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Using complex-valued neural networks for aircraft identification

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ABSTRACT

This paper presents an approach to aircraft recognition using complex-valued neural networks. The objective of the article is to study the effectiveness of complex-valued neural networks for aircraft identification tasks based on radar data, the efficiency evaluated based on criteria such as classification accuracy, robustness to noise interference, the ability to maintain high accuracy with limited training data, and an optimal trade-off between accuracy and computational complexity. The study focuses on aircraft identification using phase and amplitude characteristics of radar signals, which are essential for aviation security and airspace monitoring. The research method includes theoretical analysis, modeling, and experimental testing. The paper discusses the architectural features of artificial neural networks that utilize complex numbers for signal processing. This approach enables the incorporation of phase information, which significantly improves the accuracy of radar data analysis. The results confirm that complex-valued neural networks surpass traditional models in recognition accuracy. Specifically, the inclusion of the phase component provides an increase in accuracy by up to eight and a half percent. Additionally, complex-valued neural networks demonstrate high resistance to noise interference, maintaining classification accuracy of up to ninety-two and three-tenths percent even at a noise level of thirty percent. Despite these advantages, the primary limitation of complex-valued neural networks is their higher computational complexity compared to real-valued models. This requires significant resources for training and implementation, which can be a critical factor for applications where real-time signal processing speed is essential. The study also explores optimization possibilities for artificial neural networks by developing hybrid approaches that combine the strengths of different network types and by simplifying architectures without compromising accuracy. The findings indicate that artificial neural networks are an effective tool for aircraft classification, particularly in complex signal environments and conditions with noise interference. These networks have significant potential for widespread use in both military and civilian airspace monitoring systems, providing enhanced accuracy and reliability in recognition tasks. The results obtained in this study open new opportunities for advancing aviation security technologies and automating aircraft recognition systems.

Keywords: Complex-valued networks; radar signals; aircraft recognition; phase analysis; aviation safety; object identification

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INTRODUTION

Aircraft recognition is a key task in many industries, including aviation security, defense systems, and airspace monitoring. Modern radar systems generate large amounts of data that require highly accurate and fast processing. Traditional approaches, including classical neural networks, demonstrate limitations in the accuracy of data analysis that have a phase nature or complex amplitude-phase dependence.

An important scientific problem is the necessity for accurate and reliable identification of low-observable aircraft, particularly unmanned aerial vehicles (UAVs), whose number in airspace is rapidly increasing. This poses significant demands for the efficiency of current aircraft classification systems.

The novelty of this study lies in the development of a neural network model for UAV classification that incorporates not only amplitude but also phase information from radar and acoustic signals. This approach significantly improves classification accuracy and robustness under challenging conditions with high levels of noise.

Complex-valued neural networks, which use complex numbers to represent weights, inputs, and activations, offer an innovative approach to processing radar signals. Due to their ability to work effectively with phase information, they open up new opportunities for identifying aircraft by their unique radar characteristics [1].

The relevance of the research topic is due to the growing number of objects in the airspace, among which there are more and more inconspicuous vehicles, such as drones. This places high demands on the accuracy, speed, and adaptability of recognition systems.

The objective of the article is to study the effectiveness of complex-valued neural networks for aircraft identification tasks based on radar data, the efficiency evaluated based on criteria such as classification accuracy, robustness to noise interference, the ability to maintain high accuracy with limited training data, and an optimal trade-off between accuracy and computational complexity. The main objectives are to analyze the theoretical aspects of complex-valued neural networks (CVNNs), evaluate their advantages over traditional networks, and conduct experimental modeling.

One of the most popular deep learning models is convolutional neural network (CNN) [2], which is used mainly in images processing.

The article provides an overview of the main characteristics of complex-valued neural networks, their architecture and applications in radar signal processing. The results of experiments demonstrating the feasibility of using CVNNs for aircraft recognition are presented, and conclusions about their practical significance are formulated.

