Neural Technologies for Objects Classification with Mobile Applications

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Abstract

This paper is related to the study of the features of the neural technologies' application, in particular, ResNet neural networks for the classification of objects in photographs. The work aims to increase the accuracy of recognition and classification of objects in photographs by using various models of the ResNet neural network. The paper analyzes the features of the application of the corresponding models in comparison with other architectures of deep neural networks and evaluates their efficiency and accuracy in the classification of objects in photographs. The process of data formation for training neural networks, their processing and sorting is described. A web application and a mobile application for recognizing and classifying objects in a photo were also developed. A system for classifying objects, in particular airplanes in photographs, was developed using neural network technologies. It gives a recognition and classification accuracy of about 95%. Research results of

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ResNet models are of great practical importance, as they can improve the classification accuracy of various images. Features of ResNet, such as the use of skip connections or residual connections, make it effective in the relevant tasks. The results of the study will help to implement ResNet in various fields, including medicine, automatic pattern recognition and other areas where the classification of objects in photographs is an important task.

Keywords: Neural technologies, object classification, ResNet neural network, mobile application.

1 Introduction

The research and application of neural technologies for object classification in photographs are relevant in the field of computer vision and image processing [1–5]. The use of neural networks (NNs) for classification has become appropriate and necessary for solving various problems [2, 4, 6–8], and ResNet is one of the effective architectures of deep neural networks, which solves the problem of gradient disappearance and allows training deep models with many layers. ResNet models can effectively detect complex dependencies in data and provide high classification accuracy [1, 4, 9–11].

Computer vision is an actual direction in this work. It involves the use of algorithms and machine learning methods to analyze and process digital images and videos to obtain important information [2–4, 12, 13]. Computer vision has a wide range of practical applications, including image and video recognition, object detection and tracking, face recognition, medical image analysis, and more. With the increasing availability of digital images and videos, computer vision technologies are becoming increasingly necessary in industry, medicine, transportation, military affairs, etc. [1–6, 14–18]. Computer vision requires a lot of data. It analyzes the data again and again until it recognizes the differences and finally recognizes the image. The amount of data required to train a neural network for image classification depends on the number of different parameters, such as the difficulty of classification, the number of categories, the number of elements in each category, etc. [15, 16, 19].

2 Related Works and Problem Statement

Currently, there are a large number of publications and systems for recognizing and classifying objects in photos using neural technologies. Such objects can be cars, people, cancerous tumors on medical images, other diseases that are classified in the photo, interior items, military equipment, etc [20–23]. The task of recognizing and classifying aircraft is relevant today, since there may be classes of aircraft in the sky and on the ground that belong only to enemy forces. In addition, there is often a need to classify civil aircraft to understand what class they are dealing with for further technical support. It will also be useful to recognize aircraft and evaluate their flight and technical characteristics when training pilots in educational institutions [24–28].

The authors of the paper [29] proposed an intelligent method of recognizing types of aircraft based on audio features, aimed at eliminating the shortcomings of existing recognition methods. An advanced self-attention algorithm is used to intelligently recognize and classify aircraft. A nonlinear self-attention algorithm is proposed, which allows taking complex audio features into account. Collected audio data from 9 types of aircraft are used to train the algorithm and its recognition ability is tested through experiments.

In this work [30], the YOLOv5 detection algorithm and the MMAL-Net classification algorithm are combined for the detection of aircraft in remote images and the determination of their types. First, the YOLOv5 algorithm is used to determine the area where the aircraft is located in complex scenes. The MMAL-Net algorithm is then used to classify the aircraft at a fine-grained level and the type is determined. According to the results of the experiment, the proposed method can accurately detect aircraft and determine their types with an accuracy of 73.2%.

This paper [31] proposes a method for military aircraft recognition with only one training sample. First, HOG characteristics and invariant Hu moments are used to obtain the features. Then, a classification system based on sparse vectors is applied as a recognition algorithm. Experimental results show that the proposed method achieves better recognition accuracy compared to existing methods in the case where there is only one training sample.

