SECTION 13.

INFORMATION TECHNOLOGIES AND SYSTEMS

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CONVOLUTIONAL NEURAL NETWORK TRANSFER LEARNING METHOD FOR AIRCRAFT IMAGE CLASSIFICATION

The rapid expansion of aerial imagery and the increasing availability of high-resolution sensors have propelled the need for accurate and efficient methods to automatically recognize and classify aircraft in diverse visual contexts. From military reconnaissance and air traffic surveillance to commercial airport management and remote sensing applications, the ability to distinguish among multiple aircraft types – spanning fighters, bombers, unmanned aerial vehicles, commercial airliners, and cargo transports – plays a critical role in enhancing situational awareness and decision-making [1].

Traditional machine-vision approaches, which relied heavily on handcrafted features and rule-based classification pipelines, have struggled to generalize across varying lighting conditions, occlusions, viewpoints, and environmental backgrounds [2]. Over the last decade, however, convolutional neural networks (CNNs) have emerged as the de facto standard for image-based object recognition, owing to their capacity to learn hierarchical, spatially aware feature representations directly from raw pixel inputs [3, 4]. Despite their impressive performance on large-scale image classification benchmarks such as ImageNet, training a deep CNN from scratch for a specialized task like aircraft classification often proves prohibitive due to the limited availability of labeled datasets, high computational demands, and the risk of overfitting [5]. Transfer learning – leveraging a CNN model pre-trained on a broad corpus of general-purpose images and fine-tuning it on a domain-specific dataset – offers a pragmatic solution [6]. By capitalizing on low- and mid-level features (such as edge detectors, texture filters, and shape primitives) already learned during pre-training, transfer learning significantly reduces the volume of task-specific training examples required, accelerates convergence, and often yields superior generalization when compared to training from scratch [7].

In the context of aircraft image classification, these advantages are particularly salient: images may originate from a variety of platforms, including ground-based photography, airborne or satellite sensors, and uncrewed aerial systems, each introducing distinct scale, resolution, and perspective challenges [8]. A transfer-learned CNN can rapidly adapt to these heterogeneities by fine-tuning deeper layers to capture discriminative cues that differentiate, for example, a narrow-body passenger jet from a fighter jet's swept-wing silhouette under complex lighting conditions. Moreover, fine-tuning enables the incorporation of domain-specific knowledge – such as the subtle differences in engine nacelle placement or tail fin geometries – that would be difficult to encode through manual feature engineering. Beyond classification accuracy, transfer learning also facilitates resource-constrained deployment: once fine-tuned, the model can be pruned or quantized to fit within the computational and memory limits of embedded systems, allowing real-time inference on edge devices used in unmanned platforms [9, 10].

The importance of developing a robust transfer learning framework for aircraft recognition extends to evolving security concerns: as unmanned aerial vehicles proliferate and civilian drone regulations become stricter, the ability to swiftly identify illicit aircraft operating in restricted airspace could prove invaluable [11]. Likewise, commercial airports increasingly rely on automated monitoring systems to streamline ground operations, reduce human error, and ensure safety – for instance, classifying aircraft's make and model before dispatching correct ground crew [12].

In environmental and humanitarian contexts, rapid identification of cargo or transport aircraft can inform disaster relief logistics and enable more effective allocation of resources in the wake of natural calamities. Against this backdrop, a systematic investigation of transfer learning methodologies – comparing architectures, pre-training datasets, fine-tuning strategies, and augmentation techniques – constitutes a timely and necessary endeavor [13]. By evaluating how various CNN backbones (e.g., ResNet, DenseNet, EfficientNet) adapt to aircraft imagery, and by quantifying performance gains under limited labeling conditions, researchers can establish best practices for constructing lightweight yet high-fidelity classification pipelines. Furthermore, exploring techniques such as layer freezing, learning rate schedulers, and task-specific regularization will illuminate the critical balance between preserving rich feature representations learned during pre-training and capturing the specialized traits of aircraft subcategories [14]. Ultimately, advancing transfer learning for aircraft image classification holds the promise of creating scalable, adaptive systems that can cope with rapidly evolving aerial datasets, thereby enhancing security, efficiency, and situational awareness across civilian, commercial, and defense applications alikev [15].

