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Real-time drone type recognition using artificial intelligence

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Abstract. The rapid proliferation of drones in military, civilian and critical infrastructure requires fast and accurate systems for their recognition and classification. The study aimed to increase the efficiency and accuracy of drone identification by developing an approach to their classification using artificial intelligence methods in real time. The study involved the analysis of drone typology, comparative analysis of artificial intelligence methods, visual modelling, software prototyping, and evaluation of classification accuracy metrics. As a result of the first stage of the study, a classification of drones by design, purpose, size and technical characteristics that affect their visual recognition was formed. The study established that multi-rotor vehicles are the most common due to their ease of operation; single-rotor vehicles are distinguished by their carrying capacity and flight duration; fixed-wing vehicles provide speed and range; and hybrid vehicles combine vertical take-off and horizontal flight. Additionally, specialised types of drones (combat, reconnaissance, photographic, micro- and tactical) were identified, and drones were classified by size, used in the study to compare the dimensions, weight, payload and flight duration with the types of applications. The second stage of the study included a comparative analysis of artificial intelligence methods for identifying types of drones in real time. The study established that computer vision models, in particular, convolutional neural networks, provide high accuracy, and one-stage architectures provide fast object detection. Transformers and fully connected neural layers demonstrate accuracy but require significant resources. Classical machine learning algorithms, such as support vector machine (92%), random forest (89%), nearest neighbours (87.7%), and naive Bayesian classifier (79%), showed different performance. In addition, reinforcement learning can be used in systems to adapt to changes in the environment, and decision trees provide transparency in classification. The results obtained contribute to the development of real-time drone detection and classification systems for defence, infrastructure protection, airspace monitoring and public safety

Keywords: unmanned aerial vehicles; machine learning algorithms; computer recognition; neural networks; identification of rotary-winged drones

INTRODUCTION

In the context of rapid technological development, automatic object detection and classification systems are becoming increasingly relevant in various fields, from defence to civilian. Artificial intelligence (AI) technologies are central in this process, automating the analysis of complex data in real time. One of the most substantial sub-branches of AI is machine learning (ML), which is used to detect patterns in data and make decisions without explicit programming. In the context of object recognition, including unmanned aerial vehicles (UAVs), ML ensures that the model can adapt to new data, incorporate visual differences between object types, and improve identification accuracy. Together with the development of computer vision, deep learning (DL), and transformational architectures, this opens new opportunities for creating effective recognition systems, particularly in the security sector. However, despite the availability of many approaches and solutions, there are still significant challenges associated with real-time drone classification in practical applications: limited

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computing resources, similarity of visual features between devices, unstable shooting conditions, and the lack of a clear typology of drones for automatic identification purposes. This creates the need for a systematic approach to drone classification and an optimal selection of AI methods for their effective recognition in dynamic environments.

A.P. Babich *et al.* (2024) determined that the main difficulty in countering modern types of drones, including First Person View (FPV) and strike drones, is timely detection, which is critical for the effective use of munitions. The study substantiated the need to develop a recognition system considering the characteristics of air targets and proposed the principles of its construction using different types of intelligence. N. Yermilova *et al.* (2023) demonstrated that DL models, in particular Faster Region Based Convolutional Neural Networks (Faster R-CNN), effectively recognise small objects of complex shape, although their use in real time is advisable only when the shape of the targets is highly complex. In addition, O.O. Korostin (2024) demonstrated that AI-based systems significantly increase the efficiency of automated object recognition in complex information flows, ensuring accuracy, speed, and reliability of processing.

G.A.S. Thomas *et al.* (2025) considered the possibilities of integrating embodied AI with computer vision in drone technology, emphasising its ability to autonomously navigate, detect obstacles and make real-time decisions in dynamic environments. R.C. Aguilera *et al.* (2025) developed an expert system based on the You Only Look Once (YOLO) architecture to automatically detect defects on wind turbine blades in real time during visual inspection by drones, which ensures fast and accurate recognition without additional computational costs. Conclusions of a study by A.S. Adebayo (2025) emphasised that the use of DL and computer vision for automated species classification significantly improves recognition accuracy, reduces field research time, and facilitates large-scale environmental monitoring using drones and real-time cameras. Furthermore, S. Chanda *et al.* (2024) developed a CNN-based system for identifying indoor room numbers using drones, achieving 92.4% recognition accuracy and improving the efficiency of autonomous navigation and delivery.

In turn, F.A.S. Islam (2025) demonstrated that AI, in particular computer vision and drone surveillance technologies, significantly improves environmental monitoring, detecting pollution, climate change, and protecting biodiversity by analysing large amounts of data in real time. The results of a study by N. Umashankar & K.S. Geethanjali (2024) emphasised that the integration of AI with unmanned platforms is used to perform object recognition, adaptive navigation, and real-time decision-making using CNN, support vector machine (SVM), reinforcement learning (RL), and other algorithms, which significantly increases their efficiency in a dynamic environment. Additionally, J. Castro *et al.* (2024) demonstrated the effectiveness of using AI to automatically identify target microenvironments based on high-precision aerial photography, used for precision planting with reduced resource costs and increased success rates using drones. Despite significant advances in the use of AI for object recognition, drone navigation, environmental monitoring, and real-time target detection, most of the studies reviewed focused either on specific application examples (e.g., infrastructure, environment, logistics) or on the recognition of individual objects without a systematic approach to classifying specific types of drones as complex aerial targets.

