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Coins multi-class classification using vision TensorFlow

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Abstract

Coin classification is challenging but crucial for various applications such as vending machines, cash registers, and self-service kiosks. Coins are prevalent daily in banks, grocery stores, malls, supermarkets, and ATMs. Therefore, it is essential to have the capability to recognize coins with high accuracy automatically. Deep learning image processing models have recently shown promise in resolving the coin classification problem. These models can learn to identify and classify coins based on visual features such as shape, size, and texture. However, it is not easy as many coins appear similar, making it difficult to distinguish between different types of coins and classify them accurately. This paper proposes a coin classification system that utilizes the popular open-source library Vision Tensor Flow, which is excellent for image processing and computer vision. Our system is designed to handle multi-class classification of coins, which means it can recognize and classify multiple types of coins simultaneously. We tested our system using a dataset of various coin types from different countries, and the results were promising- it can achieve high accuracy in coin recognition. We use the Czech coins dataset to classify the coin images; we use ImageNet-21K as a pre-trained model to help our model enhance accuracy, and we train our model on VITIn.

Keywords: Coin classification; ViT; Deep learning and vision transformer; Countries

1. Introduction

The classification of coins is a difficult task. That has gained significant attention recently due to its potential applications in various fields. Not only can such systems be used in everyday life, but they can also be used for sorting in multiple organizations that work with coins. Additionally, they can help novice collectors of historical coins and experienced numismatists. Coin recognition is an open research topic, and it is surprisingly challenging to build a model that can reliably identify, classify, and recognize a particular coin.

This research proposes a vision transformer model (ViT) to classify coins. The Vision Transformer (ViT) is a transformer encoder model that has been pretrained on an extensive collection of images in a supervised manner, specifically on ImageNet-21k, at a resolution of 224x224 pixels [1]. The concept behind the ViT model is that images are presented to the model as a sequence of fixed-size patches (resolution 16x16), which are linearly embedded. Additionally, a token is added to the beginning of the sequence for use in classification tasks. The use of transformer models for computer vision tasks has been a rapidly growing field in recent years, and the ViT model has shown to be highly effective for image classification and object recognition tasks. The ViT model is trained on a massive dataset of images, allowing it to learn rich and diverse visual features. This makes it well-suited for the coin recognition task, as it can learn to recognize and classify coins based on their visual features, such as shape, size, and texture.

In addition to the ViT model, we also explore the usage of other state-of-the-art techniques for computer vision, such as convolutional neural networks (CNNs) and deep neural networks (DNNs) [2]-[4]. , to further improve the performance

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of our coin classification system. We also evaluate our proposed system on a dataset of various coin types like 1, CZK, and 2.CZK, 5 CZK, 10 CZK, 20 CZK and 50 CZK. Finally, this research presents a promising approach for coin classification using the ViT model. The use of transformer models for image classification and the large-scale pre-training on a diverse dataset makes it well-suited for the coin classification task. The proposed system is tested and evaluated on a dataset of real-world coin images, and the results show that it can achieve high accuracy in coin classification.

2. The Proposed Model

This paper aims to present a Czech coin recognition system using Vision-Transformer and a pre-trained network, ImageNet-21k. ImageNet-21K dataset is more diverse and significant than ImageNet-1K and is usually used in VIT and Mixer [5]. ImageNet-21k consists of 14 million images and 21,843 classes at resolution 224x224 to help the model train more and give higher accuracy. Also, we will change hyperparameters (epochs number, learning rate, testing, and training percentage) to achieve the highest accuracy [6].3. Results (examples/case studies related to the proposed work) This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, and the conclusions that can be drawn.

3. Related Work

3.1. Ancient Coin Classification Based on Recent Trends of Deep Learning 2022

Manzoor et al. (2022) [7] proposed a framework for recognizing ancient Roman coins automatically. The framework utilizes a hierarchical knowledge structure of coins and a CNN-based category classifier. The study focused on Roman Republican coin datasets for identification using the CNN Alex-net architecture. The results were evaluated on two different datasets of Roman Republican coins. The analysis of computational complexity and performance showed that the Alex-Net model outperforms the state-of-the-art.

