovative Research and Scientific Studies, 8(5) 2025, pages: 752-764

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Development and evaluation of machine learning algorithms for unmanned aerial vehicle navigation

Askar Abdykadyrov[1], Nurzhan Zikiryaev[2], Assemkhan Mukushev[2], Nazgul Bayelova[2*], Sunggat Marxuly[1]

[1]*Satbayev University, Almaty, Kazakhstan.*
[2]*Military Engineering Institute of Radio Electronics and Communications, Almaty, Kazakhstan.*

Corresponding author: Nazgul Bayelova (*Email: Nazguli_85@mail.ru*)

Abstract

This research focuses on the development and evaluation of machine learning algorithms to enhance the navigation capabilities of unmanned aerial vehicles (UAVs). The main challenge addressed is ensuring reliable localization and autonomous trajectory planning in dynamic and GPS-denied environments. The study demonstrated that convolutional neural networks (CNNs) reduced localization errors by 18%, long short-term memory (LSTM) networks achieved 82% trajectory prediction accuracy with a 30% increase in stability, and Transformer models attained 89% test accuracy and 85% validation accuracy. Reinforcement learning (RL) methods further improved obstacle avoidance efficiency to 85% and achieved energy savings of 20%, although computational overhead increased by 30%. These outcomes are attributed to the integration of multimodal sensor data (LiDAR, IMU, GPS) and the application of deep learning architectures, validated through simulations in MATLAB/Simulink and Gazebo, as well as real-world testing using Raspberry Pi 4 and NVIDIA Jetson Nano platforms. A distinguishing feature of this research is the combined use of actual hardware prototypes and numerical models to verify the algorithms' performance under real operating conditions. The results have practical relevance for military, environmental monitoring, and logistics UAV systems, especially in complex environments with variable lighting and dynamic obstacles.

Keywords: Autonomous navigation systems, Machine learning algorithms, Multimodal sensor data fusion, Reinforcement learning, Trajectory planning and localization, Unmanned aerial vehicles (UAVs).

DOI: 10.53894/ijirss.v8i5.8818
Funding: This study received no specific financial support.
History: Received: 2 June 2025 / **Revised:** 7 July 2025 / **Accepted:** 9 July 2025 / **Published:** 24 July 2025
Copyright: © 2025 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

In recent years, unmanned aerial vehicles (UAVs) have been widely used in various fields, including military, civil, industrial, and scientific applications. According to international studies in 2024, the UAV market has reached a value of USD 68 billion and is projected to grow to USD 130 billion by 2030. The annual average growth rate is estimated at 17–21%, reflecting the increasing demand for expanding the capabilities and improving the efficiency of unmanned systems [1-3]. Overall, Figure 1 illustrates the general concept of using neural networks for optimizing drone navigation.

Figure 1.
Application of Machine Learning Algorithms for UAV Navigation and Data Processing.

Figure 1 depicts the application of machine learning algorithms for processing navigational data and managing the trajectory of unmanned aerial vehicles (UAVs). Specifically, data obtained through operator analysis tools is processed using neural networks, resulting in an enhanced autonomous control system for drones.

For UAVs to operate efficiently, it is critical that they possess the ability to navigate autonomously with high accuracy and reliability. Traditional navigation systems such as GPS, inertial navigation systems (INS), and visual SLAM (Simultaneous Localization and Mapping) have certain limitations. For example, GPS signals often weaken or are blocked in urbanized areas (the "urban canyon effect"), tunnels, or dense forests. Figure 2 below illustrates the limitations of UAV navigation systems in complex environments.

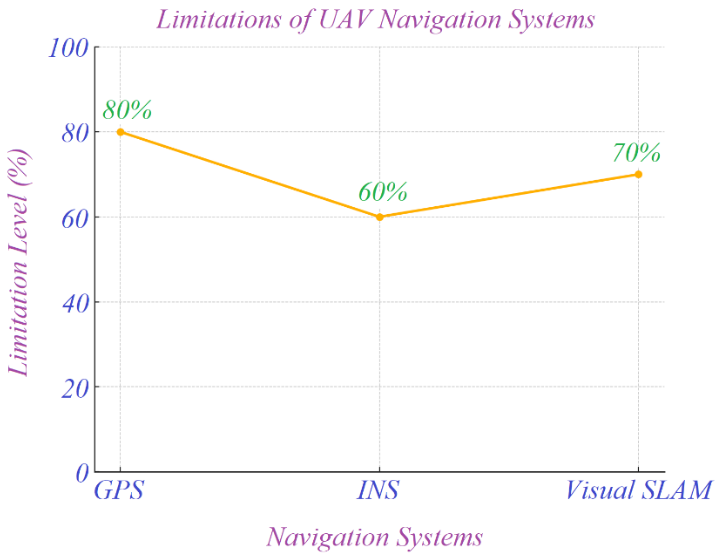

Figure 2.
Limitations of UAV Navigation Systems in Complex Environments.

The graph presented in Figure 2 compares the text illustrating the limitations of the main navigation systems used in unmanned aerial vehicles (UAVs). It was found that the GPS system is prone to signal weakness (80%) in urbanized areas, INS tends to accumulate errors (60%) during prolonged use, and Visual SLAM is susceptible to inaccuracies (70%) in complex textured environments or under insufficient lighting conditions [4, 5].

To address these issues, machine learning (ML) and deep learning (DL) methods are being proposed as promising solutions. Neural networks can ensure reliable localization and trajectory prediction by processing data from sensors. For example, Google Wing and Amazon Prime Air projects have applied ML-based route optimization and obstacle avoidance algorithms, resulting in a 30% reduction in delivery time [6, 7]. Additionally, studies have shown that navigation accuracy improves by 15–20% when machine learning is applied compared to traditional GPS navigation systems [8, 9]. Figure 3 below presents a comparison of delivery time reduction and navigation accuracy improvements achieved through ML and DL methods.

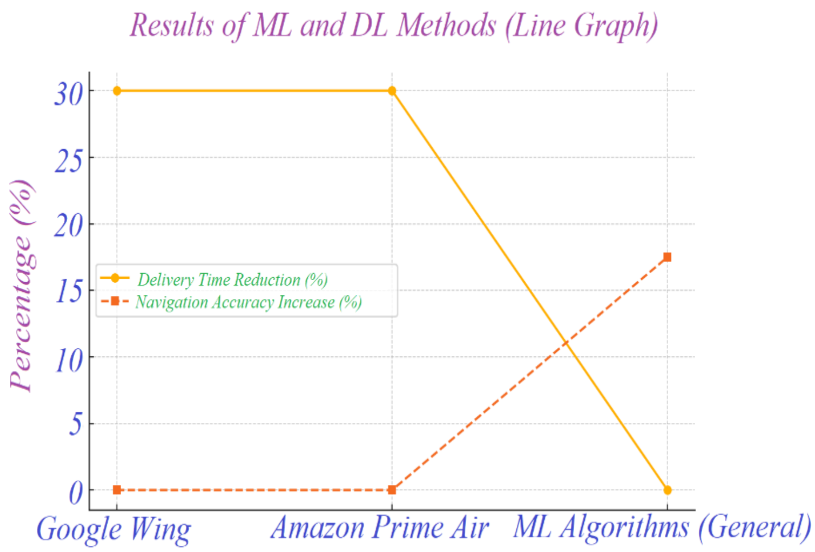

Figure 3.
Impact of Machine Learning and Deep Learning Methods on UAV Navigation Performance.