In this work [32], a new method for recognizing aircraft types on multi-projection optical images is proposed. The task is complicated by the difference in the postures of the planes, their flight altitude and other factors. Experimental results show that the proposed approach achieves a recognition accuracy of 71.3% for the best variant and 90.8% for the three best variants on a set of test images of aircraft types.

This paper [33] considers the problem of identifying commercial aircraft on satellite images near large airports. An R-CNN neural network is used,

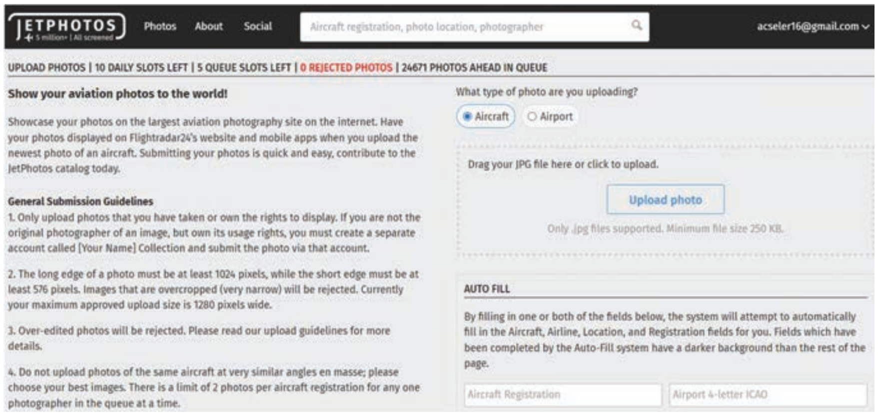


Figure 1 JetPhotos website page to download aircraft photos.

where the images are passed through convolutional layers to extract aircraft features, after which these features are fed to a binary classifier. The model was trained on 2100 satellite images with aircraft and tested on 900 images. The system can determine and localize the position of aircraft in the images with high accuracy, although there is a slight deterioration in the model performance when the number of aircraft in the frame increases.

One example of a similar system for aircraft classification is the JetPhotos website (according to Figure 1). On the site, you can download a photographed aircraft and classify it. Among the restrictions is that the photo must be of a specified extension and no more than 250 KB, so you will need to make some additional adjustments in an external photo editor to make it suitable.

In addition, among the advantages is the ability to recognize absolutely any aircraft, but the process of recognition and classification takes a lot of time, and the photo undergoes moderation before it is displayed to site users.

Another variant for similar systems is the site for object recognition from the Aspose company. This site deals exclusively with the recognition of objects in the photo. Thus, it is not possible to get the detailed name of the aircraft, only to check whether the photo shows the aircraft or something else.

Considering the research results in the above-mentioned publications and the functionality of similar systems, it should be noted that the accuracy of recognition and classification can be increased, as well as the time for network training and aircraft recognition can be reduced. In addition, it would be advisable to develop a mobile application for the recognition and classification of aircraft with the possibility of receiving a photo of the aircraft from the camera of a mobile device.

Therefore, the purpose of this work is the recognition and classification of aircraft using neural networks and mobile technologies.

3 Neural Technologies for Objects Classification

Currently, the following types of neural network architectures are distinguished in various studies: direct neural networks, recurrent neural networks, autoencoding neural networks, neural networks with arbitrary architecture, deep neural networks, neural networks with reinforcement, generative convolutional networks, networks with short message responses, neural networks with memory support [5, 6, 8, 14]. All of them are widely used for various tasks of prediction, recognition, classification, clustering, object detection, control, segmentation, etc. The spheres that effectively found the application of neural networks are economy, medicine, communication, security, transport, industry, etc. [6–8, 13–16, 34–42].