In this paper, the authors used KERAS and TensorFlow to implement Alex-Net for coin recognition. They employed the NumPy library and the "Cv2" library for efficient image processing. The model utilizes feature-based identification of images, and the CNN model was used to introduce nonlinearity and reduce dimensionality and calculations.

The authors constructed five convolutional layers, three max-pooling, and two fully connected layers. The proposed model was tested on the Roman Coins Dataset and the Roman Republican Coin dataset, achieving 96.3% and 100% accuracy, respectively. The paper explained CNN's usage mechanism and evaluated a modified CNN Alex-Net model for identifying and detecting ancient coin images. This paper showed that if the CNN model was deep and large on a challenging dataset, it could produce record-breaking results using only supervised learning.

3.2. Deep Learning-based Malaysian Coins Recognition for Visual Impaired Person 2022

In a study by Sufri, Nur, et al. (2022) [8], a currency recognition model for Malaysian coins was proposed by modeling a convolutional neural network (CNN) to recognize coin images. A Malaysian coin dataset was developed, consisting of 2400 images of four classes of coins (5 sen, 10 sen, 20 sen, and 50 sen). The photos were taken under the same lighting conditions and at a fixed distance from the subject, and the backgrounds were set to plain white to eliminate background variations. The dataset was split into training, validation, and testing, with 90% for training and 10% for testing. The study used pre-trained CNNs such as AlexNet, GoogleNet, and MobileNetV2 to perform better than previous works. The performance of each trained model was evaluated using a confusion matrix. GoogleNet performed the best with 99.2% testing accuracy, 99.2% precision, 99.18% recall, and 99.19% F1 score.

3.3. Development of an Accurate Neural Network for Coin Recognition 2021

Fonov et al. (2021) [9] researched coin classification and recognition and determined that the most effective method involves processing the input image using a convolutional neural network (CNN). They wrote a parser in Python to extract necessary information from HTML headers and used the Pytorch library to implement the CNN. The CNN test on a set of 27 types of coins resulted in an accuracy of 99.29%. However, it should be noted that this method can also be implemented using TensorFlow.

The problem in this paper was that the coin images were so sensitive to the light, so if the light was low, the coin details were unclear, and the noise was too much. So, the images in low light gave lower accuracy than images in high light. This paper used a Multi-Level Counter Propagation Neural Network (MLCPNN), the implementation of which is represented in some steps: 1. Weights' initialization, 2. The input vector X is defined, 3. determining the unit J most near the vector X, and at the end, 4. Configuring the output units' activation.

3.4. Ensemble Deep Eearning for Brazil Currency Coin Prediction 2021

Muppalaneni et al. 2021[10] proposed a machine learning model using convolutional neural networks (CNN) to recognize and reorganize Brazilian currency coins. The model was trained using ensemble learning, combining multiple supervised and unsupervised learning models to improve classification results.

The authors tested the trained model on various datasets, including images that had been shifted, rotated, and translated, and achieved an accuracy of 87.36%. This accuracy was higher than that achieved using traditional methods that rely on the physical properties of the coins, such as color, dimensions, and shape.

In this paper, researchers use a convolutional neural network (CNN) to identify and predict Brazilian coins. The accuracy rate is not high using process characteristics such as color and coin detection size. In their work, they studied Brazilian coins in denominations of 5 cents, 10 cents, 25 cents, and more. Each comes in different shapes and designs. They used a convolutional neural network, a deep learning model, to identify the Brazilian currency. They designed four different CNN models by varying the filters and network dimensions. Various deep learning models were developed and applied to the learning set to find better accuracy. Ensemble learning (EL) is another tricky deep learning (DL) technique that combines supervised and unsupervised learning models to improve classification results. They achieved an accuracy of 87.36%, surpassing that provided by models with handcrafted features.

