

A CNN-ASSISTED DECISION SUPPORT SYSTEM FOR ANCIENT WORLD COIN CLASSIFICATION

The attempt to use neural network technologies for automatic classification of coins became a matter of time. The work is devoted to solving the problem of automating the classification of coins from the ancient world. The purpose of the work is to create a neural network model and a system for the classification of ancient coins. The object of research is photographs of coins from ancient cities in the polis of the northern Black Sea region. The subject of research is the process of coin classification. A system architecture, a neural network architecture, and an application for the classification of ancient coins are proposed. The results of the system's operation are demonstrated, and the quality of network training is evaluated. The models were trained using self-generated data samples consisting of sets of color images of coins (200 by 200 resolution) of several types and images of coins that play the role of all other coins and should be classified as not belonging to a given class. The relationship between the ratio of class coins to other coins was also found. For obverse sample 783-7831, 100% accuracy in ten epochs was achieved when the ratio between samples was 1:1, with ratios of 1:4 and 1:7, 30 epochs were required to achieve 100% accuracy. The following technologies were used to implement the Web system: a framework for Python – Django for writing the server part; a JavaScript programming language for writing the user part of the system; and a jQuery library to improve the interaction of the user part with the user. For interaction between the user and the server part of the applications, the AJAX request technology was used, which allows data to be transferred to the server part imperceptibly for the user without reloading the page. SQLite3 was used as the main application database.

Keywords: analysis of ancient coins, neural networks, CNN, AI, Python, Django, JS, Ajax, Keras, UML.

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СИСТЕМА ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ ДЛЯ КЛАСИФІКАЦІЇ МОНЕТ АНТИЧНОГО СВІТУ ЗА ДОПОМОГОЮ CNN

Спроба використання нейромережевих технологій для автоматичної класифікації монет стала питанням часу. Робота присвячена розв'язанню задачі автоматизації класифікації монет античного світу. Мета роботи – створення моделі нейронної мережі та системи для класифікації античних монет. Об'єкт дослідження – фотографії монет античних міст полісів північного Причорномор'я. Предмет дослідження – процес класифікації монет. Запропоновано архітектуру системи, архітектуру нейронної мережі та створено додаток для класифікації античних монет. Продемонстровано результати роботи системи та оцінено якість навчання мереж. Для навчання моделей використовувалися створені власноруч вибірки даних, які складаються з наборів кольорових зображень монет (роздільною здатністю 200 на 200) декількох типів та зображень монет, які відіграють роль усіх інших монет і повинні класифікуватися як не належні до заданого класу. Було також виявлено залежність між відношенням монет класу до інших монет. Для вибірки аверс 783-7831 точність 100% за десять епох вдалося досягти коли відношення між вибірками було 1:1, при відношенні 1:4 та 1:7 для досягнення точності 100% знадобилося навчання протягом 30 епох. Для реалізації Web системи було використано наступні технології: фреймворк для Python – Django для написання серверної частини; мова програмування JavaScript для написання користувацької частини системи; бібліотека jQuery для поліпшення взаємодії користувацької частини з користувачем. Для взаємодії між користувацькою та серверною частиною додатків використовувалася технологія AJAX запитів, яка дозволяє непомітно для користувача та не переважаючи сторінку передати дані до серверної частини. Як основна база даних додатку використовувалася sqlite3.

Ключові слова: аналіз старовинних монет, нейронні мережі, CNN, AI, Python, Django, JS, Ajax, Keras, UML

Introduction

In recent years, there has been a rapid growth of systems that use machine vision technologies to solve practical problems. Such growth is observed due to the fact that currently quite a few frameworks have been created that allow you to create neural network models without deep mathematical training [1 – 5]. Therefore, an attempt to use neural network technologies for automatic classification of coins became a matter of time, and several systems for classifying different types of coins have already been implemented.

The aim of the work is to create a neural network model and a system for the classification of ancient coins.

To achieve the goal, the following tasks must be completed:

- create training samples for learning neural networks;
- create a neural network model and test it experimentally;
- perform computer implementation of the system.

Money is an inseparable part of any highly developed civilization, and sometimes it is almost the only trace of the existence of this civilization. Due to the fact that in ancient times, money was made from precious metals, archaeologists find quite a few of coins in the places of existence of considerable developed civilizations. Sometimes, only thanks to the images on the coins, we have an idea of what the ancient kings looked like, where the trade routes passed, and other interesting and useful information for historians.

Usually, ancient coins depicted portraits of kings and/or gods who were revered in that area. Early coins (VI–V centuries BC) mainly depicted animals and geometric figures, and they date from the IVth century. BC images of animals supersede images of people. The denomination of the coin was its material and weight, so it was not indicated on the coin.

On the territory of Ukraine in ancient times there were seven large ancient cities–polices, as well as a large part of the Bosphorus kingdom with its capital in the city of Pantikapei. Tens of thousands of gold, silver, copper, lead, iron, and other metals coins were issued during the period of existence of the city-polices (from the middle of the 6th century BC to the first half of the 5th century AD).