In contrast, the study aimed to develop a holistic approach to drone classification using AI methods, used for real-time identification of UAV types based on their visual and technical characteristics. The objectives of the study included an analysis of the main types of drones, their characteristics, classification by size and design features, as well as a review and practical demonstration of modern AI methods used for real-time drone identification.

MATERIALS AND METHODS

At the first stage of the study, a systematic analysis of the UAV typology was conducted with a focus on their visual characteristics that are key to computer recognition through a comparative analysis of technical characteristics, classification by functional and design features, and visual analysis of drone images. The study classified drones by type of construction, main technical parameters, purpose, size and visual perception features. Within the basic typology, four main categories of drones were considered: multi-rotor, single-rotor, fixed-wing, and hybrid Vertical Take-Off and Landing (VTOL). For each type, the key technical characteristics were analysed: flight duration, range, control complexity, structural complexity, hovering ability, wind resistance, thermal endurance, payload, operating costs, applications and limitations. For each type of drone, characteristic visuals were presented, showing the typical shape, rotor configuration, and overall silhouette of the vehicle (Choosing between multi-rotor…, 2025).

Next, specific types of drones that differ in purpose and operational features were considered: small drones, micro drones, tactical drones, reconnaissance drones, large combat drones, large non-combat drones, decoy drones, Global Positioning System (GPS) dependent drones, and photographic drones (Rennie, 2016). The description of each subtype included its functional purpose, main design features, and examples of real-world use. More general categories of drones were also identified based on the principle of lift: rotary, controlled lift, and hydrogen drones (Nagel, 2025). Their generalised classification was based on technical criteria such as propulsion type, lifting configuration and energy source. Additionally, examples of multi-rotor, single-rotor, fixed-wing, and hybrid VTOL drones are provided (Gong *et al.*, 2022; Nagel, 2025; Li, 2025). To detail the visual features that are substantial in the context of computer recognition, drones were classified by size (small, medium, and large drones) (Dukowitz, 2025). Each group was characterised by key parameters: body length or wingspan, weight class, maximum payload, average flight time, typical applications, and model examples.

At the second stage of the study, a comprehensive analysis of AI methods that can be used to identify UAV types in real time was conducted through visual modelling, software prototyping, evaluation of quality metrics, analysis of combined approaches, and adaptability analysis. The goal of this stage was to identify the most effective architectures and algorithms that ensure high classification accuracy, efficiency and adaptability in a real-world environment. Ten main approaches were considered in the analytical review: CNN, YOLO, vision transformer (ViT), multilayer perceptron mixer (MLP-Mixer), random forest (RF), SVM, K-nearest neighbours (KNN), naive bayes (NB), RL, and decision tree (DT) (Hasan & Cansever, 2023; Mrabet *et al.*, 2024; Emon *et al.*, 2025). For each method, the key advantages, typical disadvantages, and examples of use in the context of drone classification were identified. A combined approach that combines CNN and YOLO to improve the efficiency of recognising drone types in a video stream was presented separately. The diagram illustrated the stages of object detection and subsequent classification based on image features, and the architecture visualisation itself was created in RStudio using the R language.

In addition, an example of combining the ViT architecture with MLP-Mixer was provided to improve classification accuracy by better capturing both global and local visual patterns (Essa, 2024). The effectiveness of the classical ML algorithms (RF, SVM, KNN, NB) was tested in practice by developing a software prototype of a drone type classification system in Python in the Visual Studio Code environment. For this purpose, synthetic data (1,000 samples, 10 features: 6 informative, 2 redundant) generated by the make_classification (scikit-learn) function, which simulates the characteristics of drones (size, weight, propellers, flight) for 4 classes (multi-rotor, fixed-wing, hybrid, unknown), was used. The sample was split into training (70%, 700 samples) and test (30%, 300 samples) parts (train_test_split), and the features were standardised (StandardScaler). The models were trained, classified 10 test samples, and evaluated in terms of accuracy, precision, recall, and F-measure in a comparative report. Lastly, the potential of RL for adaptive optimisation in changing environments and the use of DT as a simple and fast, but less robust model for basic classification were discussed.

RESULTS

Typology of drones and features of their visual recognition

As of 2025, drones have become a key element of modern technological, industrial and transport systems, and are widely used in military, civilian and commercial sectors. The significant diversity of UAVs in terms of design features, size, functional purpose and technical parameters creates significant challenges for their accurate identification and classification, especially in real time. Reliable drone type recognition is highly necessary to ensure airspace safety, prompt response to potential threats, and effective management of unmanned systems. The main types of drones are listed in Table 1.

Table 1. Results of experimental verification of noise filtering algorithms

Characteristic	Multi-rotor	Single-rotor	Fixed-wing	Fixed-wing hybrid VTOL
Flight time	20-30 minutes	30-60 minutes	1-3+ hours	45-120 minutes
Range	1-5 km	5-15 km	10-100+ km	10-80 km
Ease of control	Easy	Hard	Moderate	Moderate
The complexity of CASA	Lower	Higher	Higher	Higher
Hovering capabilities	Excellent	Good	None	Excellent
Wind resistance	Moderate	High	High	High
Thermal protection	Moderate	Good	Good	Moderate
Load capacity	Low-medium	High	Average	Medium-high
Operating expenses	Moderate	High	Low	Moderate
Best suited for	Tourism, city inspections	Mining, heavy sensors	Rural areas, agriculture	Emergency services, universal operations
Not suited for	Long distances, heavy loads	Beginners and limited budgets	Urban areas, hovering	Simple missions, limited budgets