3.5. Deep Ancient Roman Republican Coin Classification Via Feature Fusion and Attention 2021

In a study by Anwar, Hafeez et al. (2019) [11], a new network model called CoinNet was proposed for coin recognition. CoinNet improves performance by incorporating compact bilinear pooling, residual groups, and feature attention layers. The researchers also created the largest and most diverse image dataset of Roman Republican coins, containing over 18,000 images belonging to 228 different reverse motifs. The CoinNet model achieved more than 98% classification accuracy and outperformed traditional bag-of-visual-words-based approaches and other state-of-the-art deep learning methods. The study aimed to classify ancient Roman coins by identifying objects on the reverse side of a new dataset of different coin designs. The proposed method outperforms the traditional BoVW model and its spatial extension, which had previously provided state-of-the-art results in ancient coin classification tasks. The experiments also showed that BoVW models tend to overfit in large image datasets. The researchers also compared the proposed CoinNet architecture to current CNN models and found that CoinNet outperforms them in accuracy. Furthermore, CoinNet was also tested on an unseen test suite, where it outperforms competing CNNs.

3.6. Ancient Roman Coin Recognition in the Wild Using Deep Learning-based Recognition of Artistically Depicted Face Profiles

Schlag et al. 2017 [12] proposed a state-of-the-art deep convolutional network model to detect the emperor on the obverse of coins as human experts would. They built fully connected, pooling, and convolutional layers trained the model on an Nvidia GTX 1080 graphics card and implemented it using TensorFlow. They collected three datasets: Data Set 1 (RIC-Hq), Data Set 2 (RPC-Scan), and Data Set 3 (RIC-Cond); the proposed model achieved 92.23, 94.11, and 97.35 accuracies on the datasets, respectively.

This study addresses a significant limitation in analyzing legacy tokens using domain-specific information. The researchers propose a coin grading method that utilizes face recognition, exploiting the fact that many Roman Empire coins feature the emperor's face. The technique employs complex networks of deep pleats consisting of various layers made of stacked tiny beads. With the most extensive, systematic, and detailed evaluation conducted to date, the method surpasses current industry standards by a significant margin.

3.7. Machine Vision for Coin Recognition with Anns: Effect of Training and Testing Parameters

In a study conducted by Chauhan et al. in 2017 [13], they investigated the factors that affect the performance of artificial neural networks (ANNs) and deep neural networks (DNNs) in coin recognition tasks. They found that the size of the dataset, the quality of images, the number of classes, and the number of images per class all impact the classification accuracy. They also determined that DNNs performed better than ANNs, mainly when fewer variations were within a class. The study also revealed that using a more realistic DTT strategy for training and testing resulted in lower accuracy than the MTT strategy. However, increasing the number of images per class improved accuracy. The authors used their findings to establish guidelines for testing protocols in pattern recognition and classification tasks.

This paper examined the use of Machine Vision Imaging (MVI) for pattern recognition, specifically using Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs). The research aimed to establish guidelines for testing protocols using the Indian Coin Detection and Grading Expedition as a case study. The results of various experiments showed that the classification accuracy is affected by factors such as the amount of data, image quality, number of classes, number of images per class, variations within the class, and the method of training and testing (MTT or DTT) and the quality of the networks used. The study found that using the MTT strategy with 360 pictures per class for 14 classes achieved 100% classification accuracy with ANNs. However, using the DTT strategy, accuracy dropped to 60%. Increasing the number of pictures per class to 500 while using the DTT strategy led to a 74% accuracy rate, showing that increasing the data improves accuracy. The research found that the number of classes also impacted the network's ability to classify images accurately. Higher accuracy was achieved with fewer output categories. For example, when there were only five output categories, the classification accuracy was 100%. When the number of classes was increased to 36 with 3600 images per class, the classification accuracy using DTT was 91%. Improving accuracy further was challenging due to the high degree of similarity between categories and the limited structure of ANN and its learning capabilities.

The research found that for pattern recognition applications with fewer variations within the class, using a Deep Neural Network (DNN) for training and testing leads to higher classification accuracy. When the same data was used as with the Artificial Neural Network (ANN), but a DNN was implemented for 36 categories, an accuracy of 99% was achieved. This high accuracy contributed to the complex multi-layered DNN structure, automatic feature selection, and many images per category.