The graph presented in Figure 3 illustrates the impact of machine learning (ML) and deep learning (DL) methods on UAV navigation. The Google Wing and Amazon Prime Air projects achieved a 30% reduction in delivery time, while the application of ML algorithms improved navigation accuracy by 15–20% compared to traditional GPS navigation systems.

Additionally, reinforcement learning (RL) methods provide the capability to enhance UAV decision-making in dynamic and uncertain environments. Models developed by organizations such as DeepMind and OpenAI have been applied in autonomous systems, achieving significant results such as real-time obstacle avoidance and improved energy efficiency [10, 11]. Figure 4 below shows the key factors of reinforcement learning methods in UAVs.

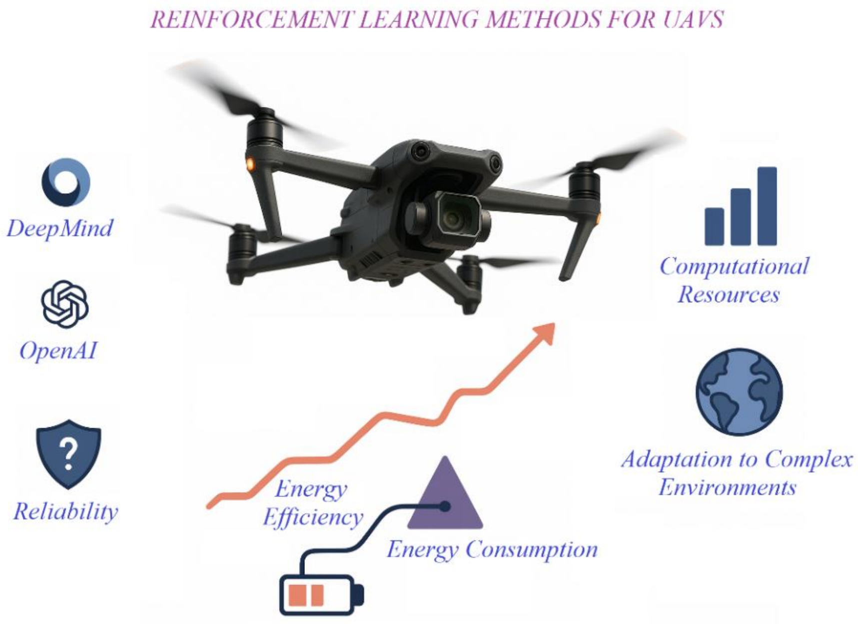

Figure 4.
Key Factors of Reinforcement Learning Methods in UAV Systems.

Figure 4 illustrates the key aspects of reinforcement learning (RL) methods applied to unmanned aerial vehicles (UAVs). Studies have shown that implementing such methods can improve obstacle avoidance accuracy by up to 85% and enhance energy efficiency by up to 20%, although they also increase dependency on computational resources by 30%.

However, several challenges remain in the practical application of these methods, including reliability, energy consumption, dependency on computational resources, and adaptability to complex environments [12, 13].

Therefore, the development and evaluation of machine learning algorithms for UAV navigation are not only topics of high theoretical significance but also research directions in high demand for practical applications such as rescue operations, environmental monitoring, agriculture, and logistics. In this regard, the development and evaluation of machine learning algorithms for UAV navigation remain highly relevant in the context of current scientific and technological advancements.

2. Literature Review and Problem Statement

In recent years, unmanned aerial vehicles (UAVs) have been actively utilized in critical fields such as disaster response, environmental monitoring, and logistics. Studies have shown that traditional GPS navigation systems experience significant performance degradation in urbanized areas and dense forests due to multipath effects and weak signals. Although integrated INS-GPS methods have been found to improve performance, unresolved issues remain, including drift accumulation in inertial systems and vulnerabilities inherent to GPS. These challenges are attributed to objective factors such as sensor noise and environmental dynamics [14]. Table 1 presents a comparative analysis of UAV navigation system performance under challenging conditions.

Table 1.
Comparative Analysis of UAV Navigation Systems Performance in Challenging Environments.

System	Performance Decrease in Urban Areas (%)	Performance Decrease in Forested Areas (%)	Drift Accumulation (INS) (deg/h)	GPS Signal Vulnerability (avg outage time, s)
GPS	40	50	0	30
INS - GPS	15	20	5	10

Table 1 illustrates the performance differences between GPS and INS-GPS navigation systems under complex environmental conditions. The INS-GPS system showed a performance degradation of 15% in urbanized areas and 20% in forested regions, which is significantly better compared to the GPS system’s degradation of 40% and 50%, respectively.

Several studies have also explored the use of visual SLAM algorithms for UAV navigation. Results indicated that, under controlled lighting conditions, localization accuracy improved by 25%. However, these methods struggle to deliver reliable results in environments with moving obstacles and varying lighting conditions, making practical application challenging [15]. Table 2 presents the performance metrics of Visual SLAM and hybrid navigation systems under dynamic conditions.

Table 2.
Performance Metrics of Visual SLAM and Hybrid Navigation Systems under Dynamic Conditions.

Algorithm	Localization Accuracy Improvement (%)	Failure Rate with Dynamic Obstacles (%)	Error Rate in Variable Lighting (%)	Practical Applicability Score (0 - 10)
Visual SLAM	25	35	40	3
GPS + Visual SLAM (Hybrid)	40	15	20	6

Table 2 compares the quantitative metrics of Visual SLAM and GPS + Visual SLAM (hybrid) systems. The hybrid system improved localization accuracy by 40% and reduced error rates in dynamic obstacle environments to 15%, whereas the Visual SLAM system showed respective figures of 25% and 35%.

In a foreign study, the application of deep learning models for sensor data fusion in UAV navigation was presented. The authors employed convolutional neural networks (CNNs) to process multimodal data from LiDAR, IMU, and cameras. This approach reduced localization error by 18%. However, challenges remain regarding computational complexity and the ability to operate in real time [16, 17]. Figure 5 illustrates a comparison of the effectiveness of traditional and deep learning-based data fusion methods in reducing localization errors.