ResNet NNs are one of the most effective and widely used networks for image classification, which is why the study of their models is very important and necessary for the development of the field of computer vision and machine learning. ResNet-50 is a variant of the ResNet model that has 48 convolution layers as well as 1 Max Pool and 1 Average Pool. It has $3.8 \times 10\hat{}9$ floating point operations. This is a widely used ResNet model [9–11, 37, 43]. The block "residual" with connections is the main block of ResNet-50, which allows the network to effectively solve the problem of vanishing gradients when training deep neural networks [9–11]. This architecture can be used for computer vision tasks such as image classification, object localization, object detection. ResNet-101 is a deep neural network that was proposed in 2015. ResNet101 has 101 layers and is a deeper model than ResNet-50. It is a rather complex model that requires a large amount of computing resources for training and application. It is usually used for image classification tasks on large datasets, such as ImageNet [43].

A more detailed description of the elements of various architectures of ResNet models is given in Figure 2.

AlexNet is a convolutional neural network developed in 2012, which for the first time gave a significant advantage in image processing using deep learning. The architecture (according to Figure 3) of the network contains 5 convolutional layers. The first two layers have a large number of filters helping to detect simple and complex features in images. After each convolutional

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 2 Various architectures of ResNet models [10].

Figure 3 AlexNet architecture [45].

layer, a pooling layer is applied to reduce the size of the original image and increase network efficiency. The 5th convolutional layer is followed by 3 fully connected layers, each of which has a dimension of 4096 neurons. These layers perform the function of classifying the image generated from the previous convolutional layer [2–4, 44–46].

The VGG architecture consists of several blocks, each of which consists of a sequence of convolutional layers and pooling layers. Each block has a fixed number of convolutional and pooling layers, allowing for easy tuning of the network depth. The VGG architecture has a large number of parameters, which has made it very powerful, but at the same time requires a large amount of computing resources for training and application. The VGG16 architecture (according to Figure 4) consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. Convolutional layers consist of filters of different sizes that perform image convolutions to extract various image features. Fully connected layers use these features to classify images into different categories [2, 5, 47–50].

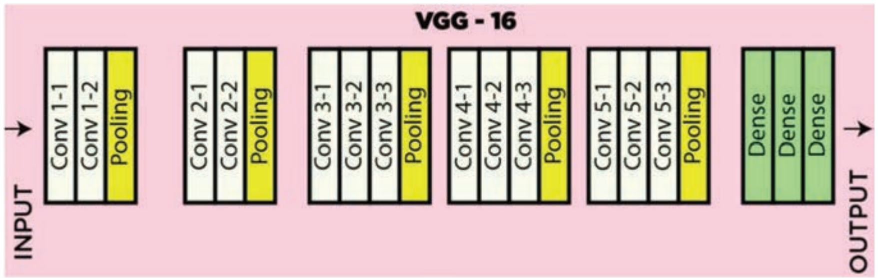


Figure 4 VGG16 architecture [49].

Completing the given task requires sufficiently powerful computing resources, so deeper and more complex architectures such as ResNet and VGG can be used for image classification, as they usually give better results compared to AlexNet [47]. At the same time, ResNet, thanks to the use of feedback blocks, allows for building an even deeper network with fewer parameters, which makes it a popular option used for many tasks in the field of computer vision. Thus, based on the basis of the conducted study of different architectures of neural networks and the obtained results analysis, it can be concluded that the ResNet architecture is a more effective tool in solving problems of image classification that require high accuracy.

In this work, ResNet was employed as the primary neural network architecture for the task at hand. Notably, Few Shot Learning Models were not utilized in the experimentation process.

4 The Software of the Developed System and the Results of Modeling and Testing

To fulfill the task, a ready-made dataset from the Internet resource *robots.ox.ac.uk* was selected, because it contains photos of more than 50 different types of aircraft. However, in the basic dataset, all airplane photos are stored in one folder, which makes the data unusable (according to Figure 5). As you know, for the correct operation of the system, you need to sort all the photos into folders with the names of specific types of aircraft. The authors of the dataset left a text file in it, where you can see what type of aircraft is shown in the photo.