3.8. Fast-Moving Coin Recognition Using Deep Learning

In a study by Yan et al. (2017) [14], it was found that deep learning has played a vital role in the development of visual object detection and recognition. Identifying rapidly moving objects is still a challenging problem in computer vision. They discovered that the best solution in deep learning for representing the characteristics of moving objects is using a recurrent neural network (RNN), particularly Long Short-Term Memory (LSTM) in RNN. Combining LSTM and CNN fully utilizes moving objects' spatial and temporal features. The paper aimed to identify fast-moving coins in digital videos using deep learning methods, specifically using a combination of LSTM and CNN. With this proposed method, they achieved high accuracy in recognizing fast-moving coins, which is superior to the human visual system. The researchers also conducted experiments using only the Faster R- CNN to attain recognition accuracy. The results of their experiments confirmed that the combination of LSTM and CNN effectively improves the identification accuracy of fast-moving coins.

3.9. The Dataset

This dataset was created for a diploma (master's) thesis about transfer learning with data augmentation. And it is publically available on Kaggle [a]. There are six types (classes) of coins - 1 CZK, 2 CZK, 5 CZK, 10 CZK, 20 CZK and 50 CZK. Coins were captured from both sides, on different surfaces, under various lighting conditions, and from different angles. Each class consists of roughly 300 images (~1800 images total), the image size is 640x640px, and the image folder size is 116.22 MB at [a]. Figure (1) is a sample of the coin categories.

4. Methodology

The proposed coin classification system is designed to handle multi-class classification of coins, allowing it to recognize and classify multiple types of coins simultaneously. This is an essential feature as it will enable the system to be used in different scenarios, such as in banks, vending machines, or even for personal use. The system can recognize and classify coins based on their denomination, country of origin, and other attributes. In this section, we describe in detail the steps we took to develop and evaluate the proposed coin classification system. We start with data preparation, loading, and preprocessing the coin dataset. Then, we train the model using the Vision Tensorflow library and fine-tune its parameters to achieve optimal performance. Finally, we evaluate the performance of the model using the accuracy. Our findings indicate that the proposed coin classification system can classify coins with high precision and has the potential to.be used in various practical applications. Figure 1 shows A sample of the coin categories.

Figure 1 A sample of the coin categories

4.1. Data Preparation

After importing the necessary libraries, we load the dataset from Kaggle, read the CSV file, and save the data in a dataset. The dataset contains many images of different types of coins and their labels. Each image is labeled with the kind of the coin. The dataset has been split into training, validation, and testing sets, where we used 80% of the dataset for testing (1502 images for training), the rest for testing and validation (376 images for testing and verification), and the train batch size is assigned to 16 like the images in the pre-trained images. This allows us to evaluate the model's performance on unseen data and estimate its performance on new coin images. We first performed preprocessing steps on the dataset to prepare the data for training. These included resizing the images to a fixed resolution like the pre-trained images sizes 224x224 pixels, converting the images to RGB, and normalizing the image pixel values with the provided mean and std from the pre-trained images. Also, we randomly resize and crop the image to a specific size and flip it horizontally. These steps ensure that the model can learn features from the images effectively and reduce the computational cost of training.

4.2. Model Training

We use the "ViTFeatureExtractor" class from the Hugging Face's transformers library to use the feature extractor method images based on the Vision Transformer (ViT) architecture to extract the features. The class is being instantiated with the from_pretrained method, which initializes the feature extractor with the pre-trained weights of the 'google/vit-base-patch16-224-in21k' model. The 'google/vit-base-patch16-224-in21k' is the ImageNet-21 pre-trained Vision Transformer (ViT) model that is trained on a large dataset of images and fine-tuned for various computer vision tasks, as we mentioned before.

The feature extractor can extract features from images, which can be passed to a separate classifier to perform downstream tasks such as image classification. This feature extractor is proper when the task is related to computer vision, and the pre-trained weights give the feature extractor the capability to understand the image and extract important features.

We initialize the model using the ViTForImageClassification class from the Hugging Face transformers library, an effective transformer-based architecture in image classification tasks. The model architecture is based on the Vision Transformer (ViT), a variant of the transformer architecture designed for image classification tasks. So, we create an instance of the ViTForImageClassification model using a pre-trained model with the name or path "google/vit-base-patch16-224-in21k". The approach for evaluating the model, we use the 'steps' strategy, the number of training epochs, the number of steps after which the model will be saved, the number of steps after which the evaluation will be done, and the learning rate used for training.