Notes: CASA – Civil Aviation Safety Authority

Source: compiled by the author based on Choosing between multi-rotor, fixed-wing, single-rotor, and hybrid VTOL drones – AUAV's complete guide for finding your perfect match (2025)

Notably, multirotor drones are the most common due to their ease of use, manoeuvrability and hovering capabilities, which makes them suitable for aerial photography, video surveillance, inspection and 3D scanning (Rennie, 2016). Their advantages include easy control and the ability to operate in tight spaces, but their limited flight time and low payload capacity reduce their effectiveness in tasks requiring long battery life or long range. A typical example is the Inspired Flight IF800 Tomcat medium-Lift Quadcopter Drone (Nagel, 2025). Fixed-wing drones, on the other hand, resemble aircraft, providing long flight times, high speeds, and the ability to cover large areas, making them optimal for mapping, agricultural monitoring, forestry surveillance, or infrastructure inspection (Rennie, 2016). At the same time, they cannot hover, need space for launching/landing, and require more pilot training. An example of such a drone is AeroVironment's JUMP 20 (Nagel, 2025).

Single-rotor drones are structurally similar to helicopters and have a high payload capacity, long flight time (especially with gas engines), and hovering capability (Rennie, 2016). They are suitable for tasks involving heavy sensors, such as laser scanning. Their disadvantages are the complexity of control, high cost, and the need for regular maintenance. A striking example is the PULSAR monocopter (Li, 2025). On the other hand, hybrid VTOL drones combine the vertical take-off/landing capabilities of multirotor drones with the horizontal flight efficiency of fixed-wing drones. They are gradually gaining popularity in logistics, including cargo delivery, monitoring of hard-to-reach areas, and patrolling. However, their technology is still evolving, and existing models may be inferior in terms of stability in certain flight modes. One example is the TX25A drone (Gong *et al.*, 2022). To illustrate the design features and differences between the types of drones under consideration, Figure 1 shows their images.

Figure 1. Main drone types: multi-rotor, fixed-wing, single-rotor and hybrid VTOL

Notes: multi-rotor drone (hexacopter) – in the upper left corner; fixed-wing drone – in the upper right corner; single-rotor drone (helicopter type) – in the lower left corner; hybrid VTOL drone – in the lower right corner

Source: compiled by the author based on Choosing between multi-rotor, fixed-wing, single-rotor, and hybrid VTOL drones – AUAV's complete guide for finding your perfect match (2025)

In addition to the above classification, it is also advisable to distinguish several specific types of drones that have a separate functional significance (Rennie, 2016). Small drones are used primarily for recreational purposes, as they are not suitable for precise surveying or complex tasks due to their low weight and instability. They are opposed by micro drones, small UAVs used for tactical reconnaissance, especially in military operations (e.g., Black Hornet), which are capable of operating in difficult conditions such as confined spaces, strong winds, and low visibility due to their built-in micro cameras. Tactical Drones are a separate group, which are moderately sized, equipped with infrared cameras and GPS, and are usually used for medium-range surveillance.

At the same time, reconnaissance drones, such as High Altitude Long Endurance drones (HALE) and Medium Altitude Long Endurance drones (MALE), can stay in the air for tens of hours, operate at altitudes above 10 km and are designed for strategic reconnaissance. Large Combat Drones, which carry missiles or bombs, have a range of over 1,000 miles and are used for precision strikes. There are also Non-Combat Large Drones, which are used in large-scale unarmed reconnaissance missions. Target and Decoy Drones, which mimic real targets to mislead air defences or the enemy, and GPS Drones, which are capable of autonomously moving along a predefined route with high positioning accuracy, are also noteworthy. As for Photography Drones with professional-grade cameras (including 4K), they are substantial in mapping, monitoring the condition of objects and creating media content.

Several other categories of drones can be distinguished (Nagel, 2025). For example, Rotary-Wing Drones, which include helicopter and multi-rotor (quadcopters, hexacopters, octocopters, etc.) models that are widely used in various fields due to their hovering and vertical take-off/landing capabilities but have a limited flight time due to high power consumption. Powered-Lift Drones are more complex hybrid devices that combine the advantages of both fixed-wing and rotary-wing drones, with the ability to switch between flight modes, but such designs have more complex mechanics and controls. In terms of power sources, most rotary drones are powered by electric lithium-polymer batteries, but alternative solutions such as solar panels, gas engines, hybrid systems, hydrogen fuel cells, and in-flight laser recharging technologies are being actively developed. Hydrogen and hybrid drones show significant potential for longer flight times, while solar technologies are best suited for fixed-wing vehicles with a large surface area. After considering the types of drones, it is also worth highlighting their size, which significantly affects the technical characteristics, functional purpose and ways of using UAVs (Table 2). Size categories can be used to classify drones by weight, payload, and flight duration, which is relevant for choosing the optimal model for specific tasks and regulatory requirements.