To sort the dataset, the authors of the work developed a console application that creates folders with the names of the desired types of aircraft and arranges photos in these folders. After dividing all the photos into classes,

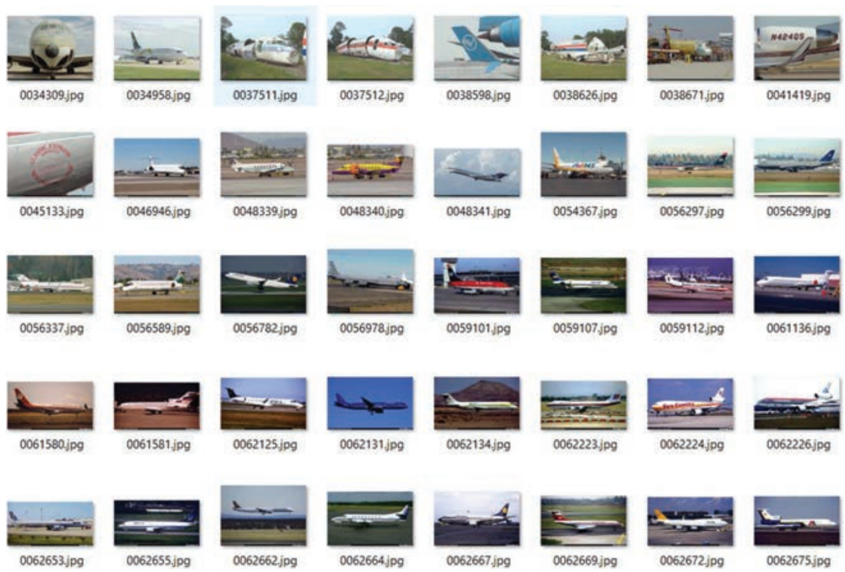


Figure 5 All aircraft photos in one folder (base dataset).

it was found that there were only 60 photos for each type of aircraft in the dataset. Therefore, for the effective training of the neural network and the operation of the classification system, it was decided to choose 4 types of aircraft and expand the existing dataset with photos from the Internet, to bring the collection of each aircraft to more than 200 photos for each type. The following 4 most popular types of aircraft were selected, such as An-12, ATR-42, Spitfire and Cessna 208. In turn, the folders containing photos of these aircraft were divided into 2 more, one for training and the other for testing neural networks. The photos between the training and test folders are split so that 73% of all aircraft photos are in the training folder and the other 27% in the test folder. It was this distribution that later turned out to be optimal from the viewpoint of training and classification accuracy.

To successfully train a neural network, photos must be of high quality and dimensionality to provide enough detail for the neural network to analyze. In addition, the photos must be representative of the classification task, that is, contain enough visual features to distinguish objects of different classes. To ensure successful learning, it is also important to have enough photos for each class. In our study, it was possible to collect a dataset of photos for training a neural network, the size of which is 802 photos for all 4 types of aircraft.