We set the number of classes to equal the number of unique labels in the dataset, which equals 6. This is important as it ensures the model can handle the different types of coins in the dataset.

Then, we use the TrainingArguments class to set the training arguments, such as the number of training epochs equal to 10 and the batch size equal to 16 pixels, meaning that 16 images were used for each training step. The learning rate was set to 2e-4. These hyperparameters were chosen based on our experiments and previous works in the literature. We train the model using the train method. During training, the model learns to extract and classify features from the images into different classes. Table 1 shows The results of the training model.

Table 1 The results of the training model

Step	Training Loss	Validation Loss	Accuracy
100	0.611900	0.466717	0.867021
200	0.408100	0.428642	0.851064
300	0.360500	0.236220	0.914894
400	0.312200	0.495551	0.851064
500	0.315600	0.567573	0.813830
600	0.161900	0.208141	0.941489
700	0.078800	0.197584	0.941489
800	0.028700	0.119796	0.957447
900	0.052200	0.087774	0.973404
1000	0.086800	0.078060	0.978723

Figure (2) shows the results of training the model that achieves 97%, 10%, and 10% accuracy, training loss, and validation loss, respectively, after 10 epochs and 1000 steps.

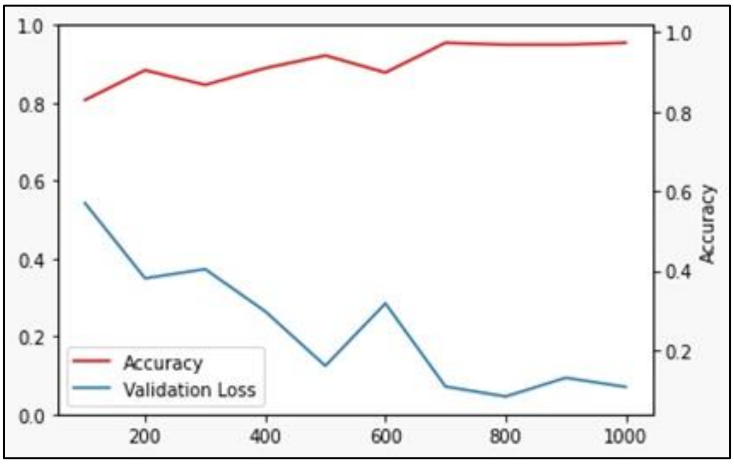

Figure 2 Accuracy and Validation loss

This figure shows that the accuracy starts at 82% and increases exponentially with the number of steps, and the validation loss starts at 57% and decreases with the increasing number of steps.

4.3. Model Evaluation

We evaluate the model's performance using the load_metric function, which was used to calculate the model's accuracy. This metric was calculated on the testing set, which allow us to estimate the model's performance on unseen data. Figure 3 shows the Prediction sample.

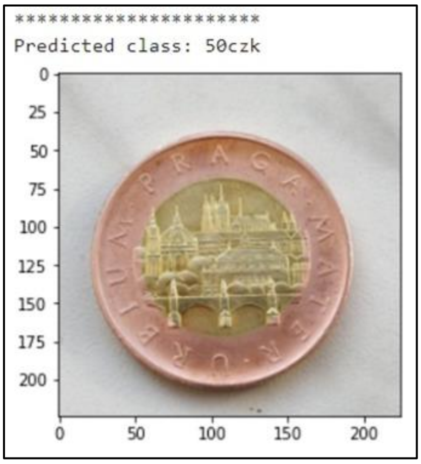

Figure 3 Prediction sample

This figure shows a coin from the 50czk class, and our model predicted its class correctly.

5. Experimentation

In our experimentations on the model, we achieved the best results in terms of accuracy by modifying the train and test ratio. We evaluated different combinations of train and test ratios, epochs, learning rates, and accuracy levels through a series of trials. We also assessed other train and test ratios such as 90% train, 10% test, 70% train, and 30% test. However, these configurations yielded less favorable results than the 80% train and 20% test ratio. Additionally, we attempted different learning rates, such as 2e-5 and 1e-3, but found that 3e-5 was the best fit for the model. In summary, through experimentation, we reached the best results in terms of accuracy by utilizing an 80% train and 20% test ratio, with 10 epochs and a learning rate of 3e-5. Table 2 shows the results of hyper-parameters.