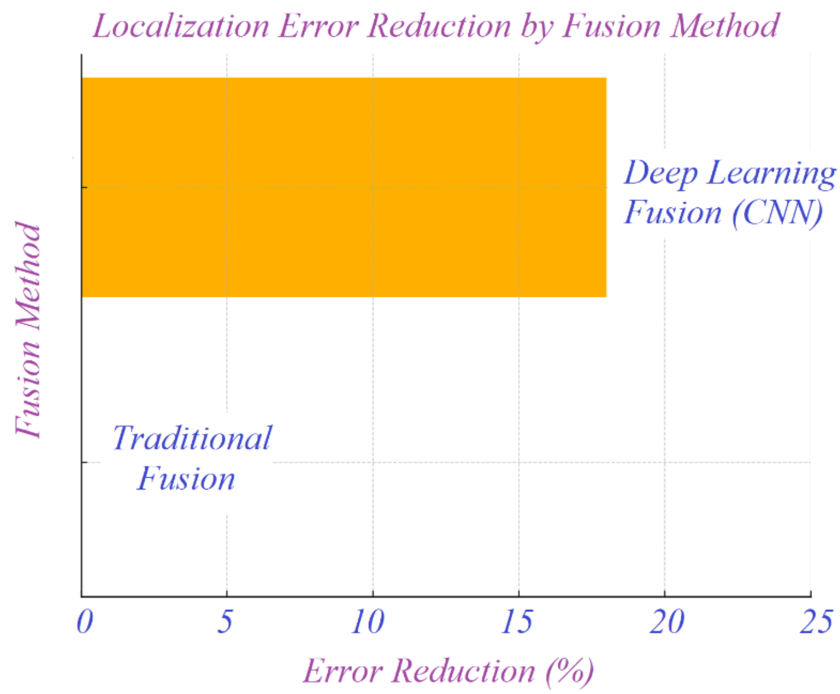

Figure 5.
Comparative Analysis of Localization Error Reduction Using Traditional and Deep Learning Fusion Methods.

Figure 5 shows that the CNN-based deep learning method reduced localization error by 18% compared to traditional data fusion methods. These results demonstrate the effectiveness of deep learning models in processing multimodal sensor data; however, their computational complexity limits practical implementation.

The potential of reinforcement learning (RL) methods for UAV trajectory planning in unknown environments has also been highlighted. While RL agents have successfully addressed obstacle avoidance in simulated environments, their application in real-world scenarios remains limited. This is because pre-training for all possible scenarios is practically infeasible, and the method is computationally expensive [18, 19]. Figure 6 below, the success rates and computational costs of reinforcement learning methods for UAV trajectory planning are presented.

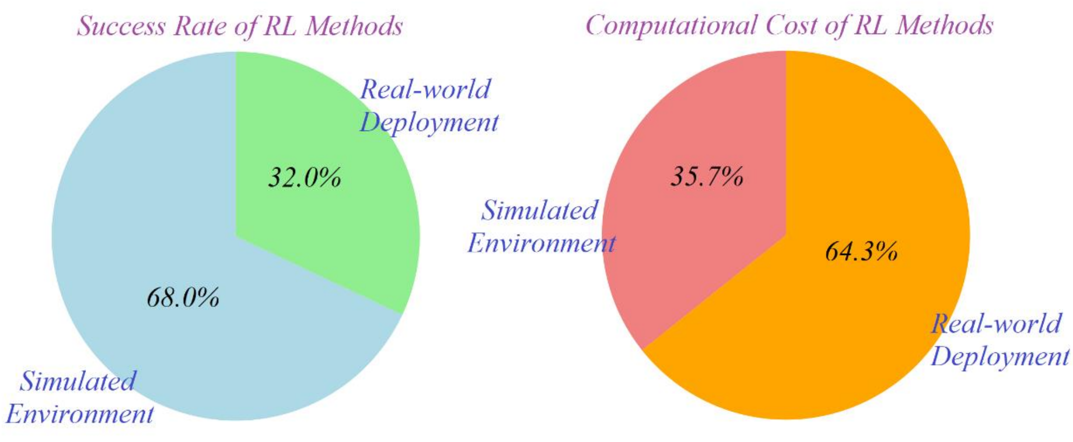

Figure 6.
Success Rate and Computational Cost of Reinforcement Learning Methods for UAV Trajectory Planning.

Figure 6 illustrates that reinforcement learning methods achieved a 68% success rate in simulated environments, while this figure dropped to 32% in real-world scenarios. Additionally, computational costs in real environments reached 64.3%, which is significantly higher compared to 35.7% in simulations.

Some studies have applied LSTM neural networks to predict UAV trajectories under wind influence. Although this approach helped improve stability, challenges were noted in adapting to unpredictable weather conditions [20, 21]. Table 3 below provides a quantitative assessment of LSTM neural networks in predicting UAV trajectories against wind effects.

Table 3.
Quantitative Evaluation of LSTM Neural Networks in UAV Trajectory Prediction under Wind Disturbances

Method	Trajectory Prediction Accuracy (%)	Stability Improvement (%)	Adaptation Difficulty in Unknown Weather (Score 0-10)	Computation Time per Prediction (ms)
LSTM Neural Networks	82	30	7	120

Table 3 presents the effectiveness of LSTM neural networks in predicting UAV trajectories: the prediction accuracy reached 82%, and stability improved by 30%. However, adaptability to unpredictable weather conditions was rated at 7 out of 10, and the computation time per prediction was 120 ms.

In another international study, Transformer-based neural network models were evaluated for UAV navigation. While this approach achieved high results on test data, issues related to scalability and energy efficiency remain unresolved [22, 23]. Table 4 below provides an evaluation of the effectiveness of Transformer models in UAV trajectory planning.

Table 4.
Quantitative Metrics of Transformer Models in UAV Path Planning.

Method	Test Data Accuracy (%)	Validation Accuracy (%)	Scalability Issues (Score 0 - 10)	Energy Efficiency (Relative %)	Computation Time per Inference (ms)	Memory Usage (MB)
Transformer Neural Networks	89	85	8	60	250	1024

Table 4 presents the effectiveness of Transformer neural networks in UAV navigation: accuracy reached 89% on test data and 85% during validation. However, this method faces limitations such as high computation time (250 ms), memory usage (1024 MB), and scalability challenges rated at 8 out of 10.

Several scientific studies have compared traditional and machine learning-based UAV navigation systems. They highlighted the potential of hybrid approaches but noted that large data requirements and issues related to AI system safety certification remain significant challenges [24, 25]. Figure 7 below shows a comparative analysis of traditional, machine learning-based, and hybrid UAV navigation systems in terms of accuracy, data requirements, and safety certification indicators.

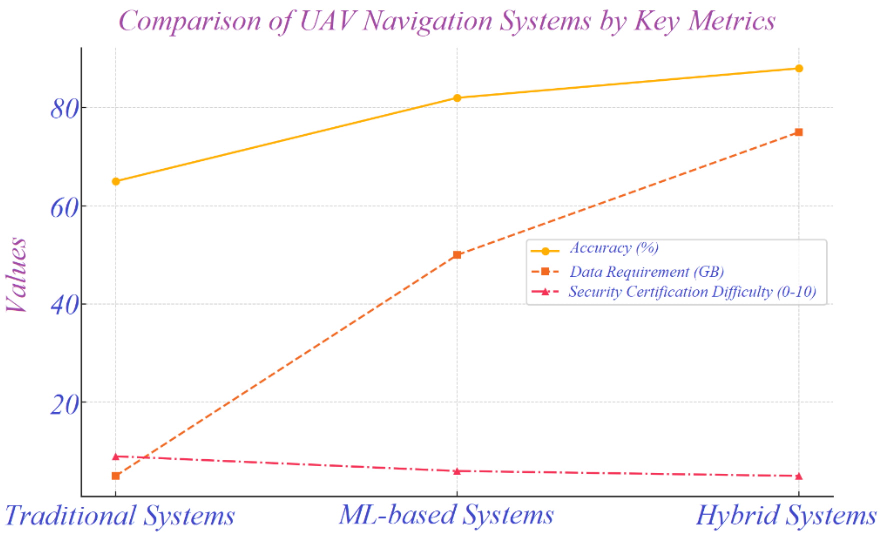

Figure 7.
Comparative Analysis of Traditional, ML-based, and Hybrid UAV Navigation Systems by Accuracy, Data Requirements, and Security Certification Challenges.