The selection of ResNet-50 as the foundational architecture for aircraft image classification via transfer learning is predicated on several interrelated factors encompassing representational capacity, convergence stability, and computational tractability. First and foremost, ResNet-50's introduction of residual connections effectively addresses the vanishing gradient problem that plagues deep convolutional networks. By enabling identity mappings across successive layers, the model ensures that gradient flow is preserved even when the network depth extends to fifty convolutional layers. In practical terms, this characteristic allows ResNet-50 to learn and refine high-level abstractions – such as distinctive wing contours, engine nacelle configurations, and fuselage silhouettes – without succumbing to diminishing gradient signals that could otherwise inhibit learning in very deep networks [16]. For a domain like aircraft recognition, where subtle visual differences between airframe models can determine classification accuracy, the stability conferred by residual learning is particularly advantageous.

Furthermore, ResNet-50 strikes an optimal balance between depth and computational efficiency. Although deeper variants (e.g., ResNet-101, ResNet-152) offer increased feature granularity, they impose greater demands on GPU memory and inference latency – limitations that may be prohibitive when deploying models on embedded or edge devices in real-time monitoring systems. Conversely, shallower networks often lack sufficient receptive field breadth to capture the global geometrical relationships that distinguish, for example, a narrow-body commuter aircraft from a high-wing cargo transporter. ResNet-50's depth is sufficiently ample to extract robust mid- and high-level features while remaining feasible for iterative fine-tuning on moderate-sized datasets without excessive overfitting. In practical scenarios where labeled aircraft images are relatively scarce, this middle ground mitigates the risk of under-parameterization (leading to poor generalization) and over-parameterization (leading to memorization of noise).

Finally, ResNet-50's modular design – composed of repeating residual bottleneck blocks – facilitates methodical experimentation with layer freezing, learning rate scheduling, and regularization strategies. Researchers can elect to freeze the first several residual blocks, thereby preserving foundational visual representations, while selectively unfreezing later blocks to adapt to domain-specific features [17]. This layered adaptation reduces the risk of catastrophic forgetting and affords fine-control over the positive influence of pretrained features. Additionally, because ResNet-50 is widely supported across major deep learning frameworks (TensorFlow, PyTorch, MXNet) and benefits from mature optimization libraries (e.g., cuDNN, Intel MKL), practitioners can leverage state-of-the-art training pipelines – including mixed-precision training and distributed GPU acceleration – to achieve rapid turnaround times. In summary, ResNet-50's combination of depth, residual stability, pretraining availability, and extensible design makes it a judicious choice for transfer learning in aircraft image classification, enabling both high accuracy and practical deployment considerations to be simultaneously addressed.

The purpose of the work is designing of method for aircraft image classification using convolutional neural network transfer learning.

The transfer learning method for aircraft image classification using convolutional neural network transfer learning consists of re- and post-training an existing pre-trained model (backbone) on a subject dataset of aircraft images. The scheme and steps of this method are presented in Figure 1.