LITERATURE REVIEW

Modern UAVs are widely used in various fields, including the military, intelligence, tactical surveillance, and cargo delivery. Given the growing number of cases of use of strike and reconnaissance UAVs, the development of effective systems for their recognition and classification is becoming critical. The use of such technologies is important to ensure safety and efficiency in various scenarios, in particular to maintain control over the airspace, as well as to provide accurate data for real-time decision-making.

The use of neural networks to solve the problem of classifying UAVs by their acoustic signature is of great interest to researchers. A study presented in [3] developed an approach based on the use of a convolution neural network to identify aircraft types based on sound data. The study demonstrates the effectiveness of such methods even with a limited amount of training data, which emphasizes the importance of high-quality dataset preparation. Given that acoustic signatures can vary depending on the type of UAV and environmental conditions, the use of neural networks allows for effective classification, even in difficult conditions.

Another study presented in [4] shows that neural networks can be effectively used to cluster attack UAVs. Using a neural network self-organization map (NN SOM) type network for first-person view (FPV) UAVs, the classification accuracy was over 98%. The results indicate the significant potential of using deep neural networks to solve the problems of separating and classifying group objects in real conditions, which is important for surveillance and monitoring systems.

The study presented in [5] deals with improving the course stability of UAVs in the absence of global navigation satellite system (GNSS). The use of additional sensors in combination with learning algorithms minimized the error in determining the course by 19.2 %. This confirms the potential of artificial intelligence to solve autonomous navigation problems in difficult conditions where the use of traditional navigation systems is impossible due to signal loss or interference.

The process of developing a technology for automating the collection and filling of a training data set for neural network recognition is considered in [6]. In particular, the use of UAVs for collecting aerial photographs, which have their own characteristics due to low flight altitude and the impact of vibrations, is investigated. The importance of creating specialized data selection methods for training neural networks that take into account these specific UAV flight conditions is considered. The study describes the creation of a software package that includes the processes of image segmentation and classification, followed by model retraining and testing on new data. It is noted that the improvement in the quality of classification after replenishing the dataset with new segments was 6 %, which indicates the effectiveness of methods for automating data collection for neural network learning.

Despite significant advances, the main challenge remains ensuring high real-time classification accuracy in a variety of acoustic environments and the presence of noise. Indeed, in real-world conditions, the sound signals received from UAVs can be distorted by external factors such as wind, other flying objects, or even weather conditions, which greatly complicates the classification task [7]. It is also necessary to take into account the limitations of computing resources inherent in autonomous systems operating in real time. These constraints require optimization of models and algorithms to ensure the accuracy and speed of classification in a resource-constrained environment.

The description of an object's image by its contour is sufficient for the classification of airborne objects and uses significantly less information compared to deep neural network analysis. This provides several advantages. Various methods of mathematical contour description are known [8], including those for determining types of aircraft.

Among the promising areas of aircraft recognition, approaches based on radar analysis and the use of correlation algorithms attracts special attention. The study in [9] considers a correlation algorithm for radar recognition of airborne objects by their long-range portraits. The main feature is the radar range portrait obtained using high-resolution sensing signals, and additional features are the trajectory characteristic and rotary modulation. Experiments for 20 types of aircraft have shown the high efficiency of the algorithm, especially for turbojets, propeller aircraft, helicopters, and missiles.

Another study [10] concerns the detection of small UAVs based on the electromagnetic spectrum. The authors propose a combined approach to detecting UAVs, which includes thermal imaging cameras, optical video cameras, radar stations, and radio monitoring systems. This approach can significantly improve the efficiency of detecting even low-visibility objects.

In this context, the use of CVNNs capable of efficiently processing the phase and amplitude characteristics of signals can play an important role. The integration of CVNNs with correlation algorithms and multispectral detection methods could significantly improve the accuracy and reliability of airborne object recognition in difficult conditions.

Thus, further research should focus on the integration of innovative signal processing algorithms with modern neural network technologies. This will not only improve existing approaches to aircraft classification and detection, but also lay the foundation for building new adaptive systems capable of operating in real time and taking into account various operating scenarios.