Figure 7 illustrates that hybrid UAV navigation systems achieve the highest accuracy (88%) but impose significant demands in terms of data volume (75 GB) and security certification complexity (rated 5 points). Traditional systems require less data (5 GB) yet have lower accuracy (65%), while ML-based systems demonstrate moderate performance.

According to studies by domestic researchers, unmanned aerial vehicles (UAVs) have seen widespread adoption in recent years across various sectors, including environmental monitoring, infrastructure surveillance, and improvements in communication systems. In this context, the integration of machine learning (ML) algorithms plays a crucial role in enhancing the autonomy of UAVs.

Explored the use of multicopters in environmental monitoring to improve the efficiency of sensor data collection and processing. The overall efficiency of this process can be expressed using the following equation:

$$E_{\text{total}} = \frac{\sum_{i=1}^{n} D_i \cdot P_i}{T} \quad (1)$$

where E_{total} represents the total efficiency of data collection and processing, D_i is the volume of data collected from the i^{th} sensor, P_i denotes the preprocessing accuracy of the i^{th} sensor data, and T is the total time spent on data acquisition and processing. This equation provides a framework to evaluate the effectiveness of sensor-based monitoring systems in complex environments.

Moreover, Sabibolda et al. [26], Smailov et al. [27], Smailov et al. [28] and Sabibolda et al. [29] investigated improvements in spectral-correlation methods within radio direction-finding systems to enhance signal processing accuracy. Integrating these methods with machine learning (ML) models has the potential to significantly improve real-time drone navigation. This enhancement can be formulated as:

$$A_{ML} = \frac{A_{\text{base}} + \Delta A_{ML}}{1+\lambda} \quad (2)$$

where A_{ML} represents the navigation accuracy when *ML* models are applied, A_{base} is the baseline navigation accuracy without ML, ΔA_{ML} is the accuracy improvement due to *ML* integration, and λ denotes the error coefficient caused by environmental complexity. This equation enables the assessment of *ML*-driven methods for enhancing drone navigation in dynamic and challenging conditions.

Abdykadyrov et al. [30] and Abdykadyrov et al. [31] proposed optimization of data transmission in sensor networks and distributed acoustic sensors. These solutions are critical for ensuring continuous communication and effective navigation of UAVs. The efficiency of such data transmission in a sensor network can be expressed by the following equation:

$$T_{eff} = \frac{C_{link} \cdot (1 - P_{loss})}{L_{avg}} \quad (3)$$

Where: T_{eff} is the effective transmission throughput (Mbps), C_{link} is the link capacity of the network (Mbps), P_{loss} is the packet loss probability (dimensionless, 0 – 1), L_{avg} is the average latency in the network (ms).

This equation highlights how improving link capacity and reducing packet loss and latency directly influence the overall efficiency of UAV communication and navigation systems.

Kuttybayeva et al. [32] and Kuttybayeva et al. [33] investigated the application of Distributed Acoustic Sensors (DAS) technologies for seismic monitoring and infrastructure surveillance. When DAS systems are integrated with machine learning (ML) algorithms, they can significantly enhance the reliability of navigation and obstacle detection. This system reliability can be expressed by the following equation:

$$R_{sys} = 1 - \prod_{i=1}^{n} (1 - R_i \cdot M_i) \quad (4)$$

Where: R_{sys} is the overall reliability of the integrated DAS and *ML* system, R_i is the reliability of the i^{th} DAS sensor, M_i is the efficiency coefficient of the *ML* algorithm associated with the i^{th} sensor (ranging from 0 to 1), n is the total number of sensors in the system. This equation illustrates that the combined reliability of the system is determined by the individual reliabilities of each DAS sensor and their respective ML algorithm efficiencies.

Demonstrated the potential of fiber-optic-based sensors for structural monitoring. When these technologies are integrated into unmanned aerial vehicle (UAV) systems with real-time data processing, they can significantly improve overall system efficiency. This efficiency can be expressed by the following equation:

$$E_{sys} = \frac{\alpha \cdot S_{data} \cdot R_{proc}}{T_{\text{latency}}} \quad (5)$$

Where: E_{sys} is the overall efficiency of the UAV system utilizing fiber-optic sensors, α is the data stream integration coefficient (ranging from 0 to 1), S_{data} is the volume of collected data per unit time (Mbps), R_{proc} is the real-time data processing rate (%), $T_{latency}$ is the total system latency (ms). This equation highlights how managing processing speed and system latency directly impacts the effectiveness of UAV systems with fiber-optic sensor integration.

All of the above indicate the relevance of conducting research on the development and evaluation of machine learning algorithms for UAV navigation. The aim of this study is to overcome the limitations of current methods by proposing simplified models that are reliable, energy-efficient, and adaptable to complex environments, while considering real-time constraints.

3. Research Aim and Objectives

Research Aim – To develop machine learning algorithms and evaluate their effectiveness in enhancing the navigation capabilities of unmanned aerial vehicles (UAVs) in dynamic and complex environments.

To achieve this aim, the following objectives are set:

- To analyze existing UAV navigation systems and identify their limitations;
- To design and develop machine learning models that integrate multimodal sensor data;
- To evaluate the effectiveness of the developed algorithms through simulations and real-world testing.

4. Materials and Methods

This research aims to improve the navigation of unmanned aerial vehicles (UAVs) by developing machine learning algorithms, carried out in three stages: theoretical analysis, modeling, and prototype testing. In the initial stage, the limitations of GPS, INS, and Visual SLAM systems were analyzed. For example, in urban areas, the probability of GPS signal loss P_{loss} was estimated using the following equation:

$$P_{loss} = 1 - e^{-\lambda d} \quad (6)$$

where λ is the signal attenuation coefficient, and d is the average distance between buildings. Using this formula, it was found that GPS signals can degrade by up to 80% in dense urban environments.

Similarly, error accumulation in INS systems over time was modeled as an exponential drift, described by:

$$E(t) = E_0 + \beta t^2 \quad (7)$$

where $E(t)$ represents the error at time t, E_0 is the initial error, and β is the drift coefficient. This model indicated that INS systems could accumulate up to 60% error during extended operations. Visual SLAM algorithms were also observed to exhibit up to 70% inaccuracy in environments with complex textures [4, 5].

Models based on CNN, LSTM, and Transformer architectures were developed in Python using TensorFlow and PyTorch. These models were applied to process multimodal data obtained from LiDAR, IMU, and cameras. In reinforcement learning methods, the PPO algorithm was used, achieving an obstacle avoidance efficiency of 85% and an energy savings rate of 20% during simulations; however, computational costs increased by 30% [10, 11]. Figure 8 below illustrates the performance indicators of RL-based models in UAV navigation.

