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UAV Integration with Neural Network in Landmine and Minefield Detection Tasks

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ABSTRACT One of the newest stages in the improvement of unmanned aerial vehicles (UAVs) is the integration of such systems with the neural networks, which, in turn, is not a novelty, but provides such systems with a further level of practical application. Having conducted a meta-analysis of the results of previous studies and available information on this topic, it was found that in the modern period, in addition to successful practical implementations of the integration of artificial intelligence with UAVs, there is already a certain classification of such processes according to the principles of optimal improvement of UAV capabilities and by areas of society. In addition to the publicly available and well-known information about the successful use of drones in the military and logistics sectors of human activity, UAVs successfully perform tasks in such sectors as agriculture, engineering, search, etc. The main purpose of the article is to analyze, review, study and systematize existing information on the positive effectiveness and feasibility of using the principles, approaches and integration of unmanned aerial vehicles with machine learning technologies to improve the efficiency of solving the problems of locating and detecting landmines and minefields, which is a major humanitarian problem for civil society located in the territory where military conflicts are currently taking place or in the territories where military clashes or conflicts have occurred in the past. In this article, a small study was conducted to develop a prototype neural network that can be further integrated with UAVs for landmine and minefield detection tasks. The described neural network was trained on an open dataset, trained using the algorithms chosen in the study, and has a fairly good final result in terms of detection accuracy, which is 1.5% higher than the accuracy of publicly available neural networks in a review of similar developments or studies.

KEYWORDS unmanned aerial vehicles, artificial intelligence, drones, machine learning, recognition of objects of various types, neural networks, a humanitarian problem, landmines and minefields detection.

I. INTRODUCTION

The technologies of the modern world are rapidly evolving and integrating into our lives. The use of unmanned aerial vehicles (UAVs), commonly known as drones, in various areas of human activity (from economic to military) is no longer a surprise, and the rapid development of information technology contributes to their modernization, improvement and becoming dynamic tools in various sectors of human activity. At the same time, the transformative power of artificial intelligence (AI) has penetrated almost every aspect of our lives. Now that we are at the intersection of these two technological frontiers, a new era is dawning - the era of integrating UAV systems with AI, which is not new, but provides such systems with a further level of practical application, pushing us into uncharted areas of efficiency, automation and endless possibilities [1].

One of the main factors in the effectiveness of such integration's the accuracy and performance of the AI model, which depends on the quality of the selected primary and secondary datasets (the data set on which the AI model is "trained"), the effectiveness of data preprocessing methods, the suitability and quality of algorithms, and the chosen machine learning methodology [1]. Machine Learning (ML) algorithms play a significant role in enhancing the capabilities of Unmanned Aerial Vehicles (UAVs) across various application areas. Some examples of how ML algorithms are used in specific industries, based on the latest research in UAVs and machine learning from the literatures [2-4]:

- **Agriculture:**
  - **Crop Monitoring:** ML algorithms can analyze drone-captured images to detect signs of diseases, pests, and nutrient deficiencies in crops. They can also predict yield based on historical data and current conditions.
  - **Weed Detection:** ML-based object detection models can identify and classify weeds in fields, helping farmers target herbicide application more precisely.
- **Construction and Infrastructure:**
  - **Defect Detection:** ML algorithms can process images and LiDAR data collected by drones to detect structural defects in buildings, bridges, and other infrastructure. These algorithms can identify cracks, corrosion, and other signs of deterioration.
  - **Progress Monitoring:** ML can analyze drone-captured images and data to compare the current state of a construction project with design plans. It can help track progress and identify delays or deviations from the plan.
- **Search and Rescue:**
  - **Object Detection:** ML models can identify objects of interest in aerial images, such as missing persons or their belongings. This can significantly speed up search and rescue operations.
  - **Path Planning:** ML algorithms can optimize the flight paths of drones during search and rescue missions,

considering terrain, weather conditions, and other factors to cover the area more efficiently.

- **Delivery and Logistics:**
  - **Route Optimization:** ML algorithms can optimize delivery routes for drones by considering real-time data, traffic conditions, and package size and weight. This ensures timely and efficient deliveries.
  - **Weather Prediction:** Machine learning models can predict weather conditions along delivery routes, allowing drones to adjust their flight plans to avoid adverse weather.
- **Military and Defense:**
  - **Target Recognition:** ML algorithms can be trained to recognize military targets, vehicles, or equipment from aerial images, assisting in surveillance and target acquisition.
  - **Swarm Coordination:** ML is crucial for coordinating swarms of drones, ensuring they work together efficiently and adapt to changing circumstances.