OBJECTIVE AND RESEARCH TASKS

CVNNs are becoming an increasingly popular tool for analyzing complex signals, such as radar and acoustic signals, due to their unique ability to process both amplitude and phase information. Traditional real-valued models often ignore the phase component of signals, which contains important information about the structure, characteristics, and features of the objects being analyzed. This significantly limits the accuracy of such models in tasks where phase characteristics play a key role, such as aircraft recognitions.

The objective of the article is to study the effectiveness of complex-valued neural networks for aircraft identification tasks based on radar data, the efficiency evaluated based on criteria such as classification accuracy, robustness to noise interference, the ability to maintain high accuracy with limited training data, and an optimal trade-off between accuracy and computational complexity. One of the central tasks was to compare the effectiveness of the CNN with traditional real-valued networks, which would allow us to assess the practical feasibility of their application. The study involved several important stages, starting with the design of the network architecture and ending with its testing on signals with different noise levels.

The main advantage of CNNs is their ability to store and process complex signals in a form that includes both amplitude and phase. For example, for radar systems, phase information allows determining the direction, speed, and even the shape of an aircraft with higher accuracy. Acoustic signals, in turn, carry phase data that helps to better recognize different types of engines or features of aircraft mechanisms.

The activation function has the problem of gradient vanish [11], which occurs in deep neural networks. CNN also uses modified rectified linear units (ReLU) function to reduce this effect. With this activation function, the gradient passes through these layers without any alteration allowing the deep models to be more reliable. It also reduces the number of parameters to be updated in each iteration, since it is a conditional function which does not depend on any parameter, except for the input to function [12].

In the study, the artificial neural network (ANN) architecture consisted of several layers: the input layer was adapted to receive complex signals, the hidden layers used special activation functions such as complex-valued ReLU, and the output layer performed the classification. The use of a modified gradient descent algorithm made it possible to take into account the specifics of complex numbers, in particular their phase nature, which was important for optimizing the learning process. Additionally, regularization methods such as Dropout and L2-regularization were used to prevent the model from overfitting.

The results of the study demonstrated a significant advantage of the ANN over traditional networks. The accuracy of aircraft classification in the ANNs reached 95.6 %, while in the really significant models this figure was 87.9 %. This confirms that phase information, which can only be processed by CNNs, plays a crucial role in recognition tasks. Particularly important was the ability of the CNNs to maintain classification accuracy even in the face of noise interference: the accuracy remained at 92.3 % with a noise level of 30%, while the truly significant models showed a decrease to 78.5 %.

However, despite their advantages, ANNs also have certain limitations. Their computational complexity is a significant problem, as processing complex numbers requires more resources and time. This can be critical in scenarios where high speed of operation is required, such as in airspace operational monitoring systems. Therefore, one of the most promising areas of development is to optimize the architecture of ANNs, for example, by using hybrid models that combine the advantages of real-valued and complex-valued networks. This approach would reduce computational costs while maintaining high accuracy.

MATERIALS AND METHODS OF RESEARCH

Considering modern works on the topic of research, it is obvious that there are a large number of CNN architectures, which provide a wide choice for each application area. At the same time, most studies provide only a general overview of neural networks for localization and classification based on common datasets. Note that there are no commonly accepted datasets for which training and verification must be performed. Therefore, the use of neural networks for localization and classification in the field of unmanned aerial vehicles requires a deeper study of localization and classification accuracy [13].

To recognize aircraft using neural networks, we chose CVNNs, which are capable of processing not only amplitude but also phase information of signals [14]. This is especially important for accurate classification analysis, since a signal containing a phase component provides more data for identifying aircraft types, and complex numbers allow storing this information.

Computer vision, and as an extension object recognition, is often negatively affected by the dynamics of real-world conditions such as bad lighting conditions, blocked perspective scenarios, or poor real-time performance.

The real-world vision scenarios were as follows.