Table 2 Results of hyper-parameters

Train	Test	Epoch	Accuracy	Learning Rate
90%	10%	10	0.9308	2e-4
80%	20%	10	0.9414	2e-4
80%	20%	15	0.92	2e-4
80%	20%	7	0.93	2e-4
70%	30%	10	0.92	2e-4
90%	10%	10	0.27	1e-3
90%	10%	10	0.93	2e-5
80%	20%	10	0.957	3e-5

6. Results

For our proposed coin classification system, we used the Czech dataset, which is publicly available on Kaggle, and the model achieved an accuracy of 98% with a validation loss of 7% in 10 epochs. It accurately classifies coin efficiency and is suitable for real-world applications such as vending machines, cash registers, and self-service kiosks. It is a valuable and helpful tool for coin-related applications that can improve the performance and efficiency of coin classification tasks.

6.1. The Related Work Vs. the Proposed Plan

This paper uses a ViT model to classify Czech coins using the pre-trained network ImageNet-21k. Our contribution is to apply the ViT model, a recent and novel architecture in deep learning, to the problem of coin classification. The ViT model is based on the transformer architecture and has shown to be effective in many computer vision tasks, such as image classification, object detection, and segmentation. To the best of our knowledge, our work is novel, as there has not been any prior research that has applied the ViT model specifically to the classification of Czech coins. Compared to other related works, we will use a new dataset from Kaggle[a] that includes a diverse range of Czech coins, whereas previous works have used more minor and more limited datasets. We plan to evaluate the performance of our ViT model on the Czech coin dataset by comparing its accuracy with the results of other deep learning models, such as CNNs and ANNs. The results are presented in the table below, which compares the accuracy and runtime of each model, providing a clear picture of the effectiveness of our proposed ViT model. Our work will contribute to coin classification by introducing a new and effective deep-learning architecture and demonstrating its potential by classifying Czech coins. Table 3 shows a Summary of related works.

Table 3 Summary of related works

Paper ref	Issue type	Model(s) used	Pre-trained networks	New challenge	Note
Our work	Czech coins classification	CNN with ViT model	No	Yes	Improved classification accuracy compared to previous studies using AlexNet
[4]	Recognition of Roman images	CNN Alex-net architecture	No	Yes	They use AlexNet architecture in the proposed plan. We will build a VIT model.
[5]	Recognition for Malaysian images	CNN	AlexNet, GoogleNet, and MobileNetV2	Yes, because of using another network	Will apply ImageNet
[6]	Recognition and classification of 27 types of coins	MLCPNN	No	Yes, because of using another dataset of 5 classes	ViT model will classify the data using a pre-trained network
[7]	Recognition and detection of Brazil currency	CNN with ensemble learning	No	Yes	The use of ensemble learning to enhance classification result
[8]	Classification of ancient roman republican	CNN	CoinNet	Yes	
[9]	Recognition of artistically depicted face profiles	CNN	No	Yes	
[10]	recognition of patterns and regularities in data	ANN, DNN	No	Yes	
[11]	Recognition and detection of coins	CNN, RNN	AlexNet, ConveNet	Yes	

7. Future Work

We plan to work with a larger dataset, as it will provide a more comprehensive representation of the coin recognition problem, allowing us to train a more robust model that can handle a broader range of coin types and variations. Additionally, we will add some noise to the images, which will help us evaluate the robustness of the model to noise and test its ability to generalize to images captured under varying lighting conditions.

8. Conclusion

In conclusion, the proposed coin classification system using the Czech dataset from Kaggle demonstrated remarkable performance, achieving an accuracy of 98% with a validation loss of 7% in just 10 epochs. This model effectively classifies coins with high precision, making it suitable for real-world applications such as vending machines, cash registers, and self-service kiosks. Its implementation can significantly enhance the efficiency and accuracy of coin classification tasks, providing a reliable and efficient solution for various industries. This study contributes to improving automated monetary systems and paves the way for future advancements in real-time coin recognition technologies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest is to be disclosed.

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