At present, the total number of ancient coins found, issued in polis located on the territory of Ukraine, significantly exceeds the mark of 30 thousand units, and every year it is replenished with new finds found both in the ground and, unfortunately, on the black market. Ukraine is not a unique state in this regard, because a similar situation, only on a larger scale, exists in all Mediterranean countries.

Analysis of Existing Solutions

Thanks to the general computerization, many online catalogs of famous coins of various orientations have appeared, and online auctions allow collectors from any country in the world to participate [6]. And with the advent of artificial neural networks that can classify graphic images, the issue of automating the classification of coins became only a matter of time. Currently, in most cases, the task of automating the classification of ancient coins is of more scientific than practical interest, and there are a number of reasons for this:

1. There are currently no universal solutions trained on huge data sets, and extremely large models trained on samples of less than 20,000 units.

[1]None of the models has stood the test of time.

[2]None of the currently existing solutions provides a 100% guarantee of correct classification.

[3]None of the models could classify coins that were unknown to it.

[4]There is no commercial need for such systems. A collector, an auction house, or an archaeologist with one or more coins would rather turn to an expert right away than the experiment with neural network models, the results of which still need to be checked by an expert.

But at present, several systems for the classification of coins of different types have already been implemented. Thus, a team of developers from Mirpul University (MUST) Pakistan proposed a network for classifying Roman coins by 100 classes. The sample consisted of 17,546 coins. To solve the problem, the researchers used the Alex-Net convolutional network architecture. The network has almost 29 million parameters, the Adam optimizer, the activation function for all layers except the last ReLU, for the last SoftMax. For 190 training epochs, the authors managed to achieve 96% classification accuracy, which is a good result for a network of such small sizes.

An interesting fact is that the authors used color images, and the vast majority of coins in the set were silver [7].

A little earlier, a group of scientists from Germany, Australia and Austria also used the data set described above to create their models. The authors developed their own model for coin classification – CoinNet. CoinNet uses rather large images of 448×448 pixels size, which are encoded using two well-known convolutional networks: DenseNet161 and ResNet50, which consist of 161 and 50 convolutional layers, respectively. After that, feature maps obtained by both networks are combined and fed to a fully connected neural network. For different data sets, the authors managed to achieve accuracy from 68% to 96% [8].

The Alex-Net network for the classification of old Indian coins was also proposed to be used by scientists from India, but unfortunately they did not share the results achieved [9].

In the qualification work of a student of the Indonesian Muhammadiyah University in Surakarta, it is proposed to use convolutional neural networks to classify modern Indonesian rupiahs in vending machines, to prevent losses due to the use of counterfeit coins by unscrupulous buyers. On different data sets (different denomination of coins), the model showed accuracy from 86% to 100% for the validation sample. The model consists of two convolutional layers, one pooling layer and two fully connected layers. The training sample consisted of only 180 units for five categories [10].

A work similar in content was published on the Habr collective blog. A number of materials were published, the author of which set the task of creating a mobile system for finding coins of interest to collectors among the standard coins of the Russian Federation (the author ignored all jubilee coins) in denominations of 1, 2, 5 and 10 roubles. However, as of the end of 2023, the cycle of articles remained incomplete, but the author had currently implemented two neural networks that he used to prepare training samples. One was responsible for finding the coin in the photos, and the other was responsible for classifying the sides of the coins: obverse and reverse. It should be noted that the designs of the coins differ only on the coin reverses, but have similar elements. The drawings of the obverses are almost the same for all coins and differ only in the year of issue of the coin. For classification, the author used a perceptron with one hidden layer. The author managed to achieve almost 100% accuracy [11, 12].

Another similar system was proposed by the user of the social network for data analysis and machine learning specialists - Kaggle under the nickname M S Somanna. The author proposed a system for classifying Indian coins into five classes: obverses of 1, 2, 5 rupees, reverses (the same for coins of all denominations), damaged coins and "junk" (anything that people can use instead of coins in vending machines). Samples for each class consisted of 350 units. The system was based on a network consisting of three layers of convolution and three layers of pooling, two fully connected layers. Activation function for all layers except the last ReLU, for the last Softmax. A total of almost 17 million parameters. The author managed to obtain 98% accuracy for the validation sample [13].

From the overview of the currently developed solutions, it is clear that automatic classification of coins is quite possible in the case of a small number of classes and can be solved by different approaches, however, there is currently no universal solution that would be suitable for solving all the problems that currently exist. Most authors choose the classical structure of convolutional neural networks, which performs quite well in most cases.

Modeling

The automatic classification of coins is a task that cannot be completely solved, due to the fact that in ancient times every city and every king minted their own coins. But there is a small (compared to the entire variety of coin types) number of coin types that occur ten times more often than others. We are not interested in why it is that some coins were minted a lot and others were minted (many coins reached us in a single copy or in a very small circulation), but we are interested in the fact that the probability of finding a coin of one type is much higher than finding a coin of another type. Therefore, if you check coins to see whether they belong to one of the popular classes, you can automatically classify most finds.