- Viewpoint variation: objects viewed from different angles may look completely different, making it challenging for detection algorithms to recognize them from various perspectives.
- Deformation: Many objects are not rigid bodies and can be deformed in extreme ways, adding complexity to their detection.
- Occlusion: Objects that are partially or completely covered by other objects can be challenging to detect.
- Illumination Conditions: Variations in lighting conditions can affect the performance of object detection algorithms.
- Real-time detection: Real-time detection not only requires fast algorithms but also fast technologies in terms of networking and possibly real-time processing, which can be challenging due to technological limitations [15].

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The neural network architecture consists of an input layer designed for processing complex signals, several hidden layers for feature extraction, and an output layer for classification. Specifically, the standard CVNN architecture includes 5 hidden layers with 128 neurons each, the simplified CVNN architecture comprises 3 hidden layers with 64 neurons each, and the standard real-valued neural network (RVNN) architecture mirrors the standard CVNN, having 5 hidden layers with 128 neurons per layer. The network uses specialized activation functions adapted to work with complex numbers, such as the complex-valued ReLU, which allows for efficient processing of such signals. The efficiency of using complex-valued ReLU is evaluated based on the following criteria: an increase in classification accuracy due to phase information processing (up to 8.5% improvement), robustness to noise (maintaining accuracy up to 92.3 % at a noise level of 30 %), and optimization of the training process by reducing the number of parameters updated. For optimization, a modified version of standard algorithms, such as gradient descent, is used, to find the optimal parameters that maximize (or minimize) the expected value of the cost function [16].

Two main types of signals were used to train and test the model: radar and acoustic. Radar signals were obtained from real radar systems that record reflected signals from aircraft, including unmanned aerial vehicles. Acoustic signals, in turn, were collected using microphones that recorded the sounds of the engines of various aircraft.

Before being fed into the neural network, radar and acoustic signals are transformed into complex-valued vectors of fixed dimension. After preprocessing steps (normalization and noise filtering), each input signal is represented as a vector containing 128 complex samples, capturing both amplitude and phase information. Therefore, the input dimension for each signal is 128 complex numbers, which allows the model to correctly learn and classify the signals. This ensured the high quality of the network training. The data collected included different types of aircraft, as well as background noise that simulate the real-world conditions in which the system will operate [17].

The network training process included several stages. First, the optimal hyperparameters for the network were selected, such as the size of mini batches, the learning rate, and the number of training epochs. The optimal hyperparameters for the neural network were determined using the Grid Search method, focusing on maximizing the classification accuracy on the validation dataset and analyzing learning curves.

The selected hyperparameter values are as follows:

- Batch size: 64.
- Learning rate: 0.001.
- Number of training epochs: 50.
- Optimization algorithm: Adam.
- Dropout rate: 0.2.

Then, the model was trained using optimization algorithms such as Adam to minimize the loss function. Regularization methods, such as Dropout and L2 regularization, were applied to prevent overfitting. After each training epoch, the network was evaluated using metrics such as accuracy, receiver operating characteristic – area under the curve (ROC-AUC), and F1-measure to understand how well the model classifies aircraft [18].

After training, the model was tested on a separate dataset to evaluate its ability to generalize, i.e., to correctly classify new signals that were not present during training. In addition, the model was tested on signals with different noise levels to assess its resistance to interference that may occur in real-world conditions. These stages allowed us to check how well the model copes with the tasks of aircraft classification in noise and interference.

To process and analyze the results, we compared the results obtained using complex-valued neural networks and traditional real-valued models. This made it possible to assess how the use of phase information and complex numbers improves the classification accuracy compared to other methods.

RESEARCH RESULTS

Classification accuracy

Table 1 shows a comparison of aircraft classification accuracy between CVNNs and traditional RVNNs. The results demonstrate a significant advantage of the CNNs, which confirms the effectiveness of using phase information in classification tasks.