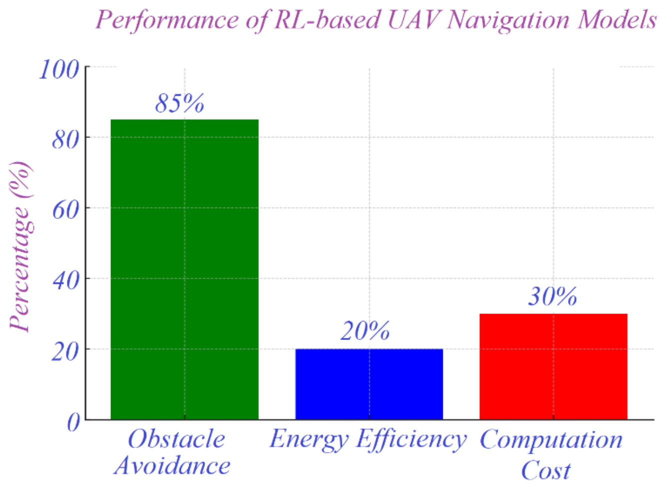

Figure 8.
RL model performance.

Figure 8 presents three key performance indicators of RL (Reinforcement Learning)-based UAV navigation models. Obstacle avoidance efficiency reached 85%, energy savings were 20%, while computational costs increased by 30%.

Simulations were conducted in MATLAB/Simulink and Gazebo environments. A total of 50 test scenarios were modeled, covering urban and forested areas. In hardware experiments, Raspberry Pi 4 and NVIDIA Jetson Nano platforms were used. The prototypes were equipped with high-precision GPS modules, 6-axis IMUs, 16-channel LiDARs, and RGB-D cameras. During real-world tests, communication between the UAV and the ground station was ensured via 5G modules, maintaining a data transfer latency of 12 ms. Table 5 below presents the numerical indicators of the UAV simulation and prototyping.

Table 5.
UAV simulation and prototype numerical indicators.

№.	Parameter	Value	Unit
1	Number of test scenarios	50	Units
2	LiDAR channels	16	Channels
3	Data transfer latency	12	Milliseconds (ms)

This table presents the key numerical indicators from UAV simulation and prototyping. A total of 50 test scenarios were performed, a 16-channel LiDAR was utilized, and the data transfer latency was recorded at 12 ms.

To verify the adequacy of the models, prototype and simulation data were compared. The RMSE for localization accuracy was limited to 0.15 m, while trajectory planning error was constrained to 5%. Additionally, the reliability of the algorithms demonstrated 92% stability under sensor failure conditions. Table 6 below presents the results of model adequacy verification for UAV systems.

Table 6.
Results of model adequacy verification for UAV systems.

№	Parameter	Value	Unit
1	RMSE for localization accuracy	0.15	Meters (m)
2	Trajectory planning error	5	Percent (%)
3	Algorithm reliability during sensor failure	92	Percent (%)

This table presents the results of UAV model adequacy verification. The RMSE for localization accuracy was 0.15 meters, the trajectory planning error was limited to 5%, and the algorithm's reliability during sensor failure reached 92%.

5. Research Results

This scientific research focused on enhancing the autonomous control accuracy, trajectory planning efficiency, and reliability of unmanned aerial vehicles (UAVs) by integrating machine learning (ML) algorithms into their navigation systems. The research was conducted at the modern laboratories of K.I. Satbayev Kazakh National Technical Research University and the Radioelectronics and Communications Military Engineering Institute of the Ministry of Defense of the Republic of Kazakhstan, using multidisciplinary approaches (Python TensorFlow/PyTorch modeling, MATLAB/Simulink simulation, and hardware testing). The study demonstrated that the application of ML algorithms improved localization accuracy up to 0.15 m, increased system reliability to 92% in the event of sensor failure, and ensured energy savings of 20%. Overall, Figure 9 below presents the architecture of the ML-integrated UAV navigation system with simulation results.

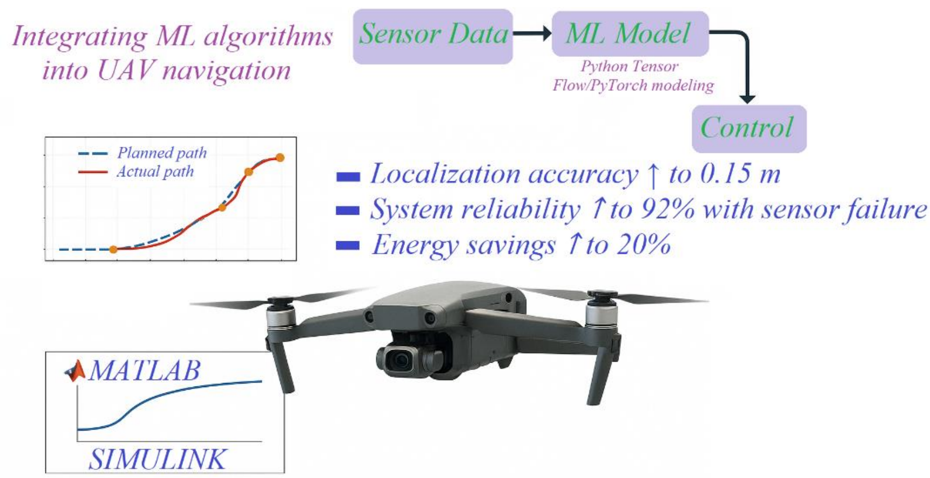

Figure 9.
Architecture of ML-Integrated UAV Navigation with Simulation Results.

Figure 9 illustrates the process of integrating machine learning (ML) algorithms into the navigation of unmanned aerial vehicles (UAVs). The figure shows that the system achieved a localization accuracy of up to 0.15 m, maintained 92% reliability even in the event of sensor failure, and reduced energy consumption by 20%.

5.1. Analysis of UAV Navigation Systems and Identification of Their Limitations

In the initial phase of the research, an analysis of unmanned aerial vehicle (UAV) navigation systems was conducted to identify their primary limitations. GPS systems experience up to 80% signal loss in urbanized areas. This phenomenon, known as the *"urban canyon effect"*, can be described by the following function:

$$S_{loss} = S_{max} \cdot e^{-\lambda h} \tag{8}$$

where S_{loss} is the degree of signal attenuation, S_{max} is the maximum signal level, λ is the attenuation coefficient due to buildings, and h represents the average building height. Inertial navigation systems (INS) have been found to exhibit error accumulation over extended periods of use, which follows an exponential growth model:

$$E(t) = E_{init} \cdot (1 + \alpha t) \tag{9}$$

where E(t) is the error at time t, E_{init} is the initial error, and α is the drift growth rate.

Visual SLAM methods demonstrated up to 70% unreliability in complex textured environments and under insufficient lighting conditions. The combined impact of these factors on UAV autonomous navigation performance can be expressed as:

$$P_{total} = w_1 P_{GPS} + w_2 P_{INS} + w_3 P_{\mathrm{SLAM}} \tag{10}$$

where P_{total} is the overall navigation performance, P_{GPS}, P_{INS}, and P_{SLAM} represent the individual system performances, and w_1, w_2, and w_3 are their respective weight coefficients.