Another problem is that the number of coins of each type is huge, which can grow rapidly. For example, if today we know three coins of a conditional type "A" and due to its rarity, it will not be included in the classification, no one will give a guarantee that in a year, or maybe even earlier, they will not find a treasure in which there will be another 20-30 such coins.

Therefore, when designing a coin classification system, it is necessary to provide solutions for the following features of such a find as a coin:

- The number of classification categories is unknown, only in Ukraine there are almost two and a half thousand types of ancient coins, not to mention other states located on the territory of the former Roman Empire and not taking into account the fact that an ancient coin can be confused with a medieval coin. It is also necessary to take into account the migration of people in ancient times, so a coin minted in Borysthenes (Mykolaiv region) can be found somewhere on the outskirts of Rome or Constantinople, and coins minted in completely other places of the empire can be found in Borysthenes.
- The main information for the classification system is not one, but two images of the same coin (on both sides).
- The coin may be partially damaged, covered with a layer of oxides (especially relevant for copper and iron coins) or dirt.
- The coin may be deformed (especially relevant for lead) or modified mechanically after stamping, e.g., its pattern is slightly different from most coins (Fig. 1).
- Coins of the same type can have completely different, but similar designs (Fig. 2 and Fig. 3). Most coins of each type have such subtle differences, and the pictures show only a few of them. Also, for example, in Fig. 3, the two coins in the lower row on the left have not a convex, but a depressed pattern. Therefore, achieving high recognition accuracy for ancient coins is not an easy task.



Fig. 1. A Comparison of the Mechanically Finished Coin on the Left with the Unfinished Coin on the Right



Fig. 2. A comparison of Coin Reverses Type 783-7831



Fig. 3. A Comparison of Coin Reverses Type 109-2075

Based on the requirements mentioned above and taking into account the described problems, I propose to design a universal neural network architecture that will be trained to classify coins of the same type. The input of such a network will be the image of the coin in grayscale (to reduce the dependence on the color of the find, because it can change significantly due to oxidation), on the one hand, and at the output receive the value of the probability with which this coin can belong to this group. Thus, in the future, the library of coins that the system will be able to classify can be increased with the addition of new trained models. Each side of the coin must be placed in the center of a square image with a white background (size 150 by 150 pixels) before uploading. Also, for better training of the network, it will be necessary to make an argumentation of data – generation of new photos by means of their random transformations. Especially relevant transformations for coins are rotations by several degrees, scaling, small pixel shifts.

But with the growth of the library, the approach described above can lead to the fact that the analysis of one coin will take a lot of machine time, so an algorithm is needed that excludes those models from the analysis run, the negative result of which can be predicted in advance.

Because of that, the work algorithm can be described as follows:

1. We load the prepared image of both sides of the coin into the program in turn. Also, together with the coin, we send contextual data that will help to conduct an initial evaluation of the coin.
2. We submit each of the parties (in turn) to the algorithm that will select models for its classification from the general library of models based on the previous day's contextual information.
3. Each side of the coin is fed in turn to a set of selected models, each of which outputs the probability that this coin belongs to its category. (The criterion for selecting models for the second side of the coin is that if, when analyzing the first side, one of the models shows a high probability value, then for the second side, the model for the second side of the coin of the same type should be put first).
4. Complex probabilities are calculated for models of both sides of coins of the same type. A report is displayed to the user.

Below is the algorithm in the form of a UML sequence diagram (Fig. 4).

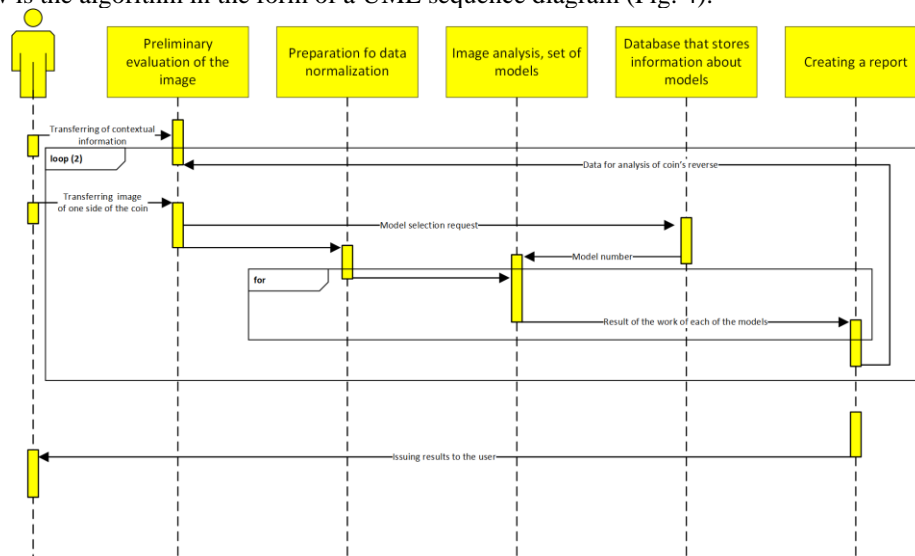


Fig. 4. Sequence Diagram

Computer Implementation of a Software System for the Classification of Ancient Coins