Table 1. **Comparison of aircraft classification accuracy**

Model type	Classification accuracy (%)	Training time (hours)	Classification time (ms)
CVNN	95.6	12	5.4
RVNN	87.9	9	4.1

Source: **compiled by the authors**

Analysis: The indicated training times (12 hours for CVNN and 9 hours for RVNN) represent the point at which the models achieve maximum accuracy, beyond which additional epochs do not significantly improve performance. As can be seen from the table, complex-valued networks showed 7.7 % higher classification accuracy compared to traditional real-valued networks. This result is significant because it demonstrates the benefits of taking into account phase information that cannot be effectively processed by conventional models. However, ANNs require more training time due to the complexity of processing complex numbers, although the classification time is slightly faster than that of real-valued models.

Influence of phase information

Table 2 shows a comparison of the classification results between models that use only amplitude information and those that take into account both amplitude and phase. The use of phase information has led to a significant increase in accuracy.

Table 2. **Comparison of classification results between models**

Model	Classification accuracy (%)	Classification time (ms)
Amplitude signals only	87.1	4.8
Amplitude + Phase	95.6	5.4

Source: **compiled by the authors**

Analysis: The use of phase information further improved the classification accuracy by 8.5 %. This was made possible because the phase component of the signal contains additional characteristics that allow for more accurate recognition of aircraft types, particularly in conditions where signals have similar amplitude profiles. The additional classification time is insignificant and does not affect real-world application scenarios where the classification speed remains within acceptable limits for operational systems.

Resistance to noise

Table 3 compares the classification accuracy as a function of noise level for complex-valued and true-valued models. Testing was performed on signals with different noise levels (10 %, 20 %, 30 %).

Table 3. **Classification accuracy as a function of noise level**

Noise level (%)	CVNN	RVNN
10	98.2	91.4
20	95.1	85.7
30	92.3	78.5

***Source:* compiled by the authors**

Analysis: Complex-valued neural networks demonstrate higher robustness to noise at all noise intensity levels. At a noise level of 10%, the CVNNs achieved an accuracy of 98.2 %, while the RVNNs showed a result of 91.4 %. As the noise level increases, the accuracy of the CVNNs decreases, but remains significantly higher than that of the ANNs. This suggests that complex models have a better ability to filter out noise, as phase information provides additional markers that help maintain classification in the face of noise.

Influence of dataset size on classification accuracy

One of the important tasks was to evaluate how the size of the training dataset affects the performance of the CVNNs compared to the true supervised models (TSMs). For this purpose, several subsets of the dataset of different sizes were used: 25 %, 50 %, 75 %, and 100% of the total data set.

Table 4. **Influence of training dataset size on classification accuracy**

Dataset size (%)	CVNN: Accuracy (%)	RVNN: Accuracy (%)
25	84.2	76.8
50	89.5	82.1
75	93.1	85.6
100	95.6	87.9

***Source:* compiled by the authors**

Analysis: The 100 % dataset size corresponds to the full dataset containing 10,000 samples (signals). As can be seen from the table, CVNNs demonstrate higher accuracy in all cases regardless of the size of the dataset. The difference between models remains stable across various dataset sizes, reaching a maximum (7.7 %) when using the full dataset (100 %). However, even with a limited dataset (25 %), the CVNN outperforms the RVNN by 7.4 %, indicating the consistent advantage of the complex-valued model. This indicates that complex models make better use of the available information due to the phase component of the signals. This feature is critical in tasks where access to large amounts of data is limited.

Training time for different architectures

Another aspect of the study was to compare the time required to train models of different architectures, including standard ANNs, simplified ANNs with fewer parameters, and multilayer neural networks (MLNs). The results are shown in Table 5.

Table 5. **Comparison of training time for different architectures**

Architecture type	Training time (hours)	Accuracy (%)	Neurons per hidden layer	Number of hidden layers
CVNN (standard)	12	95.6	128	5
CVNN (simplified)	8.5	93.4	64	3
RVNN (standard)	9	87.9	128	5

***Source:* compiled by the authors**

Analysis: The standard architecture of the CVNN requires more training time (12 hours) but provides maximum classification accuracy (95.6%). The simplified CVNN architecture contains fewer parameters compared to the standard model. Specifically, the number of hidden layers was reduced from 5 to 3, and the number of neurons per hidden layer decreased from 128 to 64. This reduction significantly shortened the training time while preserving high accuracy. This version allows for a significant reduction in training time (by 3.5 hours) with a slight loss of accuracy (2.2 %). This demonstrates the potential for further model optimization. The real-valued models have an advantage in training time, but their accuracy is much lower, which limits their use in tasks requiring high accuracy.