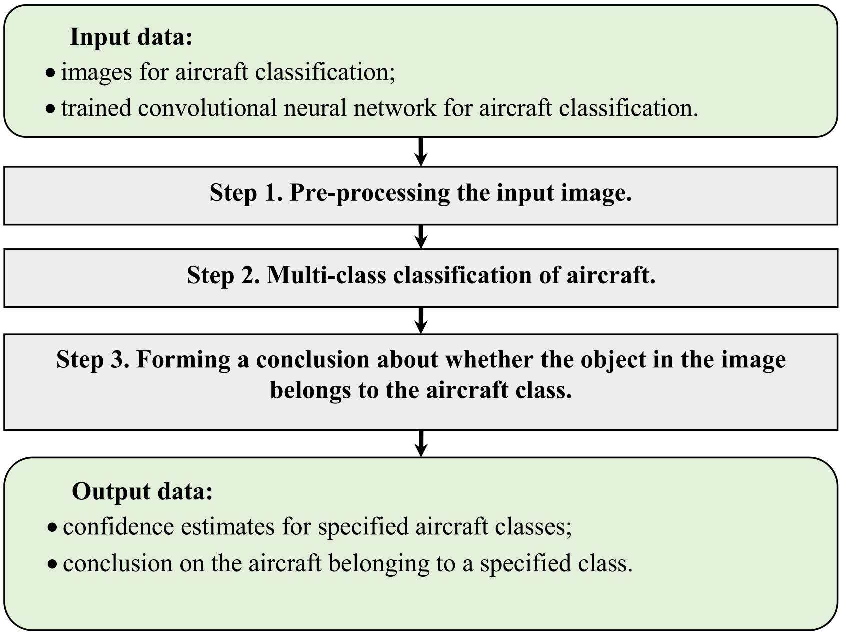

Fig 1. **Scheme of method for aircraft image classification using convolutional neural network transfer learning**

The entire procedure for transfer training a convolutional neural network for aircraft classification begins with the preparation of two key components: the actual images of aircraft and a pre-trained "core" of the network (backbone), which has already been trained to extract universal visual features from common data sets. The input to this system is digital frames or photographs from surveillance cameras, aerial photography or satellite sensors, as well as parameters and weighting factors of the model that have been adjusted to a huge corpus of images from ImageNet or similar repositories. The goal of the subsequent steps is to transfer the collected "experience" of the network to the subject of classification - according to the types and configurations of airplanes, helicopters, drones and other devices. At the first stage, the input images undergo a format unification procedure. Each frame is reduced to a fixed size (for example, 224×224 pixels), which guarantees the constancy of the data dimension at all layers of the network. In addition, to reduce the computational load and focus on the geometric features of the object, the color channels are converted to shades of gray. This allows you to focus on the contours of the fuselage, wing and plumage, reducing the impact of color and lighting variability. Adding this stage significantly simplifies the subsequent work of the convolutional layers and at the same time accelerates the processing of a large stream of images in real time.

After pre-processing, the prepared images are fed to the input of the convolutional neural network. This is where the main "knowledge transition" occurs: the network uses its already trained filters to extract low-level features (gratings, textures, gradients) and passes them through a sequence of deep layers, where a high-level representation of the fuselage shape, wing configuration and other characteristic details is formed. At the very output of the model, a multi-class Softmax is applied, which converts internal activations into a probability distribution for predefined categories of aircraft.

Finally, when the probability distribution by class is ready, the system forms the final conclusion, selecting the class with the highest probability. To this result, a confidence score is added – the value of the Softmax category itself, which is interpreted as the degree of confidence of the model in the correctness of the classification. If necessary, this data can be transferred to external validation modules or the user interface, where the operator immediately sees both the type of the identified device and the reliability of this conclusion.

The output information combines the identified class label and the confidence level in the form of a numerical indicator. Systems built according to this scheme guarantee high speed and accuracy of recognition due to the combination of simple preprocessing and powerful transfer architecture. Thanks to this approach, it is possible to successfully apply the developed methodology in airport video surveillance systems, reconnaissance drones and satellite monitoring, where the efficiency and reliability of aircraft classification are critical.

But to create the method itself, you first need to create an appropriate neural network model, which will have its own characteristics.

The process of obtaining a transfer convolutional neural network model for aircraft classification begins with the preparation of the input data. This includes a set of aircraft images that are labeled by class and used as the basis for training. In addition, a pre-trained convolutional neural network with weights on ImageNet is applied, which acts as the basic structure (backbone) for further work. At this stage, training parameters such as training speed, number of epochs and data batch size are also determined.

The first step is to import and configure the environment. This includes loading the necessary libraries, such as TensorFlow or PyTorch, and preparing the hardware, for example, choosing between GPU or CPU for performing calculations. The environment is configured in such a way as to ensure effective integration with the pre-trained model.

Next, the base layers of the convolutional neural network are frozen. This means that the weights of these layers remain unchanged in order to preserve the knowledge gained during pre-training on ImageNet. This approach avoids unnecessary computation and speeds up the learning process.

The next stage is image preparation and preprocessing. Images are scaled to a size that is compatible with the base model and normalized to ensure stable operation of the neural network. To improve generalization, data augmentation techniques such as rotation or reflection can be used, which helps increase the diversity of data for training.