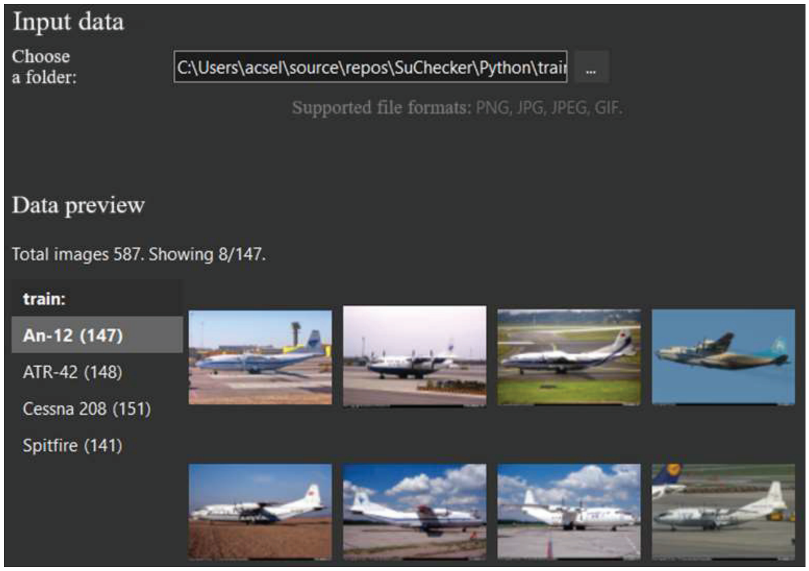


Figure 6 Data selection window for training.

First, a model was created and trained in the ML.Net environment [3, 6, 51–53], and a web application was developed using Visual Studio 2022 to test the created neural network. A machine learning model was added to the created web application and the "image classification" scenario was selected in it. Next, the environment for training the image classification model was chosen, in our study it is local training of the model on an existing PC. The next step was to select data for training (according to Figure 6).

The next step was one of the most important, namely model training. The neural network coped very well with this task, training with an accuracy of 92.16% in 117.67 seconds, which is a very good result. Finally, the model ResNet-50 was checked for the correctness of image classification. As a result, the classification accuracy of this model was 89%.

To improve classification accuracy, the authors also created ResNet-50 and ResNet-101 models using the Python programming language [54–57].

After the program code was written, we ran it and received in the console (according to Figure 7) the number of photos that are used to train the ResNet-50 neural network model which is used to check the accuracy of aircraft classification. You can also see the progress of the training, which will last 40 iterations, each of which will take an average of 73 seconds and obtain a training accuracy of 92%.

```
PS D:\Study\Python>  & 'C:\Python311\python.exe' '--' 'D:\Study\Python\NeuralImage\resnet50_PC.py'
Found 587 images belonging to 4 classes.
Found 215 images belonging to 4 classes.
Epoch 40/40
19/19 [==============================] - 73s 4s/step - loss: 0.7328 - accuracy: 0.9223
1/1 [==============================] - 2s 2s/step
```

Figure 7 Result of ResNet-50 model training.

```
Found 587 images belonging to 4 classes.
Found 215 images belonging to 4 classes.
Epoch 40/40
19/19 [==============================] - 104s 5s/step - loss: 0.6838 - accuracy: 0.9435
1/1 [==============================] - 3s 3s/step
```

Figure 8 Result of ResNet-101 model training.

Figure 9 The interface of the developed web application for aircraft classification.

Next, the ResNet-101 model was created. The results of training are shown in Figure 8.

The figures illustrate that ResNet-101 learns longer than ResNet-50, although the number of epochs and power are the same. This is because ResNet-101 has more layers (101) than ResNet-50 (50). Thus, ResNet-101 has more parameters to train, which usually results in longer training times. The web application was created using the ASP.Net MVC framework. The interface for users to upload their photos and get the results is shown in Figure 9.

Testing of the developed web application for aircraft classification showed that all developed models (ResNet-50 and ResNet-101) in ML.Net and Python environments demonstrated high accuracy, which is 95% on average. This proves the high efficiency of the corresponding models.

The results of testing, for example, in the Python environment are shown in Figure 10. It can be seen that the aircraft is classified with high accuracy

```
1/1 [==============================] - 3s 3s/step
[[2.4610324e-02 5.3406924e-02 6.2719273e-04 9.2135555e-01]]
The image is a Spitfire
1/1 [==============================] - 1s 1s/step
[[0.03881193 0.95321876 0.00222073 0.00574855]]
The image is a ATR-42
1/1 [==============================] - 3s 3s/step
[[5.5893522e-04 3.0018433e-04 9.9912554e-01 1.5271478e-05]]
The image is a Cessna 208
```

Figure 10 The results of testing in the Python environment.