For this article, a separate topic was chosen - landmines and minefields detection using AI UAVs. The purpose of the study is to analyze, research, review and systematize existing information on the positive effectiveness and feasibility of using the principles, approaches and integration of unmanned aerial vehicles with AI technologies to improve the efficiency of mine detection tasks, as well as to present the author's own vision of the optimal application and improvement of the quality of such integration.

II. DETECTING LANDMINES AND MINEFIELDS USING AI-POWERED UAVS

Landmines are a serious humanitarian problem, as they remain active long after conflicts end and can harm civilians, including children, who accidentally come across them. Many international treaties and organizations work to ban landmines, clear existing minefields and provide assistance to victims of landmine accidents. The most famous treaty prohibiting the use, production, stockpiling and transfer of landmines is the Ottawa Treaty (also known as the Landmine Ban Treaty) [5].

Landmine detection is a complex and important task, as it involves the identification and clearance of hidden explosive devices to prevent harm to civilians and military personnel. Various methods and technologies have been developed to detect landmines (metal detectors, ground penetrating radar, electromagnetic induction sensors, acoustic sensors, etc.), all of which show high efficiency in accomplishing their tasks, although they differ greatly in the methodology and specifics of detection technology. However, there is something that unites all of the above technical devices - for their correct use, an operator is required, a person who is qualified to use any of the proposed tools. And there is nothing unexpected in this, except for one thing - such a specialist has to work in dangerous conditions, his work takes place directly on the territory strewn with mines, which poses a huge danger to the health and sometimes even the life of a qualified specialist. This is one of the main factors that has significantly influenced the rapid integration of drones and their further development in the field of landmine detection [6].

The use of unmanned aerial vehicles to detect landmines is becoming an increasingly valuable and effective method of humanitarian or military demining. UAVs can quickly cover large areas, provide high-resolution imagery and minimize the risk to human operators [7].

By analyzing various situations in depth and accurately, a huge amount of data is required to make decisions. This work is no exception. Developing, training, and testing neural network models requires large amounts of high-quality data. It is possible to find open data of various scans of mined areas using various sensors. Based on such data, we can create a ready-made dataset - a set of data on which we will train the artificial intelligence model. The problem at this stage is that data of this nature is often considered confidential or even has the status of a military secret, which makes it extremely difficult to find such a set of statistics for a small study. However, we're able to find an open-source dataset generated in a laboratory, as suggested by the authors in. It consists of a set of records of scans of mined areas obtained from unmanned aerial vehicles [8]. They have been tested in various operating situations. The set contains 525 records, each of which contains about 1.2 million counts showing the amplitude value of a quantity. The work process was quite detailed, and the tests were conducted in areas that differ not only in landscapes but also in some geodesic characteristics.

We can draw conclusions from the data we received – the ratio of the presence of landmines to their absence in the presented datasets is 77% to 23%. The latter facilitates noise avoidance analysis. This dataset can be used to obtain not only the results of landmine detection, but also to obtain a certain classification by mine type (PTM, AVM, Claymore). The full distribution of data for the task of detecting and classifying certain types of landmines is presented below in the dataset in Table 1.

TABLE 1. Data from an open data set on mine type classification.

Class	Segments	Samples 10^6	Sample Percentage %
No mines	46	910	19.46
APMs	81	1560	36.17
AVMs	77	1430	33.73
Claymore	24	510	10.64

The result is a dataset containing 20610 items and 1984 features. We divided the dataset into samples: training sample, validation sample, and test sample. The distribution of the described samples is shown in Table 2.

TABLE 2. Data from an open data set on mine type classification.

Class	Training set	Validation set	Test set
No mines	3040	460	910
APMs	5560	810	1560
AVMs	5320	770	1430
Claymore	1580	240	510

The ratio of samples is 60:15:25, respectively. The samples were distributed in proportion to the data in the original dataset [9].

The next step was to find and slightly modify the architecturally constructed neural network used in studies on detecting the presence and types of landmines [10]. The selected neural network consists of four layers of two-dimensional convolution, five layers of one-dimensional maximum pooling, and nine layers of three-dimensional convolution. The rectified linear unit (ReLU) was also chosen as the activation function for the convolutional layers of the neural network. This is followed by two fully connected layers with 4096 neurons each and ReLUs used as activation functions. The last layer of the presented neural network is a fully connected layer with four outputs (by class number). At this stage, the activation function is the Softmax function. Softmax is used in various multiclass classification methods, such as multiclass linear separation analysis, multinomial logistic regression (Softmax regression), artificial neural networks, and naive Bayesian classifier.

To classify the characters for the entire presented data set, this study uses such metrics as: reliability, precision, and recall. The study calculated a normalized confusion matrix for the selected dataset to determine the accuracy of each class model. Thus, the percentage of correct outputs of the chosen algorithm, which is called accuracy (α), is calculated using Eq. 1:

$$\alpha = \frac{P_t+N_t}{P_t+P_f+N_t+N_f}, \quad (1)$$

where P_t – positive true, N_t – negative true, T_f – positive false, N_f – negative false.