The main or central part of the system is a neural network architecture that can be trained for any coin. In the course of a number of experiments with different architectures of convolutional neural networks, because it is the architecture that shows itself best in working with graphic images, it was found that the optimal architecture is a network consisting of four convolutional layers with a 2×2 convolutional kernel and four pooling layers, each of which reduces the input vector by a factor of 4. Dropout layers, located after the first and second groups of convolution-pooling with a factor of 0.2, are used to control retraining. The structure is shown in more detail in table 4.4. The activation function on all layers except the output ReLU, the activation function of the output Softmax layer, which gives the probabilities that the coin belongs or does not belong to a given type, which can be useful when using the system by an expert: currently the system chooses a larger value to classify the coin, but in the situations where the probability indicators are quite similar, such a choice may lead to an incorrect result. The loss function is categorical crossentropy, the optimizer is adam. In total, the model has approximately 2 million parameters, which will require 8.66 MB of RAM. All tests used the Tensorflow framework and its extension for Python – Keras.

Network variants that use color RGB images instead of monochrome have also been tested, and although this model is slightly better at distinguishing gold coins, it shows absolute inefficiency for any other metals, due to their tendency to oxidize. The task of comparing colors and sorting gold coins from non-gold coins is solved using a conventional algorithm, so the idea of using a three-channel model was rejected.

Table 1

Structure of the Model

| Layer (type) | Output Shape | Param # |
|--------------------------------|----------------------|---------|
| conv2d (Conv2D) | (None, 149, 149, 32) | 160 |
| max_pooling2d (MaxPooling2D) | (None, 74, 74, 32) | 0 |
| dropout (Dropout) | (None, 74, 74, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 73, 73, 64) | 8256 |
| max_pooling2d_1 (MaxPooling2D) | (None, 36, 36, 64) | 0 |
| dropout_1 (Dropout) | (None, 36, 36, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 35, 35, 128) | 32896 |
| max_pooling2d_2 (MaxPooling2D) | (None, 17, 17, 128) | 0 |
| conv2d_3 (Conv2D) | (None, 16, 16, 256) | 131328 |
| max_pooling2d_3 (MaxPooling2D) | (None, 8, 8, 256) | 0 |
| flatten (Flatten) | (None, 16384) | 0 |
| dense (Dense) | (None, 128) | 2097280 |
| dense_1 (Dense) | (None, 2) | 258 |

The models were trained using self-generated data samples consisting of sets of color images of coins (200 by 200 resolution) of several types and images of coins that play the role of all other coins and should be classified as not belonging to a given class. All photos of coins were taken by the authors from open Internet catalogs <https://bosporan-kingdom.com/> and <https://tauriscoins.ru/>, obverses and reverses (separately) of the following coins were used as datasets: 109-2075 (78 pcs.), 783-7831 (21 pcs.), 111-3002 (100 pcs., selected from more than 1000 coins of the catalog, others taken all). The selection of other coins consisted of ~170 images (obverses and reverses combined).

Coins 109-2075, 111-3002, and obverse 783-7831 achieved 100% accuracy for the validation sample. It was not possible to train the model for reverses 783-7831 due to the great variability of minting (Fig. 2). The conclusion of failed learning was based on the fact that in 100 epochs the network was unable to exit the state in which all coins were classified either as belonging to a class or as not belonging to a class. The composition of the validation sample is approximately 10% for all cases. Training took place during 20 epochs.

For more details, see the graphs in Figures 5 – 8 [14].