Table 2. Classification of drones by size and main characteristics

Drone size	Small	Average	Large
Size (length/wingspan)	Less than 30 cm (<12 inches)	30-60 cm (12-24 in)	Over 60 cm (>24 in) or wingspan >1.8 m (6 ft)
Weight class	Less than 0.9 kg (<2 lbs)	0.9-4.5 kg (2-10 lb)	4.5-25+ kg (10-55+ lb)
Maximum load capacity	Up to 0.45 kg (1 lb)	1-4.5 kg (2-10 lb)	Up to 226+ kg (500+ lb)
Flight time	10-25 minutes	20-40 minutes	30-60+ minutes
Sphere of use	Recreational use, social media	Photography, inspections, mapping	Agriculture, delivery, laser radar sensing, and the film industry
Example of the model	DJI Mini 2 SE, Ryze Tello	DJI Air 3, Mavic 3 Pro	DJI Matrice 350 RTK, Alta X, Griff 300

Notes: DJI – Da-Jiang Innovations; SE – Special Edition; RTK – Real Time Kinematic
Source: compiled by the author based on Z. Dukowitz (2025)

Thus, the modern typology of drones covers a variety of design and functional categories, from light multi-rotor vehicles to large fixed-wing and hybrid VTOL models, as well as specialised tactical, reconnaissance and combat drones. Each type has advantages, limitations and applications, which determine the choice of a specific model for various tasks from recreation and photography to agricultural monitoring, logistics and defence. To efficiently and accurately recognise and classify such diverse types of drones in real time, it is recommended to use modern AI methods that provide high data processing speed and adaptability to changing flight conditions and environments.

Artificial intelligence methods for real-time identification of drone types

In a modern environment, real-time drone identification requires the use of efficient AI methods capable of rapid adaptation, high classification accuracy, and operation in conditions of limited computing resources. The use of computer vision and DL models is particularly relevant, as they can be used for the automatic selection of relevant features, minimise human intervention, and ensure the functioning of recognition systems in a complex environment. The main AI methods used to recognise UAV types are shown in Table 3.

For instance, CNN is a deep neural network specialised in image processing. It consists of convolutional layers that automatically extract spatial features (contours, shapes, textures) and dense layers that perform classification. CNNs are effective for classifying objects that have already been found, for example, identifying the type of drone based on an image fragment (multi-rotor, fixed-wing, hybrid, etc.). However, CNN does not detect objects in the image but only classifies them. YOLO, on the other hand, is a one-step recognition model that detects and classifies objects in an image in one pass through a neural network. It is fast and works in real time and can quickly detect drones in a video stream while determining their coordinates and types. YOLO is suitable for situations where speed is critical, such as interception, monitoring, or air defence systems. The combined approach of YOLO and CNN is shown in Figure 2.

Table 3. AI methods used to identify drone types in real time

Method/Architecture	Advantages	Disadvantages	Examples of use
CNN	High accuracy, efficient on photos	Needs to be scaled, does not incorporate time	ResNet, MobileNet, EfficientNet
YOLO	Speed, real-time, compactness	Lower accuracy on small objects	YOLOv5, YOLOv8
ViT	Highly accurate, learns the global context	High memory consumption	ViT-Base, Swin Transformer
MLP-Mixer	Simplified structure, no folds	Poorer generalisability on complex data	MLP-Mixer (Google Research)

Continued Table 3.

Method/Architecture	Advantages	Disadvantages	Examples of use
RF	Speed, interpretability	Low efficiency for images	Early filtering, after vectorisation
SVM	High accuracy for small data sets	Does not scale for large amounts of data	Two-stage classification
KNN	Easy to implement, no training required	Slow real-time classification	Initial prototype systems
NB	Simplicity, efficiency on sparse data	Inefficient on correlated features	Initial recognition based on metadata
RL	Ability to adapt to changing conditions	Difficulties with building a reward function	Autonomous control of UAVs
DT	Simplicity, quick construction	Retraining, limited accuracy on complex samples	Basic classification systems

Notes: ResNet – Residual Network
Source: compiled by the author based on S.H. Hasan & G. Cansever (2023), M. Mrabet *et al.* (2024), S.I. Emon *et al.* (2025)