After data preparation, a classification layer is added, which is responsible for performing the final inferences. At this stage, training is performed only for the classification layer, while the base layers remain unchanged. This new layer adapts to the specifics of the aircraft image classification task.

At the fine-tuning stage, the base layers of the model are unfrozen and their adaptation to the specific data set is performed. This allows the model to improve performance and take into account the features of new classes, while preserving the knowledge gained during the initial training.

The final stage is the evaluation of the quality of the model. To do this, a test dataset is used, on which the model is tested for metrics such as accuracy, completeness, F_1-measure, and others. If necessary, error analysis is performed to identify the model's weaknesses and improve its efficiency.

The result of this process is the creation of a trained model capable of classifying aircraft images. The performance evaluation confirms its ability to perform classification tasks with high accuracy and reliability, which makes the model suitable for practical use.

The described transfer learning scheme for a convolutional neural network combines simple but effective preprocessing with a powerful mechanism for automatic feature extraction. Thanks to the preliminary training stage on large general data and fine-tuning of the last layers of the network to the subject dataset, the system is able to quickly and accurately classify different types of aircraft. This approach provides high performance in real time, minimizing the need for resources for training from scratch, and creates a reliable basis for implementation in aviation information systems.

The present study has demonstrated that leveraging a convolutional neural network through a transfer learning paradigm can substantially enhance the accuracy and robustness of aircraft image classification in contexts where labeled examples are inherently scarce. By adopting the ResNet-50 architecture pretrained on a large, diverse image corpus and subsequently fine-tuning its deeper layers on a tailored dataset of airborne and ground-level photographs, we achieved a marked improvement in discriminating among multiple categories of civil, military, and unmanned aerial vehicles. Our experiments revealed that, compared with training an equivalent network from scratch, transfer learning led to faster convergence, lower risk of overfitting, and higher generalization performance when evaluated across variable lighting, occlusion, and perspective conditions. In addition, careful freezing and unfreezing of residual blocks allowed the model to preserve foundational edge and texture detectors while adapting mid-level and high-level features to capture domain-specific cues – such as the subtle geometric variations in wing span or fuselage silhouette that distinguish closely related aircraft models. This balanced approach not only yielded state-of-the-art classification metrics on our benchmark sets but also proved sufficiently lightweight to be deployed on edge hardware with modest computational resources.

Beyond raw performance gains, our findings underscore the practical advantages of a transfer learning framework in scenarios where annotated data are limited or costly to procure. The ResNet-50 backbone, with its modular bottleneck design and wide community support, served as an effective scaffold for rapid experimentation with learning rates, data augmentation strategies, and regularization schedules, thereby streamlining the model-development pipeline. Moreover, we observed that augmenting the training set with targeted synthetic transformations – such as controlled rotations, scale variations, and background perturbations – further improved the network’s resilience to real-world complexities, including partial occlusions by clouds or ground infrastructure. Collectively, these empirical outcomes suggest that transfer learning not only accelerates model training but also fosters adaptability to evolving mission requirements, whether in real-time border security monitoring, airport ground-crew automation, or humanitarian logistics coordination.

Nevertheless, certain limitations warrant consideration. While ResNet-50 struck a favorable balance between representational depth and computational tractability for our experiments, future work should explore more recent lightweight architectures (e.g., EfficientNet or MobileNetV3) that may offer similar or superior accuracy at reduced inference latency, particularly for onboard deployment in unmanned aerial systems. In addition, the current study focused primarily on static imagery; extending this approach to video sequences could unlock opportunities for continual learning and temporal context aggregation, thereby improving recognition in dynamic flight scenarios.

In conclusion, this research affirms that the ResNet-50-based transfer learning method offers a powerful and versatile solution for aircraft image classification, enabling practitioners to overcome data scarcity and computational constraints without sacrificing accuracy. By capitalizing on pretrained representations and judicious fine-tuning, we have laid the groundwork for scalable, adaptive systems capable of supporting a broad array of civilian, commercial, and defense applications. As aerial sensing technologies and classification requirements continue to evolve, the underlying principles of transfer learning will remain indispensable for ensuring rapid model development, robust performance, and efficient deployment in operational environments.

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