However, this value has one important feature that needs to be taken into account. It assigns equal weight to all types of landmines, which may be incorrect if the distribution of mines in the training set is heavily skewed toward one or more classes, for example, in the "mine present" and "mine absent" classification task. In the situation presented, the classifier will make more adequate decisions within the first class because it has more information about the first class. In practice, this leads to an error of, say, 70%, but within a certain class, the classifier works extremely poorly, incorrectly identifying even a third of those mines that are not detected when scanning the area with the appropriate sensors.

Training the classifier on a balanced and specially prepared data set is one of the correct ways out of this situation. Another way is to change the approach to quality assessment. Although this metric is intuitive, it doesn't work well with class imbalances. In addition to precision, we introduced precision (σ) and recall (ρ) metrics, which are presented in Eq. 2 and Eq. 3:

$$\sigma = \frac{P_t}{P_t+P_f},$$

$$\rho = \frac{P_t}{P_t+N_f}. \quad (3)$$

Based on the above, accuracy and recall indicators are focused on false positive and false negative results, respectively. To combine these results into one, we introduce a parameter f_a and use the Eq. 4:

$$2 \times \frac{\sigma\times\rho}{\sigma+\rho} = \frac{P_t}{P_t+\frac{1}{2}(P_f+N_f)}. \quad (4)$$

As a loss function (λ), the categorical cross-entropy was used, which is presented in Eq. 5:

$$\lambda = \sum_{i=1}^{output\ size} x_i \times \log_2(x_i). \quad (5)$$

The Adam algorithm with a learning rate of 0.00001 was chosen as the optimization algorithm. This choice is easily explained by the fact that Adam is one of the best optimization algorithms for deep learning, and its popularity is growing rapidly. Its adaptive learning speed,

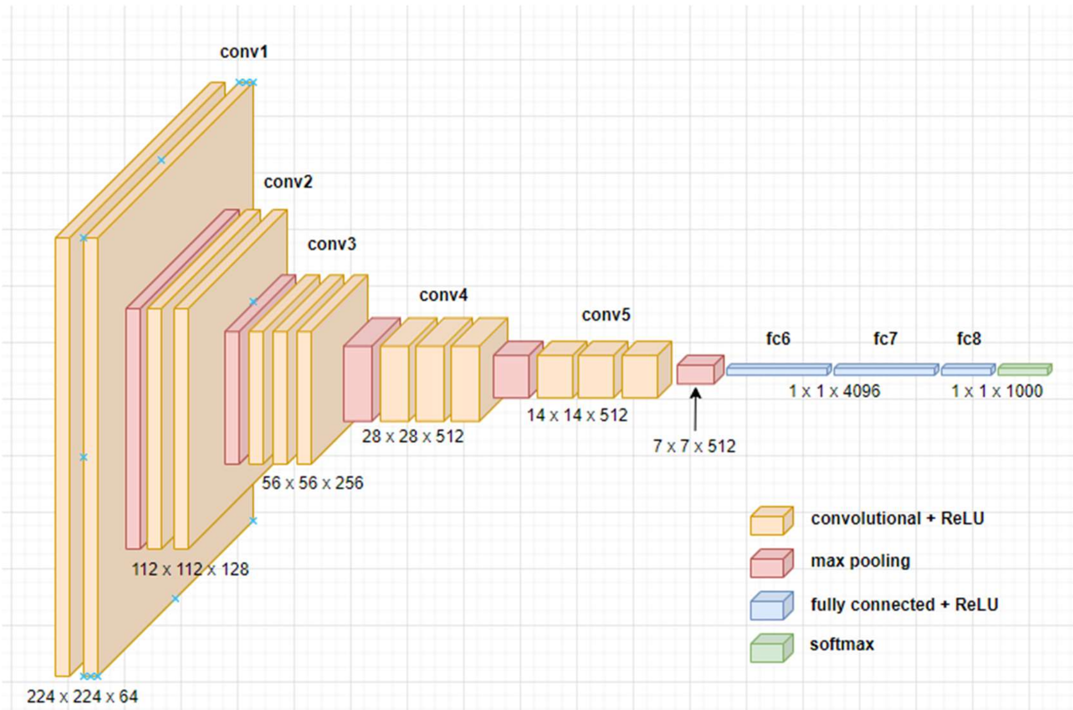

FIG. 1. Visualization of the considered neural network.

optimization efficiency, and robustness make it a popular choice for training neural networks. It should be noted that such optimization algorithms as Adam will remain important tools in the field of deep learning development for a long time. The training lasted 4500 epochs. A validation sample was run and validated at the end of each epoch. The model with the best accuracy was retained. The categorical cross-entropy of the loss function was used for all neural networks [11].