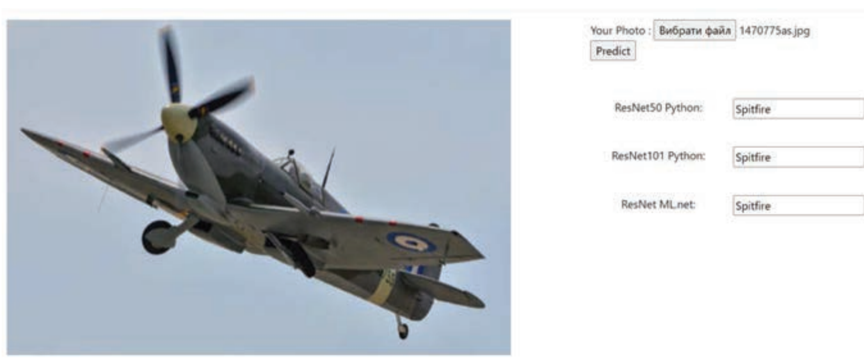


Figure 11 Spitfire aircraft classification.

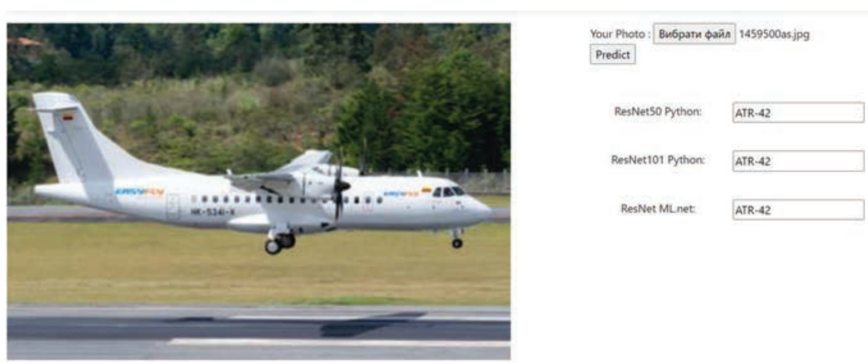


Figure 12 ATR-42 aircraft classification.

(92.13% for the Spitfire class aircraft, 95.32% for the ATR-42, and 99.91% for the Cessna 208).

The results of aircraft classification, for example, Spitfire and ATR-42 using the developed web application are shown in Figures 11 and 12.