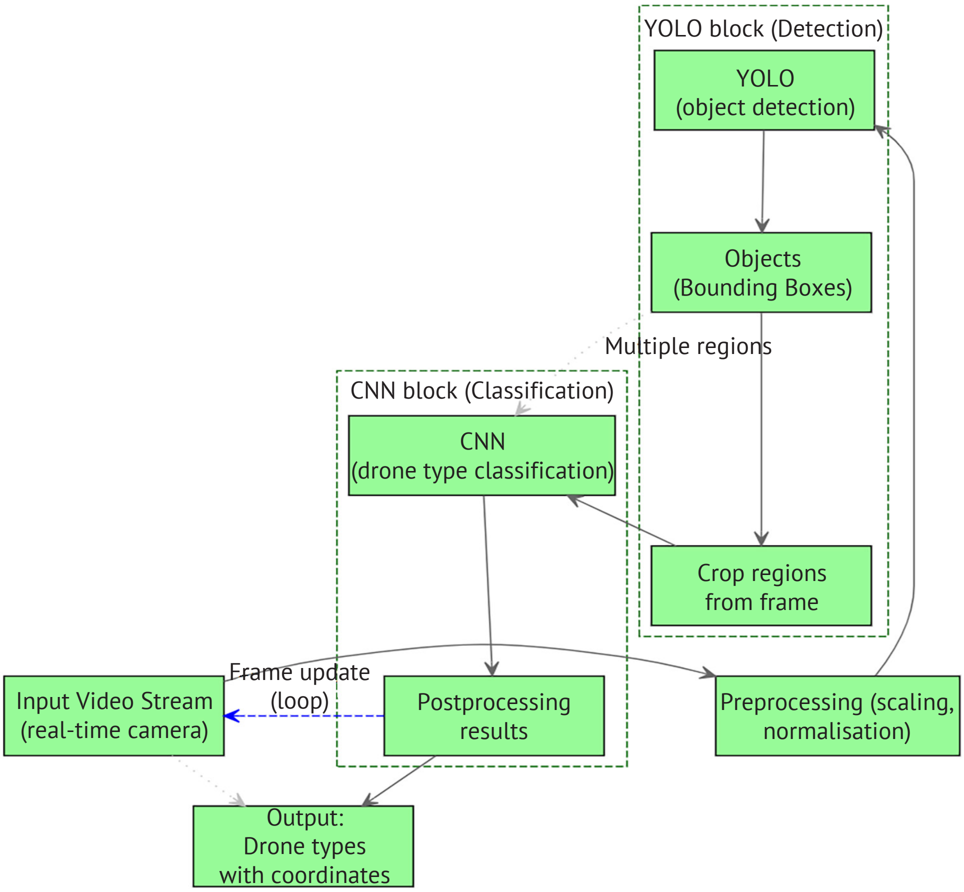

Figure 2. A combined YOLO and CNN approach for real-time drone type recognition
Source: compiled by the author

This diagram illustrates the step-by-step process of real-time drone type recognition using a combination of YOLO and CNN methods. It demonstrates how fast detection (YOLO) can be combined with accurate recognition (CNN) to effectively identify drone types in a video stream. The ViT model, which uses the transformer architecture popular in natural language processing to analyse images, is also useful. It breaks the image into patches, transforms them into a sequence of vectors, and analyses the global dependencies between these patches, which ensures efficient context capture at different scales. ViT provides high classification accuracy based on improved recognition of global visual patterns of the drone, such as the overall shape and positioning of elements. However, the model requires significant computational resources and memory, which can be a limitation when used in embedded systems or devices with limited power.

MLP-Mixer, on the other hand, is a neural network architecture that replaces traditional convolutional layers with a sequence of layers of fully connected neurons (MLPs). It handles sequences of input image patches, processing information by patch and feature in turn, which simplifies the model structure. In addition, MLP-Mixer offers a simpler architecture with fewer computations compared to traditional CNNs or transformers. However, due to the lack of local processing (convolution), it may not be able to handle details and complex visual features as well, which reduces the accuracy of drone classification against complex backgrounds or in unstable shooting conditions. To improve the accuracy and reliability of real-time drone type identification, ViT and MLP-Mixer models can be combined. ViT efficiently captures both local and global context of images, while MLP-Mixer provides simple and effective feature integration. For example, several ViT architectures such as Dual Attention ViT (DaViT), Inception Transformer (iFormer), and Group Propagation ViT (GPViT) can be combined through MLP-Mixer, which will combine the strengths of each model for comprehensive visual data analysis (Essa, 2024). This approach demonstrates high accuracy and robustness in complex recognition tasks, which makes it promising for use in real-time drone identification systems.

In general, ML is a substantial component of AI that can be used to automatically detect patterns in data and in subsequent decision-making. ML algorithms can be used to classify input information processed by preliminary computer vision stages, such as detection or segmentation. Among the classical ML algorithms that are the most effective for drone recognition, the following are worth highlighting: RF, SVM, KNN, and NB. For example, RF is an ensemble method that combines several DTs to improve classification accuracy and robustness. It can process vectorised drone features (e.g., body shape, wing length, number of propellers) obtained after the detection stage and classify the type of drone. Due to its structure, RF is less sensitive to overfitting than a single tree. In addition, SVM is a method that finds the hyperplane that best separates data between classes. For drone classification, SVM can work effectively with a small or medium feature set, especially if the features are pre-normalised. The algorithm is efficient in detecting complex boundaries between classes, which is an advantage when there is a variety of drone types.

KNN is an intuitively simple but robust method that determines the class of an object by its nearest neighbours in the feature space. It does not require a training phase but is sensitive to the scale of the features. In the current context, KNN can be used as a reference model or a basic classifier in the early stages of system development. Additionally, NB is a probabilistic model based on Bayes' rule with the assumption of feature independence. In the drone classification task, it is suitable for initial sorting or quick filtering of data, especially when using sparse or categorical features such as sensor type or geographic location. An example of a Python program that demonstrates the use of these ML algorithms to classify drone types is shown below (Fig. 3).

```python
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

models = {
    'Random Forest': RandomForestClassifier(random_state=42),
    'SVM': SVC(probability=True),
    'KNN': KNeighborsClassifier(),
    'Naive Bayes': GaussianNB()
}

all_reports = []

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    print(f"\n==== {name} ====")
    print("Classification examples for the first 10 samples:")
    for i in range(10):
        print(f"[{i+1}] Actual: {drone_labels[y_test[i]]} | Predicted: {drone_labels[y_pred[i]]}")

    report_dict = classification_report(y_test, y_pred, target_names=drone_labels.values(), output_dict=True)

    df_report = pd.DataFrame(report_dict).transpose()
    df_report['Model'] = name

    all_reports.append(df_report)
```

Figure 3. A code snippet for classifying drone types using ML algorithms
Source: compiled by the author

The programme demonstrates the application of the considered ML algorithms (RF, SVM, KNN, and NB) to classify drone types based on synthetic data. Data is generated, divided into training and test samples, after which each model is trained and predicts the results. Examples of the classification of the first 10 test samples are displayed, and detailed reports with key metrics are generated to compare the performance of the algorithms in one report. As a result, all algorithms showed the ability to classify drone types with varying accuracy (Fig. 4). The best results were obtained by SVM (92% accuracy) with high prediction accuracy, recall and F-measure, especially for hybrid and fixed-wing types of drones. RF also demonstrated a high result (accuracy ~89%), KNN is slightly lower (~87.7%), and NB has the lowest accuracy (~79%). The main errors occurred for the fixed-wing type of drone due to the similarity of features.