General conclusions

Comparing the results of all five tables allows us to make the following generalizations:

1. Accuracy: The ANNs significantly outperform the traditional models in terms of classification accuracy, especially in cases where the use of phase information is critical.
2. Robustness: CNNs demonstrate higher robustness to noise, maintaining accuracy even in high noise environments.
3. Efficiency on small data: CNNs are more efficient with small amounts of data, making them suitable for resource-constrained applications.
4. Computational cost: Although CNNs require more time for training, their accuracy justifies this cost, and simplified versions of the models reduce training time without significant loss of accuracy.

Thus, complex-valued neural networks are the undisputed leader for aircraft classification tasks, providing high accuracy, noise resistance, and the ability to work efficiently with phase information. This makes them a promising choice for integration into modern airspace monitoring and object recognition systems.

DISCUSSION OF RESULTS

Advantages of the approach

In conclusion, this paper provides an extensive survey of CVNNs, highlighting significant advancements in their AFs and learning algorithms. Despite the computational and implementation challenges associated with CVNNs, their potential to outperform RVNNs in various applications is undeniable [19].

Phase information in signals, which contains important characteristics about objects, such as engine type or structural features of aircraft, gives neural networks additional opportunities to more accurately identify an object. This is especially useful when dealing with radar signals, where the amplitude response may be similar for different aircraft, but their phase profiles differ significantly [20].

Complex-valued neural networks have also shown higher resistance to noise, which is an important advantage in real-world applications. They are able to work effectively with signals with high noise levels while maintaining classification accuracy, making them ideal for use in airspace monitoring systems where signals are often interfered with by other sources.

Limitations of the study

Despite its many advantages, the use of complex-valued neural networks has certain limitations. One of the main drawbacks is the higher computational complexity of these networks compared to traditional models. Processing complex numbers requires more time and resources for training, as well as more computing power for classification [21]. This can be critical in scenarios where high speed of real-time signal processing is important, such as in rapid response systems or in conditions where instant object identification is required.

Another problem is the complexity of working with large amounts of data. Although CNNs show high accuracy, processing large arrays of signals can be difficult due to the need for more complex computations. This can be a problem for systems that operate in real time, where the amount of data to be processed can be very large, for example, in the case of monitoring a large number of objects simultaneously.

Opportunities for improvement

Given these limitations, there are several ways to improve the architecture of complex-valued neural networks. One of the most promising ways is to develop hybrid approaches that combine the advantages of both complex-valued and real-valued models. This approach allows maintaining the classification accuracy by taking into account phase information, but at the same time reduces computational costs by combining different types of models to process different types of signals.

Another direction is to optimize the network architecture to reduce its computational complexity. This can be achieved through techniques such as networks with fewer parameters or by using faster learning algorithms that reduce the time required to process data without losing accuracy. Such optimizations will make these networks more accessible for use in real-world systems where not only accuracy but also efficiency is important.

You can also work on improving noise and interference filtering algorithms. The use of more sophisticated methods for signal processing at the pre-processing stage can further reduce the impact of interference, increasing the system's resistance to external interference.

Possibilities of application in real systems

The developed complex-valued neural networks have significant potential for use in real aircraft recognition systems. Particularly relevant are their capabilities for use in military airspace monitoring systems, where the accuracy and speed of object identification are critical to security. Complex-valued models can be effectively used to analyze radar signals, which allows timely detection and classification of different types of aircraft [22].

These networks can also be used in civilian security systems, such as aviation monitoring, where it is necessary to recognize aircraft and drones at a great distance, even in difficult weather conditions or in conditions of active interference from other signal sources.

Complex-valued neural networks can be integrated into autonomous monitoring systems to ensure airspace safety, where accuracy and noise immunity are important factors to maintain the effective operation of such systems.