Using the Keras [12] and Tensorflow [13] frameworks of the Python, having calculated the necessary parameters, we have a graphical representation of the selected neural network model – Fig. 1.

As noted, the development of a full-fledged neural network is a rather difficult task within the framework of a small study, so having a basic set of code for its further full and successful launch, it was decided to integrate existing and accumulated materials into the already existing neural network development within the framework of this study. We chose Landmine Detector, an open-source project by a single developer on the GitHub platform. Link to the project itself [14].

In the presented project, the author offers a fully developed system for detecting landmines. The system includes a user interface and a server for autonomous detection of landmines in a given area. The landmine detection systems are designed to cover the maximum possible area of the minefield to detect landmines. The detected mines along with the scanned and abandoned area are displayed on a visual map. The entire set of tasks is designed to be performed with minimal human intervention, making it safer and more efficient at the same time.

The final step is to combine the proposed neural network prototype with the ready-made code described above. After that, the next step is to load the dataset selected in this work into the finished project and run it. Table 3 presents the final output data together with the results that were obtained in the research process.

TABLE 3. The obtained metrics of the research results.

Precision σ	Accuracy α	Recall ρ	f_a
0.9143	0.8987	0.9326	0.9233

As a result, we obtained a convolutional neural network that statistically outperforms some described open-source neural networks developed in the context of landmine and minefield detection research by 1.5% in terms of accuracy, recall, and metrics.

It is important to emphasize again that the above only modeled the use of a neural network for landmine detection in a small study, but even here we see that the effectiveness of such developments is significant.

III. CONCLUSION

In general, based on the meta-analysis and study of the data collected on this topic, practical modeling of a neural network for mine detection and minefields, it can be concluded that the process of integrating ML algorithms into UAVs allows these vehicles to operate autonomously, performing tasks and making decisions based on data in real time, processing large amounts of data obtained from various types of sensors on board UAVs, and profitably solving and optimizing many problematic aspects of using UAVs in any field of human activity, which makes such integration quite promising for the near future of humanity.

AUTHOR CONTRIBUTIONS

A.K. – methodology, conceptualization, software, formal analysis, validation, resources, investigation, writing-original, draft preparation, visualization; H.L. – conceptualization, resources, validation, investigation, methodology, writing-review and editing, visualization, supervision.

COMPETING INTERESTS

The authors declare no competing interests.

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Інтеграція БпЛА зі нейронною мережею у завданнях із виявлення наземних мін та мінних полів

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АНОТАЦІЯ Одним з новітніх етапів удосконалення безпілотних літальних апаратів (БпЛА) є інтеграція таких систем із нейронними мережами, що, в свою чергу, не є новинкою, але забезпечує таким системам подальший рівень практичного застосування. Провівши мета-аналіз результатів попередніх досліджень та наявної інформації за даною тематикою, було виявлено, що в сучасний період, окрім успішних практичних реалізацій інтеграції штучного інтелекту з БпЛА, вже існує певна класифікація таких процесів за принципами оптимального вдосконалення можливостей БпЛА та за сферами життєдіяльності суспільства. Окрім загальнодоступної та загальновідомої інформації про успішне використання дронів у військовій та логістичній сферах людської діяльності, БпЛА успішно виконують завдання в таких галузях, як сільське господарство, інженерія, пошук тощо. Головною метою статті є процес аналізу, огляду, дослідження та систематизація існуючої інформації щодо позитивної ефективності та доцільності використання принципів, підходів та інтеграції безпілотних літальних апаратів з технологіями машинного навчання для підвищення ефективності вирішення завдань із розташування та виявлення наземних мін та мінних полів, що є важливою гуманітарною проблемою для громадянського суспільства, яке знаходиться на території, де наразі відбуваються військові конфлікти, або на територіях, де в минулому відбувалися військові зіткнення чи конфлікти. У рамках даної статті було проведено невеличке дослідження із розробки прототипу нейронної мережі, що в подальшому можна інтегрувати із БпЛА для задач із виявлення наземних мін та мінних полів. Описана нейронна мережа навчалась на відкритому наборі даних, тренувалась за обраними у дослідженні алгоритмами та має досить непоганий кінцевий результат по точності виявлення, що в свою чергу більший на 1.5%, ніж точності загальнодоступних нейронних мереж в огляді схожих розробок, чи досліджень.

КЛЮЧОВІ СЛОВА безпілотні літальні апарати, штучний інтелект, дрони, машинне навчання, розпізнавання об'єктів різного типу, нейронні мережі, гуманітарна проблема, виявлення мін та мінних полів.