	Model	precision	recall	f1-score	support
Multirotor	Random Forest	0.881579	0.848101	0.864516	79.000000
Fixed-Wing	Random Forest	0.869565	0.869565	0.869565	69.000000
Hybrid	Random Forest	0.927711	0.927711	0.927711	83.000000
Unknown	Random Forest	0.875000	0.913043	0.893617	69.000000
accuracy	Random Forest	0.890000	0.890000	0.890000	0.890000
macro avg	Random Forest	0.888464	0.889605	0.888852	300.000000
weighted avg	Random Forest	0.890066	0.890000	0.889854	300.000000
Multirotor	SVM	0.852273	0.949367	0.898204	79.000000
Fixed-Wing	SVM	0.936508	0.855072	0.893939	69.000000
Hybrid	SVM	0.963415	0.951807	0.957576	83.000000
Unknown	SVM	0.940299	0.913043	0.926471	69.000000
accuracy	SVM	0.920000	0.920000	0.920000	0.920000
macro avg	SVM	0.923123	0.917323	0.919047	300.000000
weighted avg	SVM	0.922642	0.920000	0.920151	300.000000
Multirotor	KNN	0.843373	0.886076	0.864198	79.000000
Fixed-Wing	KNN	0.813333	0.884058	0.847222	69.000000
Hybrid	KNN	0.938272	0.915663	0.926829	83.000000
Unknown	KNN	0.918033	0.811594	0.861538	69.000000
accuracy	KNN	0.876667	0.876667	0.876667	0.876667
macro avg	KNN	0.878253	0.874348	0.874947	300.000000
weighted avg	KNN	0.879891	0.876667	0.877010	300.000000
Multirotor	Naive Bayes	0.769231	0.632911	0.694444	79.000000
Fixed-Wing	Naive Bayes	0.712500	0.826087	0.765101	69.000000
Hybrid	Naive Bayes	0.923077	0.867470	0.894410	83.000000
Unknown	Naive Bayes	0.766234	0.855072	0.808219	69.000000
macro avg	Naive Bayes	0.792760	0.795385	0.790544	300.000000
weighted avg	Naive Bayes	0.798057	0.793333	0.792187	300.000000

Figure 4. Comparative report of models by the main metrics of drone type classification
Source: compiled by the author

That is, SVM and RF are the most suitable for identifying drone types in real time. In addition, it is worth analysing RL and DT, which are also substantial components of AI in the context of drone recognition. RL is a method where an agent learns to make a sequence of decisions in an environment through a system of rewards and punishments. It is useful for adaptation in dynamic, changing environments, such as autonomous drone control or developing strategies to counter threats. RL can also be used to adaptively optimise the parameters of a recognition system in real time. Moreover, DTs are interpreted models that divide data into subsets using sequential feature-based rules. They are simple to implement and fast to learn but can be overtrained on complex data and have limited accuracy. In drone recognition tasks, DTs can be used for basic classification based on simple visual or sensory features, especially when transparency of decisions is required.

Thus, modern AI methods for real-time drone-type identification combine high accuracy, speed, and adaptability. The most effective are computer vision models, in particular CNN and YOLO, which provide high-quality classification and fast detection, respectively. ViT and MLP-Mixer offer new opportunities for deeper image analysis, although they have higher resource requirements. Classical ML algorithms such as RF and SVM have proven to be reliable and accurate in classifying drone types based on vectorised features, while KNN and NB can serve as complementary methods. Additionally, RL and DT methods complement AI systems by ensuring adaptation in dynamic environments and interpretability of results. Overall, a combined approach using different models and algorithms creates a robust, efficient, and flexible drone-type recognition system that meets the requirements of real-time and complex operating environments.

DISCUSSION

A holistic approach to real-time drone type classification using YOLO was implemented, covering visual and technical characteristics. The results highlighted that YOLO, as a one-step architecture, can not only localise drones in the image, but also immediately determine their type, which is critical in conditions of limited decision-making time. In turn, P. Sumathi *et al.* (2025) proposed a drone detection system based on YOLOv8 using a labelled dataset and implemented in a Flask application. The results of both studies are consistent in the context of YOLO's real-time performance, but the present study addressed the typological classification of drones, which incorporates their technical and design features, increasing the practical value of the model.

While YOLO is considered for fast object detection in a video stream, CNN is used to accurately determine their types based on visual characteristics. Instead, D. Li *et al*. (2024) applied a hybrid CNN + Long Short-Term Memory + self-attention model to detect drones as threats in perimeter security using acoustic data. That is, the results of both studies confirm the effectiveness of CNN in drone classification, but in contrast to the current model, which emphasised visual recognition of UAV types, the approach focuses on sensory detection of unauthorised intrusion without distinguishing between drone types. In general, the results addressed real-time drone type recognition using AI techniques to improve the accuracy of drone identification in security and monitoring environments. At the same time, N. Jain & S. Lenka (2025) analysed the role of drones and AI in precision agriculture, emphasising their importance for resource optimisation, increasing yields and automating agricultural processes. Thus, the results of the studies complement each other: both approaches demonstrate the practical value of AI drones, but for different purposes: safety and classification in the current case, and agricultural efficiency in the analysed study.