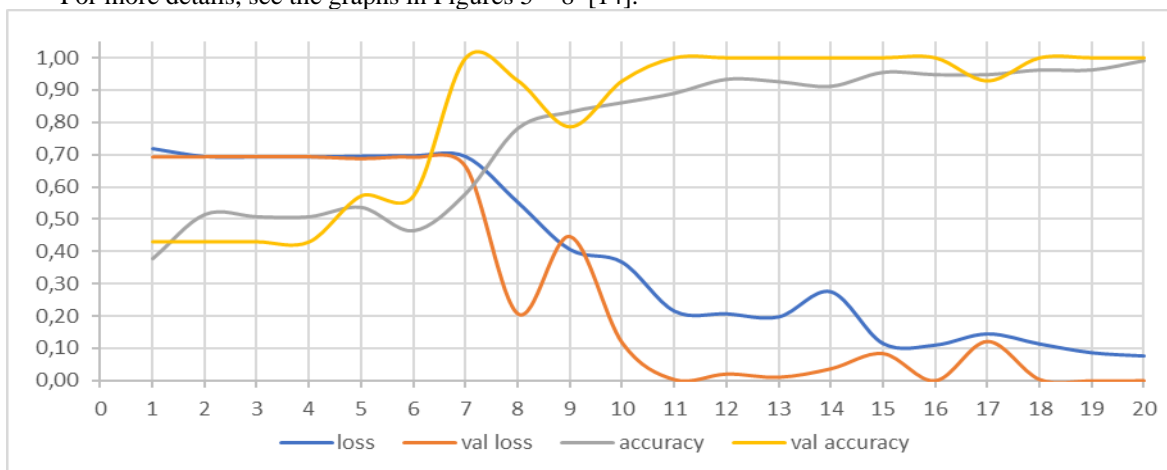


Fig. 5. Neural Network Training Graph for Obverse 109-2075

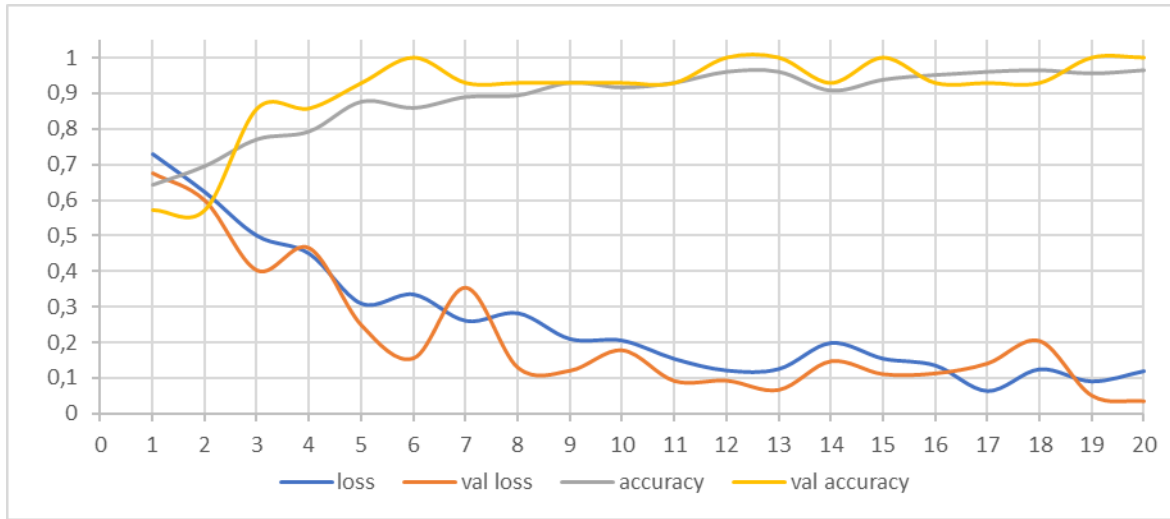


Fig. 6. Neural Network Training Graph to Reverse 109-2075

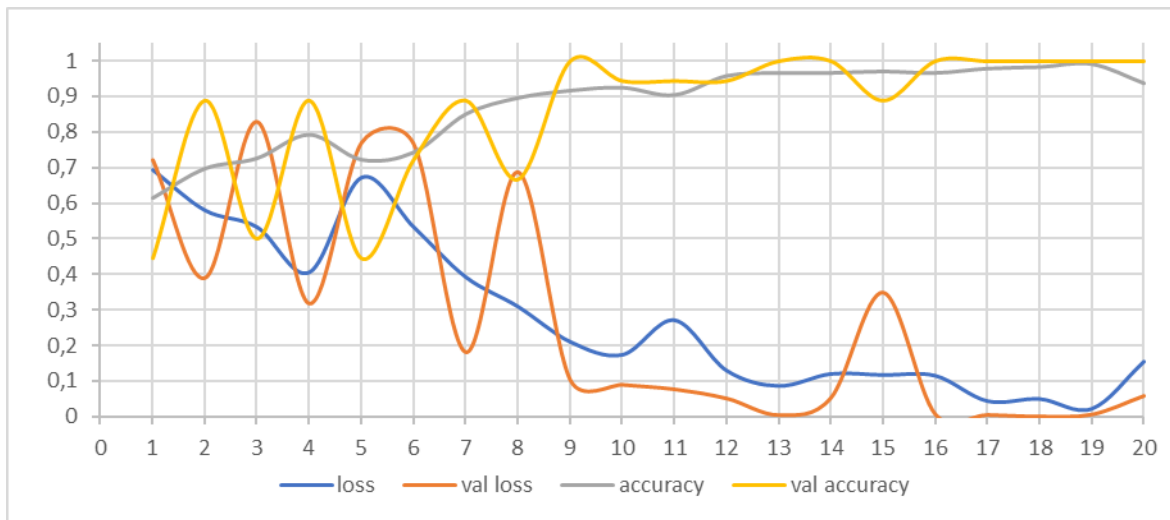


Fig. 7. Neural Network Training Graph for Obverse 111-3002

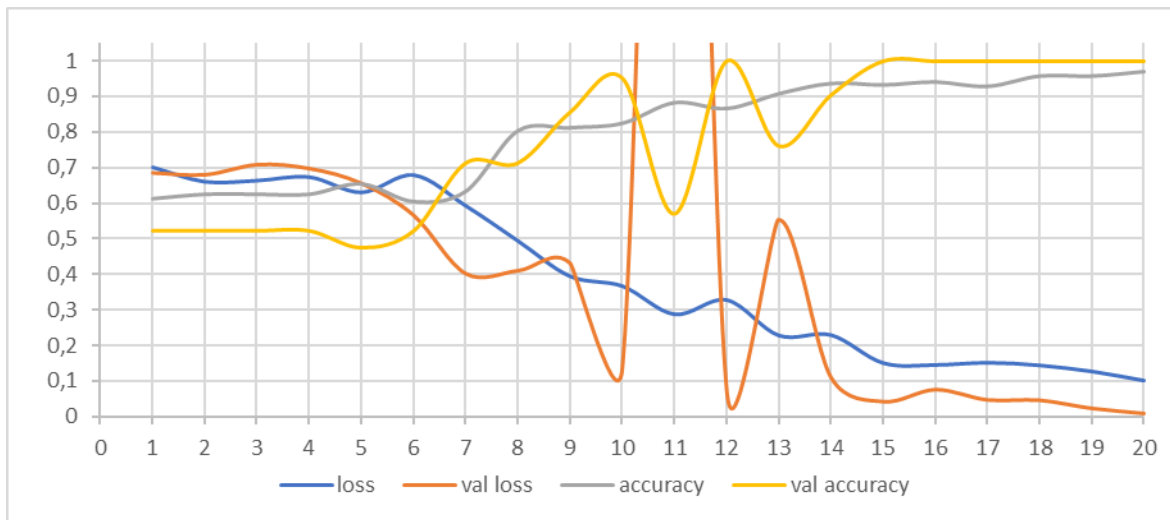


Fig. 8. Neural Network Training Schedule for Reverse 111-3002