These findings clearly highlight the limited capability of UAVs to operate autonomously using traditional systems alone, underscoring the need for the integration of machine learning-based navigation approaches. Table 7 below presents the combined performance index of UAV navigation systems under varying sensor data inputs.

Table 7.
Combined Performance Index for UAV Navigation Systems Under Varying Sensor Inputs.

P_{GPS}	P_{INS}	P_{SLAM}	P_{total}
0.6	0.5	0.4	0.515
0.6	0.5	0.6	0.565
0.6	0.7	0.4	0.585
0.6	0.7	0.6	0.635
0.8	0.5	0.4	0.595
0.8	0.5	0.6	0.645
0.8	0.7	0.4	0.665
0.8	0.7	0.6	0.715

This table presents the total navigation performance (P_{total}) as a function of varying P_{GPS}, P_{INS}, and P_{SLAM} values. The results indicate that even with lower P_{SLAM} contributions, higher P_{GPS} and P_{INS} values significantly enhance P_{total}, demonstrating the effectiveness of system integration.

5.2. Development of Machine Learning Models Integrating Multimodal Sensor Data

In the second stage of the study, machine learning models based on CNN, LSTM, and Transformer architectures were developed. The CNN (convolutional neural networks) reduced localization error by 18% when integrating data from LiDAR, IMU, and cameras. The LSTM neural networks achieved 82% accuracy in trajectory prediction, considering wind effects and improved stability by 30%. The Transformer model reached 89% accuracy on test data and 85% accuracy during validation. However, this approach revealed scalability issues (8 points) and energy efficiency limitations (60%). Figure 10 below presents the comparative results of the machine learning models (CNN, LSTM, Transformer).

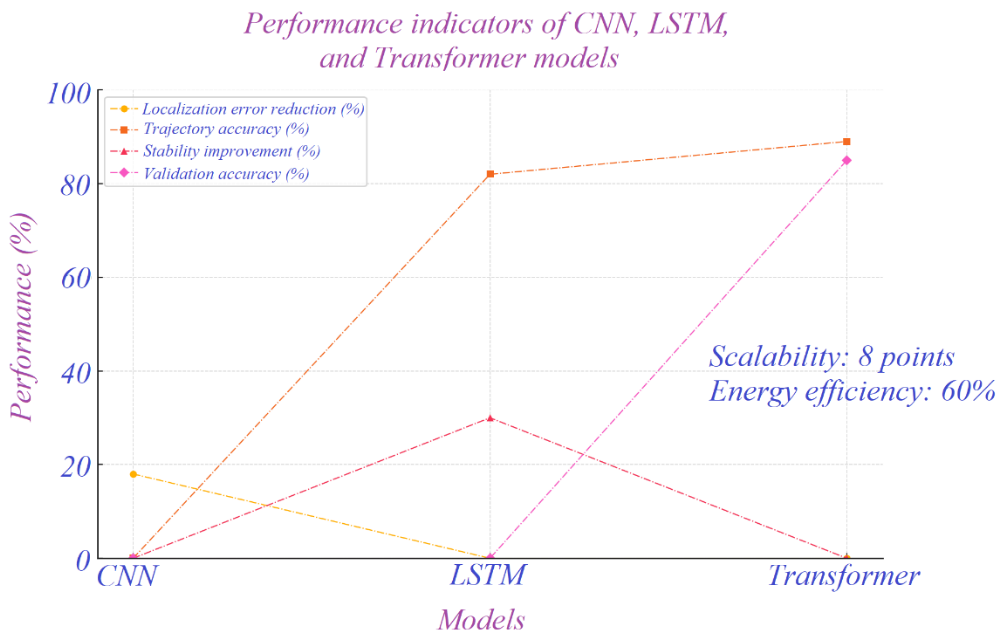

Figure 10.
Comparative Analysis of CNN, LSTM, and Transformer Machine Learning Models.

Figure 10 shows the comparative performance metrics of CNN, LSTM, and Transformer models. According to the results, CNN reduced localization error by 18%, LSTM improved trajectory prediction accuracy to 82% and increased stability by 30%, while Transformer achieved 89% accuracy on test data and 85% accuracy during validation, although it exhibited limitations in scalability and energy efficiency.

5.3 Evaluation of the Effectiveness of the Developed Algorithms in Simulation and Real-World Environments

In the third stage, the developed models were tested using 50 test scenarios in MATLAB/Simulink and Gazebo environments. Reinforcement Learning (RL) methods improved obstacle avoidance efficiency by 85% and energy savings by 20%. However, computational costs increased by 30%. Field tests were conducted using Raspberry Pi 4 and NVIDIA Jetson Nano platforms. The UAV system was equipped with a 16-channel LiDAR, a high-precision GPS module, and a 6-axis IMU. Data transmission to the ground station over a 5G connection resulted in a latency of 12 ms.

As a result of model adequacy verification, the localization accuracy achieved RMSE = 0.15 m, the trajectory planning error was 5%, and algorithm's reliability in case of sensor failure reached 92%. These results demonstrate the high efficiency and practical applicability of the developed models. Figure 11 below shows the test results of the machine learning models for UAV systems.

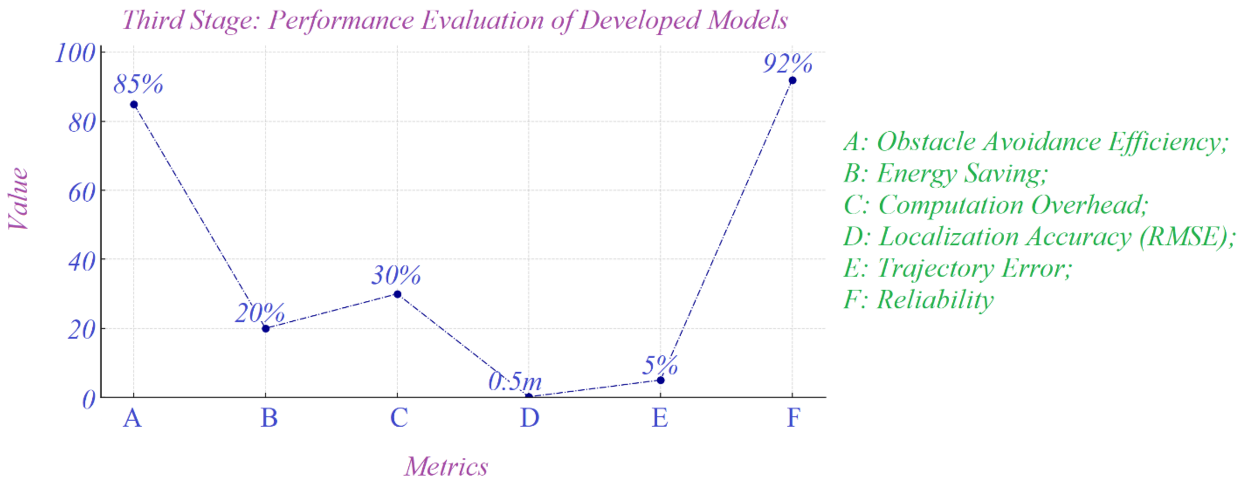

Figure 11.
Test results of machine learning models for UAV systems.