This study also demonstrated the effectiveness of using ViT and MLP-Mixer models for deep classification of drone types based on visual features, where ViT provides global recognition of the object structure, and MLP-Mixer simplifies the architecture without losing key characteristics. At the same time, H. Wasswa *et al*. (2025) evaluated the performance of ViT-MLP architectures in multi-class classification tasks, showing their high accuracy and stability compared to graph-based approaches. Thus, both studies confirm the feasibility of combining ViT and MLP in complex recognition tasks, although the present study addressed drone typology, while the aforementioned study investigated structured data and overall model performance.

This paper implements an approach to real-time classification of drone types using AI methods, with a focus on visual and design features of UAVs for monitoring, security, and situational awareness. Instead, M.A.R. Estrada (2025) proposes the concept of an autonomous NeuronDrone-Box module that makes combat decisions (attack/defence) based on chaotic dynamics algorithms and the author's methodology of econometrics, which combines economic and topographic parameters to model strategic scenarios. Although both works are based on the application of AI in drone systems, the current research is focused on recognising drone types in the visual field of view for peaceful and security tasks, while the aforementioned development focuses on autonomous combat control. The findings highlighted the importance of ML algorithms, including RF and SVM, for classifying drone types based on vectorised features after image preprocessing, which provided high accuracy (SVM 92%, RF ~89%) with efficient classification even in complex cases. Similarly, in M. Kassab *et al*. (2023), SVM and RF were used to classify drones, with SVM showing the highest accuracy among the classical methods. Both approaches confirm the effectiveness of these ML algorithms in aerial object classification tasks, but the present research addressed typological drone recognition, which makes it more targeted and applicable within visual monitoring systems.

Among the drones reviewed, multirotor drones are singled out as one of the most common types of UAVs due to their manoeuvrability, ease of control, hovering capability, and suitability for inspection, tourism, and video surveillance, despite their limited range and payload. In the same context, S. Hoang & I.Y. Shen (2024) analysed in detail the behaviour of a large multi-rotor (18-rotor) drone in wind gusts, which demonstrated the high sensitivity of the trajectory to gust parameters and the difficulty of predicting the response without the use of stochastic models. Thus, the results of the studies complement each other: the current approach outlines where and how multirotor systems should be used, while the authors cited above clarify their physical limitations in modelling and operation.

Compared to the current study, which addressed real-time recognition and classification of drone types using visually oriented AI methods, P.A. Darwinto *et al*. (2025) analysed autonomous drone control, sensor data processing, and UAV behaviour modelling to improve energy efficiency and navigation accuracy. Both approaches fulfil the potential of AI in drone systems, but with different goals: the current approach was focused on typological classification of drones for security purposes, while the aforementioned one was aimed to improve autonomy and controllability. The results of these works can be considered complementary in the context of expanding the functionality of AI-based drones.

The study also used KNN and NB algorithms as basic models for classifying drone types, with further evaluation of their effectiveness by accuracy, completeness, and F-measure. In turn, S.R. Medarametla & G. Thallapally (2025) compared these algorithms in the context of recommended systems in terms of performance and resource efficiency. In both cases, the superiority of KNN in classification accuracy was confirmed, while NB demonstrated higher speed and lower memory consumption. This correlates with the current results, where KNN showed better recognition quality and NB was effective for fast pre-filtering at low computational cost. While this paper implements real-time classification of drone types based on visual characteristics using ML and DL methods, including RL, R. San-Segundo *et al*. (2024) proposed a hybrid navigation system for drones that combines RL and expert rules for decision making in complex environments. Both approaches use AI in the context of unmanned systems, but with different goals. Moreover, the results of both papers highlight the benefits of combined AI solutions: in the current case, it is a combination of YOLO and CNN for accurate recognition, and in the above case, the integration of RL and rule-based logic to improve control efficiency.

One of the key types of drones studied in this paper is fixed-wing drones, which are considered a separate class with a characteristic aerodynamic structure, long flight range, high wind resistance, and suitability for monitoring large areas, in the agricultural or forestry sectors. M.-H. Chae *et al*. (2024) also addressed this type of drone, but in the context of developing a system to counter them. The study implemented the RL method for autonomous redirection of fixed-wing drones by manipulating the Global Navigation Satellite System (GNSS) signal. Thus, both papers not only analyse fixed-wing drones as a research object but also demonstrate the effectiveness of RL: in the current case, for adaptive control and optimisation of classification systems in real time, and in the above paper, for the implementation of autonomous strategies in counter-drone defence systems.

Alongside RL as a means of adaptive control in a dynamic environment, this paper also considers DT as a simple and interpretable model for initially classifying drones based on their visual and technical characteristics. S. Milani *et al*. (2023) combined RL with DT in the framework of explanatory AI, where RL is responsible for strategic learning and DT for transparency and explanation of agent actions. Thus, the results of both studies are consistent: the combination of RL and DT provides flexible, adaptive, and at the same time interpretable drone control and classification systems, which is especially valuable for security and monitoring applications. Finally, comparing the results of the current study with the study by A. Khan *et al*. (2025), a common desire for the multisectoral application of AI methods in solving applied problems is notable. In the aforementioned paper, AI is viewed as a driver of innovation in various fields from energy and medicine to robotics, security, and digital technologies, including drone systems. Similarly, in the current study, AI algorithms (CNN, YOLO, ViT, MLP-Mixer, SVM, RF, RL, and DT) were used to identify drone types in real time, which is critical in the areas of security, monitoring, and automation. However, in contrast to the generalised cross-disciplinary review of the aforementioned study, the current research addressed the practical implementation of AI in the specific task of visual UAV classification, supplemented by the analysis of drone technical characteristics.