The relationship between the ratio of class coins to other coins was also found. For obverse sample 783-7831, 100% accuracy in ten epochs was achieved when the ratio between samples was 1:1, with ratios of 1:4 and 1:7, 30 epochs were required to achieve 100% accuracy. For more details, see the graphs in Figures 9 – 10.

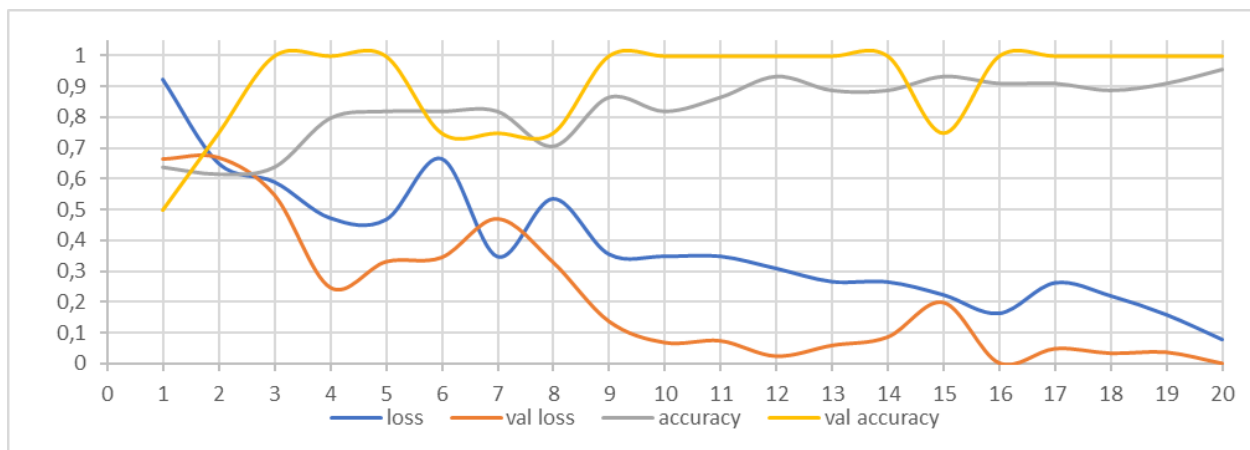


Fig. 9. Neural Network Training Graph for Obverse 783-7831 (20 Epochs, 1:1 Sampling Ratio)