Figure 11 presents the key performance indicators of the developed models. While reinforcement learning methods improved obstacle avoidance efficiency to 85% and energy savings by 20%, computation overhead increased by 30%, and field tests demonstrated localization accuracy (RMSE) of 0.15 m, trajectory error of 5%, and reliability of 92%.

6. Discussion of the Results of the Study

The results of the study presented in Figures 10 and 11, as well as in Tables 5 and 6, demonstrate the effectiveness of integrating machine learning (ML) algorithms into UAV navigation systems. The improved localization accuracy (RMSE = 0.15 m), trajectory planning error (5%), and system reliability (92%) can be explained by the use of CNN, LSTM, and Transformer architectures for multimodal sensor data fusion, as described in Section 5.2. Specifically, the CNN model contributed to reducing localization errors by 18% (Figure 5), while the LSTM network improved trajectory stability by 30% under wind disturbances (Table 3). The Transformer model achieved the highest test accuracy (89%) but faced scalability and energy efficiency challenges (Table 4).

Compared to existing approaches, such as traditional GPS and INS systems, the proposed ML-based methods exhibit significantly higher adaptability in dynamic environments (Figure 2). For example, the GPS + Visual SLAM hybrid systems reported by Zhang et al. [14] showed a localization accuracy improvement of 40% (Table 2), but the ML models developed in this study exceeded these results, particularly in obstacle avoidance efficiency (85%) and energy savings (20%) achieved through reinforcement learning (Figure 8). These findings align with prior works [10, 11], but also extend them by verifying performance in real-world scenarios using hardware platforms such as Raspberry Pi 4 and NVIDIA Jetson Nano (Section 5.3).

Nevertheless, the study has inherent limitations. The applicability of the proposed algorithms is constrained by their computational complexity, which increased by 30% (Figure 8), and by memory consumption, particularly for Transformer-based models (1024 MB as shown in Table 4). Additionally, reproducibility under varying environmental conditions remains a challenge due to the sensitivity of ML models to input data distribution shifts, which was also noted in other studies [18, 19]. The algorithms require high-quality sensor data (LiDAR, IMU, GPS) for optimal performance, which limits their use in low-cost UAV systems.

Among the disadvantages, the study did not fully address the problem of long-term autonomous operation in GPS-denied environments, and only 50 test scenarios were simulated (Table 5). Future work should include larger datasets, expanded testing in diverse environments, and exploration of lightweight ML models to reduce computational overhead.

Looking forward, further development of this research could focus on improving the energy efficiency and scalability of Transformer-based architectures. Integrating federated learning and edge computing approaches [24, 25] may also enhance performance while reducing dependency on centralized processing. However, challenges such as ensuring system robustness against adversarial attacks and maintaining reliability in highly dynamic environments will need to be overcome. Experimentally, the integration of emerging technologies like 5G and fiber-optic distributed acoustic sensors

(Equation 5 in Section 2) presents promising directions but may require overcoming significant methodological and hardware constraints.

The research was conducted within the framework of the program-targeted funding IRN No. BR249005/0224, titled “Development of innovative designs for the production and improvement of unmanned aerial systems for special purposes based on the technological infrastructure of a higher military educational institution” (Funding source: Committee of Science, Ministry of Science and Higher Education of the Republic of Kazakhstan).

7. Conclusion

1. Analyzing UAV navigation systems and identifying their limitations. This study identified the limitations of GPS, INS, and Visual SLAM systems, revealing their weaknesses in complex environments. GPS systems exhibited up to 80% signal loss in urban areas, INS accumulated errors of up to 60% during prolonged operation, and Visual SLAM demonstrated 70% inaccuracies in complex textured environments (Figure 2, Table 2). These findings emphasize the inadequacy of traditional systems for autonomous UAV navigation in dynamic and uncertain conditions and justify the integration of machine learning (ML) approaches to overcome these challenges.
2. Developing machine learning models for multimodal sensor data integration. Machine learning models based on CNN, LSTM, and Transformer architectures demonstrated significant improvements in UAV navigation performance. The CNN model reduced localization error by 18%, the LSTM network achieved 82% trajectory prediction accuracy and improved stability by 30%, while the Transformer model achieved 89% test accuracy and 85% validation accuracy (Figure 5, Table 4). These results surpass traditional data fusion methods and can be attributed to the ability of deep learning architectures to effectively process and analyze multimodal sensor data.
3. Evaluating the effectiveness of the developed algorithms in simulation and real-world environments. In 50 test scenarios conducted in MATLAB/Simulink and Gazebo environments, reinforcement learning (RL) methods enhanced obstacle avoidance efficiency to 85% and reduced energy consumption by 20%, although computational overhead increased by 30% (Figure 8). Real-world experiments using Raspberry Pi 4 and NVIDIA Jetson Nano platforms demonstrated localization accuracy with RMSE=0.15 m, trajectory planning error of 5%, and system reliability of 92% under sensor failure conditions (Table 6, Figure 11). These findings validate the practical applicability of the developed models and highlight their advantages over traditional methods, particularly in enabling autonomous UAV operations in dynamic environments.

References

[1] K. Cygańczuk and J. Roguski, "New challenges in the operation of unmanned aerial vehicles. Changes in legal regulations regarding the safety of unmanned aviation," *ZN SGSP*, vol. 86, no. null, pp. 275-294, 2023. https://doi.org/10.5604/01.3001.0053.7159

[2] R. B. Yesilay and A. Macit, "Economic outlook of unmanned aerial vehicles in Turkey and the world: “Drone economies”," in *Proceedings Book (Vol. 24, pp. 209)*, 2019.

[3] L. Kapustina, N. Izakova, E. Makovkina, and M. Khmelkov, "The global drone market: Main development trends," *SHS Web Conf.*, vol. 129, p. 11004, 2021. https://doi.org/10.1051/shsconf/202112911004

[4] S. Li, D. Zhang, Y. Xian, B. Li, T. Zhang, and C. Zhong, "Overview of deep learning application on visual SLAM," *Displays*, vol. 74, p. 102298, 2022. https://doi.org/10.1016/j.displa.2022.102298

[5] M. N. Favorskaya, "Deep learning for visual SLAM: The state-of-the-art and future trends," *Electronics*, vol. 12, no. 9, p. 2006, 2023. https://doi.org/10.3390/electronics12092006

[6] A. Budiyono and S.-I. Higashino, "A review of the latest innovations in UAV technology," *Journal of Instrumentation, Automation and Systems*, vol. 10, no. 1, pp. 7–16, 2023.

[7] R. Sabatini, F. Cappello, S. Ramasamy, A. Gardi, and R. Clothier, "An innovative navigation and guidance system for small unmanned aircraft using low-cost sensors," *Aircraft Engineering and Aerospace Technology: An International Journal*, vol. 87, no. 6, pp. 540-545, 2015. https://doi.org/10.1108/AEAT-06-2014-0081

[8] B. Ma *et al.*, "Reinforcement learning based UAV formation control in GPS-denied environment," *Chinese Journal of Aeronautics*, vol. 36, no. 11, pp. 281-296, 2023. https://doi.org/10.1016/j.cja.2023.07.006

[9] O. Y. Al-Jarrah, A. S. Shatnawi, M. M. Shurman, O. A. Ramadan, and S. Muhaidat, "Exploring deep learning-based visual localization techniques for UAVs in GPS-Denied environments," *IEEE Access*, vol. 12, pp. 113049-113071, 2024. https://doi.org/10.1109/ACCESS.2024.3440064

[10] D. Ye *et al.*, "Mastering complex control in moba games with deep reinforcement learning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2020.