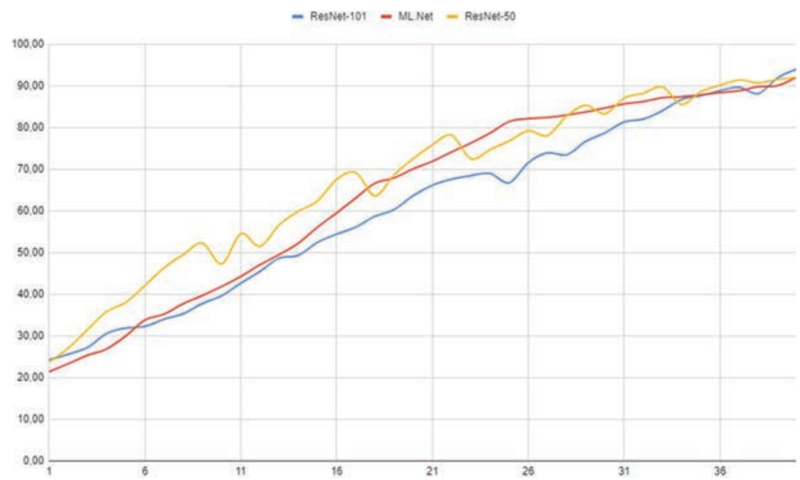


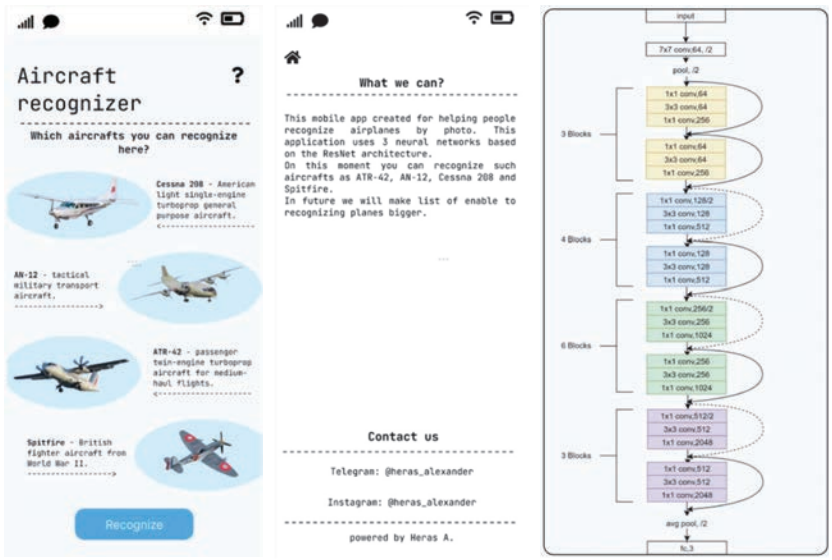
Figure 13 Diagram of comparisons of training accuracies of neural networks on a segment of 40 epochs.

After creating various ResNet neural network models and testing the developed web application, we will analyze the results of model training to evaluate their effectiveness. For that purpose, a diagram of the accuracy of learning neural networks (according to Figure 13) was created. The diagram shows that the ML.Net neural network with the ResNet-50 architecture reached more than 80% accuracy the fastest, taking only 25 epochs, while the neural network with the same architecture in Python crossed the 80% training accuracy mark only on the 28th epoch, and the neural network with the ResNet-101 architecture in Python did it only on the 31st epoch.

Also, our neural networks underwent rigorous testing, including aggressive attacks, and consistently demonstrated stable performance. Geometric transformation models were also implemented, which not only accelerated the training process of the network, but also significantly increased accuracy and speed, exceeding performance benchmarks when testing a modified neural network outside of our study.

The obtained results of the accuracy of training and classification of aircraft by ResNet-50 and ResNet-101 models in comparison with other similar studies demonstrate an increase in accuracy and a decrease in training time, which are important indicators, especially when used on different mobile devices.

The authors also developed a mobile application for the recognition and classification of aircraft. The start window (according to Figure 14a) is the



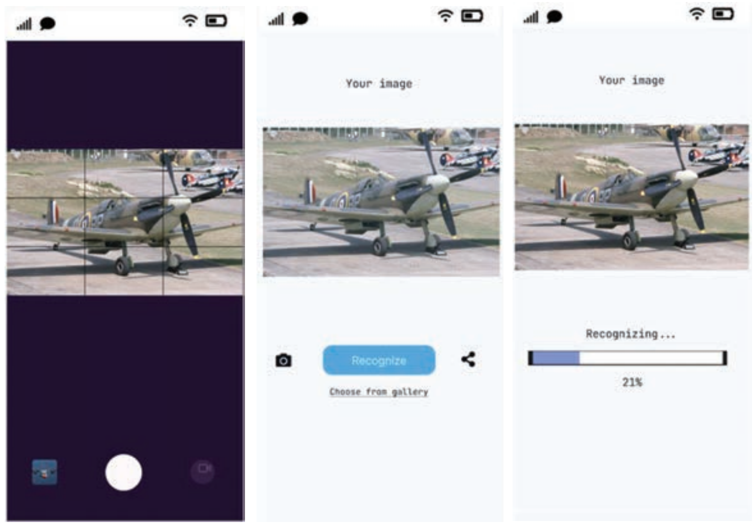
(a) (b) (c)

Figure 14 Windows of the developed mobile application: (a) start window, (b) window with contact information, (c) "How it works" window.

main page of the "Air recognizer" application, which describes the main capabilities of the system and what it can work with. The application can go to the "About us" window (according to Figure 14b) or press the "Recognize" button. The "About us" window (according to Figure 14b) is designed to briefly inform the user about the developed application and contact details of one of the authors. The "How it works" (according to Figure 14c) window is intended for a brief description of neural networks with the ResNet architecture used in this application.