Thus, complex-valued neural networks show high potential for application in real-world aircraft recognition systems. They provide significantly higher accuracy, noise tolerance, and can effectively work with phase information of signals, making them ideal for complex classification tasks. However, to achieve optimal performance, computational complexity and optimization issues need to be addressed, which are key to their implementation in real-world systems.

CONCLUSIONS

The conducted study confirms the effectiveness of CVNNs for aircraft recognition tasks using radar and acoustic signals.

Key results include:

Improved Accuracy: CVNNs demonstrated significantly higher classification accuracy (95.6%) compared to traditional real-valued neural networks (87.9%), primarily due to the utilization of phase information.

Robustness to Noise: CVNNs maintained high accuracy (92.3 %) even at a noise level of 30%, outperforming real-valued models (78.5%), highlighting their robustness in challenging signal conditions.

Effectiveness with Limited Data: CVNNs preserved high accuracy (84.2 %) even when trained on only 25 % of the dataset, indicating their efficiency in scenarios with limited training data.

Computational Complexity: Although CVNNs require greater computational resources, simplified architectures significantly reduced training time (by approximately 30 %) without substantial loss in accuracy (93.4 %), demonstrating potential for practical real-time applications.

Overall, CVNNs present a reliable and robust method for advanced aircraft classification, suitable for integration into both civilian and military airspace monitoring systems. Future research should focus on computational optimizations and hybrid network architectures to further enhance practical applicability.

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Використання комплекснозначних нейронних мереж для визначення повітряних суден

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АНОТАЦІЯ

У статті представлено підхід до розпізнавання літальних апаратів за допомогою комплекснозначних нейронних мереж. Метою цього дослідження є визначення ефективності комплекснозначних нейронних мереж порівняно з традиційними підходами до розпізнавання. Дослідження зосереджено на ідентифікації повітряних суден за допомогою фазових і амплітудних характеристик радіолокаційних сигналів, які є важливими для авіаційної безпеки та моніторингу повітряного простору. Метод дослідження включає теоретичний аналіз, моделювання та експериментальну перевірку. У статті обговорюються особливості архітектури штучних нейронних мереж, які використовують комплексні числа для обробки сигналів. Такий підхід дозволяє включати фазову інформацію, що значно підвищує точність аналізу радіолокаційних даних. Результати підтверджують, що комплекснозначні нейронні мережі перевершують традиційні моделі за точністю розпізнавання. Зокрема, включення фазової складової забезпечує підвищення точності до восьми з половиною відсотків. Крім того, комплекснозначні нейронні мережі демонструють високу стійкість до шумових перешкод, зберігаючи точність класифікації до дев'яноста двох і трьох десятих відсотка навіть при рівні шуму в тридцять відсотків. Незважаючи на ці переваги, основним обмеженням комплекснозначних нейронних мереж є їхня вища обчислювальна складність порівняно з реальнозначними моделями. Це вимагає значних ресурсів для навчання та впровадження, що може бути критичним фактором для додатків, де швидкість обробки сигналу в реальному часі є важливою. Дослідження також досліджує можливості оптимізації для штучних нейронних мереж шляхом розробки гібридних підходів, які поєднують сильні сторони різних типів мереж і шляхом спрощення архітектур без шкоди для точності. Отримані дані свідчать про те, що штучні нейронні мережі є ефективним інструментом для класифікації літальних апаратів, особливо у складних сигнальних середовищах та умовах із шумовими перешкодами. Ці мережі мають значний потенціал для широкого використання як у військових, так і в цивільних системах моніторингу повітряного простору, забезпечуючи підвищену точність і надійність у задачах розпізнавання. Результати, отримані в цьому дослідженні, відкривають нові можливості для вдосконалення технологій авіаційної безпеки та автоматизації систем розпізнавання літаків.

Ключові слова: комплекснозначні мережі; радіолокаційні сигнали; розпізнавання літаків; фазовий аналіз; авіаційна безпека; ідентифікація об'єкта

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