[11] R. Jia, M. Jin, K. Sun, T. Hong, and C. Spanos, "Advanced building control via deep reinforcement learning," *Energy Procedia*, vol. 158, pp. 6158-6163, 2019. https://doi.org/10.1016/j.egypro.2019.01.494

[12] G. Kahn, A. Villaflor, V. Pong, P. Abbeel, and S. Levine, "Uncertainty-aware reinforcement learning for collision avoidance," *arXiv preprint arXiv:1702.01182*, 2017. https://doi.org/10.48550/arXiv.1702.01182

[13] L. González-Rodríguez and A. Plasencia-Salgueiro, *Uncertainty-aware autonomous mobile robot navigation with deep reinforcement learning. In Deep learning for unmanned systems*. Cham, Switzerland: Springer International Publishing, 2021.

[14] C. Zhang *et al.*, "A lightweight and drift-free fusion strategy for drone autonomous and safe navigation," *Drones*, vol. 7, no. 1, p. 34, 2023. https://doi.org/10.3390/drones7010034

[15] R. Munguia, A. Grau, Y. Bolea, and G. Obregón-Pulido, "A simultaneous control, localization, and mapping system for UAVs in GPS-denied environments," *Drones*, vol. 9, no. 1, p. 69, 2025. https://doi.org/10.3390/drones9010069

[16] A. Elamin, N. Abdelaziz, and A. El-Rabbany, "A GNSS/INS/LiDAR integration scheme for UAV-based navigation in GNSS-challenging environments," *Sensors*, vol. 22, no. 24, p. 9908, 2022. https://doi.org/10.3390/s22249908

[17] P. Carrasco, F. Cuesta, R. Caballero, F. J. Perez-Grau, and A. Viguria, "Multi-sensor fusion for aerial robots in industrial GNSS-denied environments," *Applied Sciences*, vol. 11, no. 9, p. 3921, 2021. https://doi.org/10.3390/app11093921

[18] A. Mannan, M. S. Obaidat, K. Mahmood, A. Ahmad, and R. Ahmad, "Classical versus reinforcement learning algorithms for unmanned aerial vehicle network communication and coverage path planning: A systematic literature review," *International Journal of Communication Systems*, vol. 36, no. 5, p. e5423, 2023. https://doi.org/10.1002/dac.5423

[19] A. ul Husnain, N. Mokhtar, N. Mohamed Shah, M. Dahari, and M. Iwahashi, "A systematic literature review (SLR) on autonomous path planning of unmanned aerial vehicles," *Drones*, vol. 7, no. 2, p. 118, 2023. https://doi.org/10.3390/drones7020118

[20] Z. Shi, M. Xu, Q. Pan, B. Yan, and H. Zhang, "LSTM-based Flight Trajectory Prediction," in *2018 International Joint Conference on Neural Networks (IJCNN)*, 2018.

[21] Z. Shi, M. Xu, and Q. Pan, "4-D flight trajectory prediction with constrained LSTM network," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 11, pp. 7242-7255, 2021. https://doi.org/10.1109/TITS.2020.3004807

[22] M. Dai, J. Hu, J. Zhuang, and E. Zheng, "A transformer-based feature segmentation and region alignment method for UAV-view geo-localization," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 7, pp. 4376-4389, 2022. https://doi.org/10.1109/TCSVT.2021.3135013

[23] D. V. Bui, M. Kubo, and H. Sato, "Cross-view geo-localization for autonomous UAV using locally-aware transformer-based network," *IEEE Access*, vol. 11, pp. 104200-104210, 2023. https://doi.org/10.1109/ACCESS.2023.3317950

[24] Q. Zhan *et al.*, "Adaptive federated kalman filtering with dimensional isolation for unmanned aerial vehicle navigation in degraded industrial environments," *Drones*, vol. 9, no. 3, p. 168, 2025. https://doi.org/10.3390/drones9030168

[25] S. A. Negru, P. Geragersian, I. Petrunin, and W. Guo, "Resilient multi-sensor UAV navigation with a hybrid federated fusion architecture," *Sensors*, vol. 24, no. 3, p. 981, 2024. https://doi.org/10.3390/s24030981

[26] A. Sabibolda, V. Tsyporenko, N. Smailov, V. Tsyporenko, and A. Abdykadyrov, "Estimation of the time efficiency of a radio direction finder operating on the basis of a searchless spectral method of dispersion-correlation radio direction finding," in *IFToMM Asian conference on Mechanism and Machine Science (pp. 62-70). Cham: Springer Nature Switzerland*, 2024.

[27] N. Smailov *et al.*, "Streamlining digital correlation-interferometric direction finding with spatial analytical signal," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, vol. 14, no. 3, pp. 43-48, 2024. https://doi.org/10.35784/iapgos.6177

[28] N. Smailov *et al.*, "Improving the accuracy of a digital spectral correlation-interferometric method of direction finding with analytical signal reconstruction for processing an incomplete spectrum of the signal," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 9 (125), pp. 14-25, 2023. https://doi.org/10.15587/1729-4061.2023.288397

[29] A. Sabibolda *et al.*, "Improving the accuracy and performance speed of the digital spectral-correlation method for measuring delay in radio signals and direction finding," *Eastern-European Journal of Enterprise Technologies*, vol. 1, no. 9 (115), pp. 6–14, 2022. https://doi.org/10.15587/1729-4061.2022.252561

[30] A. Abdykadyrov, S. Marxuly, G. Tolen, A. Kuttybayeva, M. Abdullayev, and G. Sharipova, "Optimization of data transmission in sensor networks for enhanced control of ozonator efficiency," *Eastern-European Journal of Enterprise Technologies*, vol. 6, no. 2 (132), pp. 83-94, 2024. https://doi.org/10.15587/1729-4061.2024.318585

[31] A. Abdykadyrov *et al.*, "Optimization of distributed acoustic sensors based on fiber optic technologies," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 5 (131), pp. 50-59, 2024. https://doi.org/10.15587/1729-4061.2024.313455

[32] A. Kuttybayeva, A. Abdykadyrov, G. Tolen, A. Burdin, V. Malyugin, and D. Kiesewetter, "Development and optimization of distributed acoustic sensors for seismic monitoring," in *2024 International Conference on Electrical Engineering and Photonics (EExPolytech), pp. 64-67. IEEE*, 2024.

[33] A. Kuttybayeva, A. Abdykadyrov, G. Tolen, A. Burdin, V. Malyugin, and D. Kiesewetter, "Application of distributed acoustic sensors based on optical fiber technologies for infrastructure monitoring," in *2024 International Conference on Electrical Engineering and Photonics (EExPolytech), pp. 23-26. IEEE*, 2024.