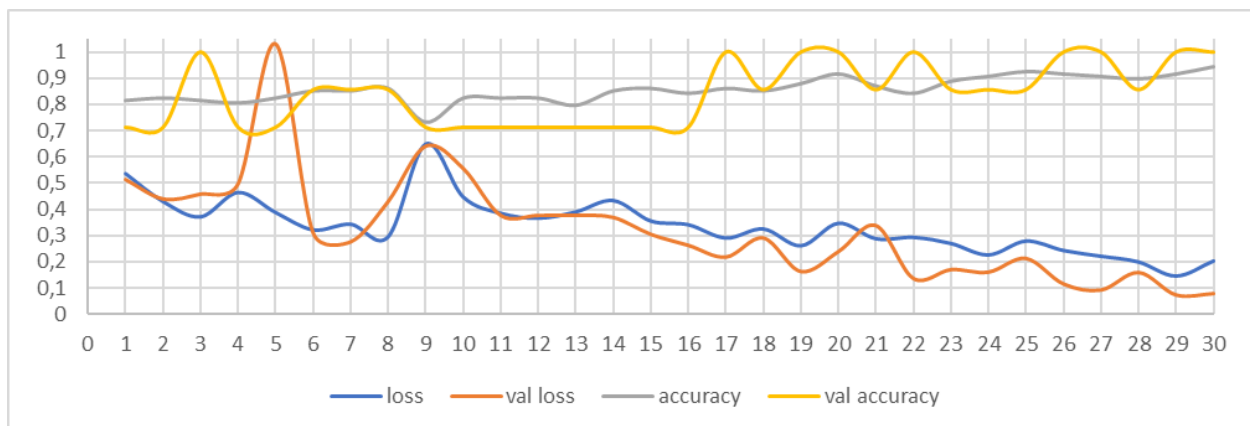


Fig. 10. Neural Network Training Graph for Obverse 783-7831 (20 Epochs, Sample Ratio 1:4)

The following technologies were used to implement the Web system:

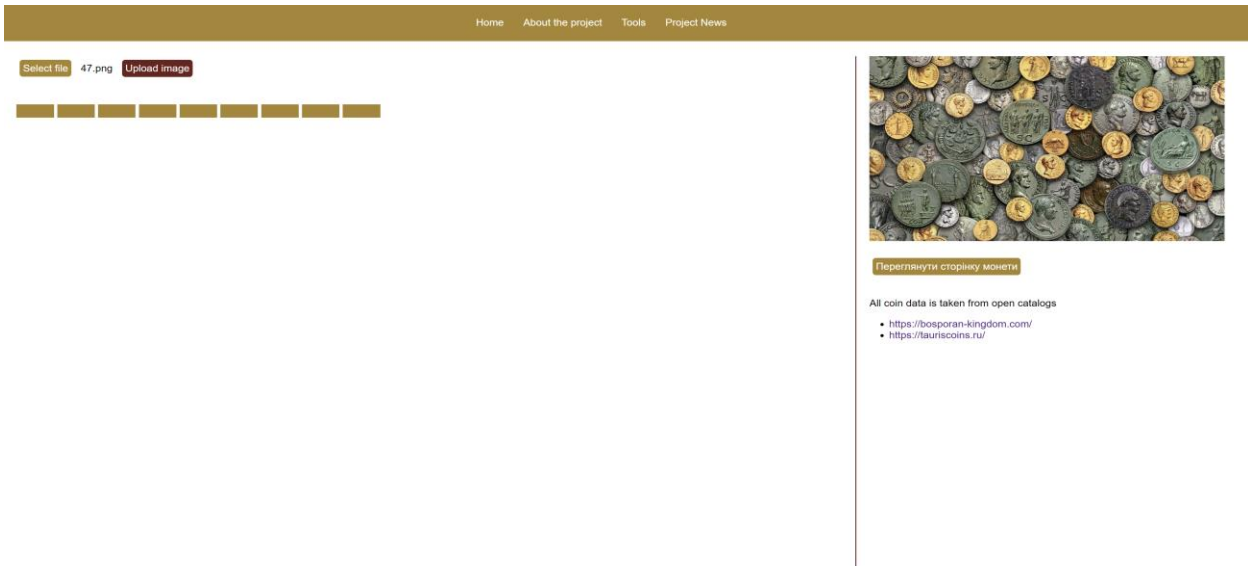
1. framework for Python – Django for writing the server part;
2. JavaScript programming language for writing the user part of the system;
3. the jQuery library to improve the interaction of the user part with the user;

4. the following libraries were also used to create the server part: tensorflow and keras – for working with neural network models, io – for working with memory allocation for processing files received from the user, Pillow – for processing images received from the user, JOSN – for working with JOSN data format, NumPy – for processing data presented in the form of vectors, OpenPyXL – for interaction with .xlsx type files.

For interaction between the user and the server part of the applications, the AJAX request technology was used, which allows data to be transferred to the server part imperceptibly for the user and without reloading the page. sqlite3 was used as the main application database.