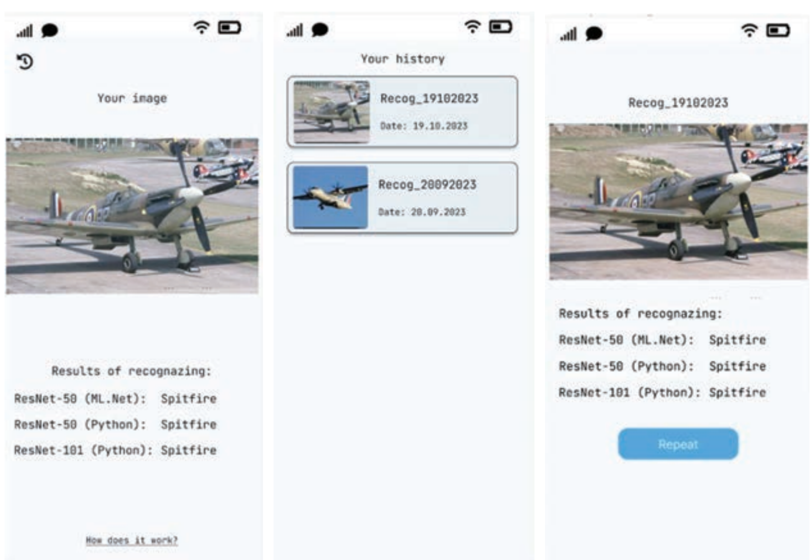
The "Camera view" window (when clicking the "Recognize" button on the main window) allows users to take photos of aircraft in real-time through the camera of a mobile device for their further classification (according to Figure 15a). The "Picture view" window (according to Figure 15b) is created for viewing a photo taken in the "Camera view" window, with the subsequent possibility of recognizing this photo, sharing it in social networks, returning to the "Camera view" page and choosing another photo from the gallery.

The "Recognizing" window (according to Figure 15c) displays the progress of the process of recognizing the aircraft in the photo using 3 neural networks.



(a) (b) (c)

Figure 15 Windows of the developed mobile application: (a) “Camera view” window, (b) “Picture view” window, (c) “Recognizing” window.



(a) (b) (c)

Figure 16 Windows of the developed mobile application: (a) “Result” window, (b) “History” window, (c) “History result” window.

The “Result” window (according to Figure 16a) displays the result of the recognition and classification of the aircraft in the photo by each of the 3 neural networks. The “History” window (according to Figure 16b) is created for saving and viewing previous results of aircraft recognition and classification. The “History result” window (according to Figure 16c) allows you to view specific results of aircraft recognition and classification with detailed information.

5 Conclusions

As part of this work, research was conducted on ResNet neural network models for object classification in photographs. In the research process, three models were created, namely ResNet-50 in the Python programming language, ResNet-101 in the Python programming language, and ResNet-50 in the C# programming language (using ML.Net).

The obtained results showed that all three models demonstrate high accuracy when classifying objects in photographs. In particular, the best result was obtained using the ResNet-101 model, which showed a training accuracy of 94% and a classification accuracy of about 95%.

The results of the study showed that the best option for developing and training neural networks is to use the Python programming language, as it allows for high development speed and reduction of network training time.

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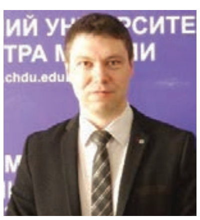
Biographies



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