Thus, the study demonstrates a holistic, multi-level approach to real-time drone type classification that combines visual models with traditional ML algorithms and RL methods. The obtained results confirm the effectiveness of AI in security, monitoring, and situational awareness tasks, providing high recognition accuracy, adaptability to changing conditions, and transparency of decision-making. Compared to other studies that focus on specific aspects such as navigation, recommender systems, sensory processing, or autonomous control, the current study is notable for the focus on typological drone recognition as a component of intelligent visual analysis systems. This is a significant contribution to the development of applied AI in drone technology, especially in the context of real-time and mission-critical application scenarios.

CONCLUSIONS

The results of the first stage showed that for 2025, the main structural types of drones are multi-rotor (20-30 minutes of flight time, 1-5 km range), single-rotor (30-60 minutes, 5-15 km), fixed-wing (1-3+ hours, 10-100+ km) and hybrid VTOL (45-120 minutes, 10-80 km), which differ in terms of payload, wind resistance, control complexity and application. The size classification showed a wide range of technical characteristics: flight time from 10 to over 60 minutes, payload from 0.45 kg to over 226 kg, which determines the effectiveness in various areas from recreation to agricultural monitoring and military operations. Multi-rotor drones dominate due to their ease of control and hovering capabilities but have limitations in terms of flight time and range. Fixed-wing and hybrid models provide a longer range, expanding their capabilities for large-scale missions. The wide variety of types and characteristics creates challenges for accurate visual recognition in real time, requiring the use of highly efficient AI methods.

The findings of the second stage confirmed that AI methods that combine accuracy, speed, and adaptability are the most effective for identifying drone types in real time. CNN provides high accuracy in image classification, while YOLO ensures fast detection and classification of drones in a video stream in real time. The ViT model achieves high accuracy by analysing the global context but requires significant computing resources. MLP-Mixer is promising for model integration but requires improvements in recognising complex features. Among the classical ML algorithms, RF and SVM proved to be the most reliable, with an accuracy of about 89% and 92%, while KNN and NB are of secondary importance. RL and DT methods complement the system by ensuring adaptability and interpretability of solutions. The integrated use of these methods creates a robust, flexible platform for real-time drone identification with limited resources. The main limitations of the study are the need for large amounts of training data, high power consumption of complex models (ViT, MLP-Mixer) and limited accuracy of classical algorithms in difficult conditions. This reduces the efficiency of drone-type recognition in mobile or resource-limited systems. Further research should focus on hybrid models, optimisation of architectures, and development of adaptive learning to improve accuracy and versatility in real-time.

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Розпізнавання типів дронів у реальному часі за допомогою штучного інтелекту

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Анотація. Стрімке поширення дронів у військовій, цивільній та критичній інфраструктурі вимагає створення швидких і точних систем для їх розпізнавання та класифікації. Мета дослідження полягала у підвищенні ефективності і точності ідентифікації дронів шляхом розроблення підходу до їх класифікації з використанням методів штучного інтелекту в умовах реального часу. У процесі дослідження застосовано аналіз типології дронів, порівняльний аналіз методів штучного інтелекту, візуальне моделювання, програмне прототипування та оцінку метрик точності класифікації. У результаті першого етапу дослідження сформовано класифікацію дронів за конструкцією, призначенням, розміром і технічними характеристиками, що впливають на їх візуальне розпізнавання. Встановлено, що мультироторні апарати є найпоширенішими через простоту керування; однороторні – вирізняються вантажопідйомністю та тривалістю польоту; фіксованокрилі – забезпечують швидкість і дальність; гібридні – поєднують вертикальний зліт і горизонтальний політ. Додатково виокремлено спеціалізовані типи безпілотників (бойові, розвідувальні, фотографічні, мікро- та тактичні), а також класифіковано дрони за розміром, що дозволило зіставити габарити, вагу, вантажопідйомність і тривалість польоту з типами застосування. Другий етап дослідження охопив порівняльний аналіз методів штучного інтелекту для ідентифікації типів дронів у реальному часі. Встановлено, що моделі комп'ютерного зору, зокрема згорткові нейронні мережі, забезпечують високу точність, а одноетапні архітектури – швидку детекцію об'єктів. Трансформери й повнозв'язні нейронні шари демонструють точність, але потребують значних ресурсів. Класичні алгоритми машинного навчання, зокрема метод опорних векторів (92 %), випадковий ліс (89 %), метод найближчих сусідів (87,7 %) та наївний баєсівський класифікатор (79 %) показали різну ефективність. Крім того, підкріплювальне навчання дозволяє адаптувати системи до змін середовища, а дерева рішень забезпечують прозорість класифікації. Отримані результати сприяють розробці систем виявлення та класифікації дронів у реальному часі для оборони, охорони інфраструктури, моніторингу повітряного простору та громадської безпеки

Ключові слова: безпілотні літальні апарати; алгоритми машинного навчання; комп'ютерне розпізнавання; нейронні мережі; ідентифікація роторних безпілотників