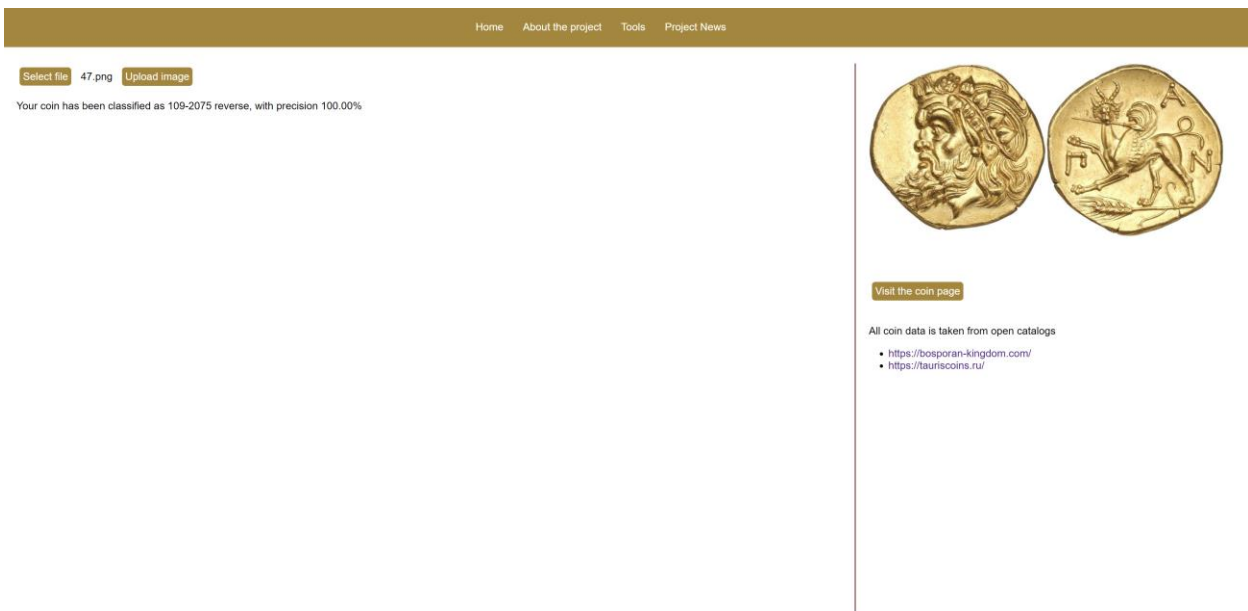
The interface of the application for classification of coins looks very simple, after uploading the image, all processes take place automatically on the server side, the user is presented with a progress bar, the indicators of which are not related to the stages of the algorithm on the server. The time to display the progress bar was chosen experimentally based on the average processing time of one image ≈ 2.6 seconds.

After successful classification, an image of the coin of the same type as the one uploaded by the user appears on the right side of the site (or at the bottom, for the mobile version). By clicking on the button under the image, the user can go to the page of this coin in the Internet catalog. In case of unsuccessful classification, the button disappears, and the image changes to the standard one (Fig. 13).



Feedback Капелешук Андрій
для кваліфікаційної роботи магістра 2023

Fig. 11. Ancient Coin Classification Application Interface (Classification Process)



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Fig. 12. Ancient Coin Classification Application Interface (Successful Classification)

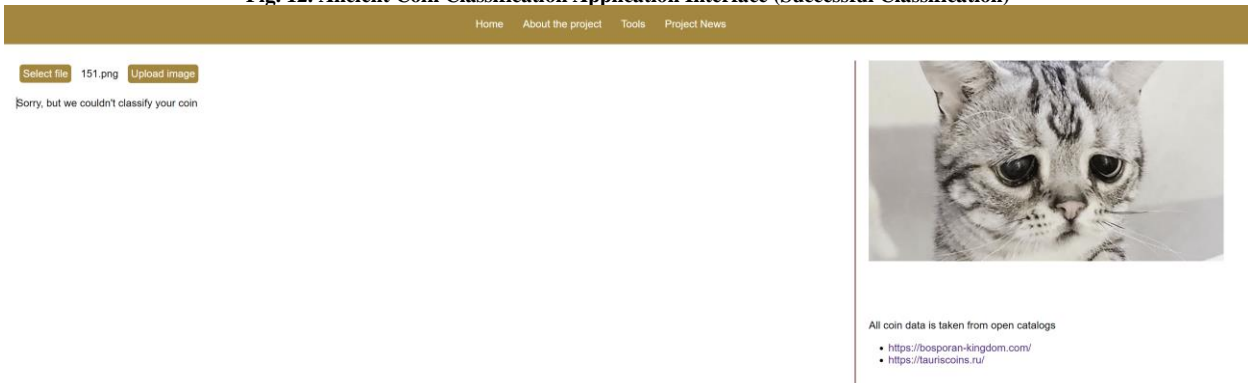


Fig. 13. Ancient Coin Classification Application Interface (Unsuccessful Classification)

Conclusions

A system for the classification of ancient coins was developed and the architecture of the system, which claims universality, was proposed. The results of the system's operation are demonstrated and the quality of network training is evaluated.

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