

Currency Classification System Using Deep Learning

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ABSTRACT

In recent years, deep learning has become the most popular research direction. It mainly trains the dataset through neural networks. There are many different models that can be used in this research project. Throughout these models, accuracy of currency recognition can be improved. Obviously, such research methods are in line with our expectations. In this paper, we mainly use transfer learning (MobileNet) model based on deep learning as the framework, Convolutional Neural Network (CNN) model to extract the features of paper currency, so that we can more accurately classify the currency. Our main contribution is through using CNN and MobileNet, the average accuracy of currency classification is up to 99%.

Article Info

Publication Issue :

Volume 8, Issue 4
July-August-2022

Page Number : 287-293

Article History

Accepted: 10 August 2022

Published: 28 August 2022

Keywords : Currency image dataset, CNN algorithm, MobileNet, Data Augmentation, Tensorflow.

I. INTRODUCTION

In the past, people could only authenticate money, but the observation ability of the human eyes are limited, and they are difficult to distinguish the truth or fake without the technology. Although UV recognition technology is already in existence, with the development of counterfeiting technology, this technology is not enough to help people to identify the counterfeit currency with more advanced fraud techniques. But now, based on image recognition, different viewpoints were shared by analyzing the currency color, design features and specific data of currency, then specific identification methods were given. Currency classification methods for data argumentation through color analysis of currency

images, image enhancement, rotation angle and so on were provided. Deep learning belongs to a neural network. First, it needs a set of big data. By analyzing training dataset, the accuracy of currency classification could be continuously improved and our expectations for experimental results could be achieved. Convolutional neural network (CNN) plays a vital role in the recognition process and can improve the accuracy of the overall training through using CNN model. We use CNN as a feature extractor under the framework of Transfer learning (MobileNet) model. In the process of currency recognition, we first need to consider whether the size of the dataset is sufficient, because our data collection was from the images by splitting the video into a single frame, but in the process it may have distortion or blurring may

occur, so it is first necessary to edit the images and make the image clearer to a certain extent, which also contributes to the accuracy after training.

In the process of deep learning, overfitting is also prone to occur. It is easy to make the training process more complicated, increase training difficulty and training time; the training also allows us to study drop technology and avoid over fitting.

II. RELATED WORKS

[1] Deng, L., & Yu, D. (2014) Deep learning: methods and applications. *Foundations and Trends in Signal Processing*, 7(34), 197-387.

This article proposes an effective method for real-time banknote recognition, using digital image processing. The new Series 7 New Zealand banknotes are considered, as a case study, for intelligent real-time recognition. The composite feature of a banknote containing the elements of color and texture is extracted, and a three-layer backpropagation neural network is trained for classification. The proposed method has demonstrated excellent recognition results in an indoor environment and is comparatively less time-consuming that makes it suitable for real-time applications. This article fills in the vacancy of real-time recognition of the newly released paper currency. Practically, our proposed approach can be served as the uppermost for the future development of the prototype assisting the blind or the visually impaired in recognizing the new series of New Zealand banknotes.

[2] Wang, G., Wu, X., Yan, Q. (2017) The State-of-the-Art Technology of Currency Identification: A Comparative Study. *IJDCF* 9(3): 58-72

The security issue of currency has attracted awareness from the public. Despite the development of

applying various anti-counterfeit methods on currency notes, cheaters are able to produce illegal copies and circulate them in market without being detected. By reviewing related work in currency security, the focus of this paper is on conducting a comparative study of feature extraction and classification algorithms of currency notes authentication. We extract various computational features from the dataset consisting of US dollar (USD), Chinese Yuan (CNY) and New Zealand Dollar (NZD) and apply the classification algorithms to currency identification. Our contributions are to find and implement various algorithms from the existing literatures and choose the best approaches for use.

[3] Hoo-Chang, S., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogue, I., ... & Summers, R. M. (2016) Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. *IEEE Transactions on Medical Imaging*, 35(5), 1285.

Remarkable progress has been made in image recognition, primarily due to the availability of large-scale annotated datasets and deep convolutional neural networks (CNNs). CNNs enable learning data-driven, highly representative, hierarchical image features from sufficient training data. However, obtaining datasets as comprehensively annotated as ImageNet in the medical imaging domain remains a challenge. There are currently three major techniques that successfully employ CNNs to medical image classification: training the CNN from scratch, using off-the-shelf pre-trained CNN features, and conducting unsupervised CNN pre-training with supervised fine-tuning. Another effective method is transfer learning, i.e., fine-tuning CNN models pre-trained from natural image dataset to medical image tasks. In this paper, we exploit three important, but previously understudied factors of employing deep convolutional neural networks to computer-aided detection problems. We first explore and evaluate

different CNN architectures. The studied models contain 5 thousand to 160 million parameters, and vary in numbers of layers. We then evaluate the influence of dataset scale and spatial image context on performance. Finally, we examine when and why transfer learning from pre-trained ImageNet (via fine-tuning) can be useful. We study two specific computer-aided detection (CADe) problems, namely thoracoabdominal lymph node (LN) detection and interstitial lung disease (ILD) classification. We achieve the state-of-the-art performance on the mediastinal LN detection, and report the first five-fold cross-validation classification results on predicting axial CT slices with ILD categories. Our extensive empirical evaluation, CNN model analysis and valuable insights can be extended to the design of high performance CAD systems for other medical imaging tasks.

[4] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. In European conference on computer vision (pp. 21-37).

We present a method for detecting objects in images using a single deep neural network. Our approach, named SSD, discretizes the output space of bounding boxes into a set of default boxes over different aspect ratios and scales per feature map location. At prediction time, the network generates scores for the presence of each object category in each default box and produces adjustments to the box to better match the object shape. Additionally, the network combines predictions from multiple feature maps with different resolutions to naturally handle objects of various sizes. SSD is simple relative to methods that require object proposals because it completely eliminates proposal generation and subsequent pixel or feature resampling stages and encapsulates all computation in a single network. This makes SSD easy to train and straightforward to integrate into systems that require a detection component. Experimental results on the

PASCAL VOC, COCO, and ILSVRC datasets confirm that SSD has competitive accuracy to methods that utilize an additional object proposal step and is much faster, while providing a unified framework for both training and inference. For $300 \times 300 \times 300$ input, SSD achieves 74.3 % mAP on VOC2007 test at 59 FPS on a Nvidia Titan X and for $512 \times 512 \times 512$ input, SSD achieves 76.9 % mAP, outperforming a comparable state of the art Faster R-CNN model. Compared to other single stage methods, SSD has much better accuracy even with a smaller input image size.

5. Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. *Journal of Big Data*, 2(1), 1.

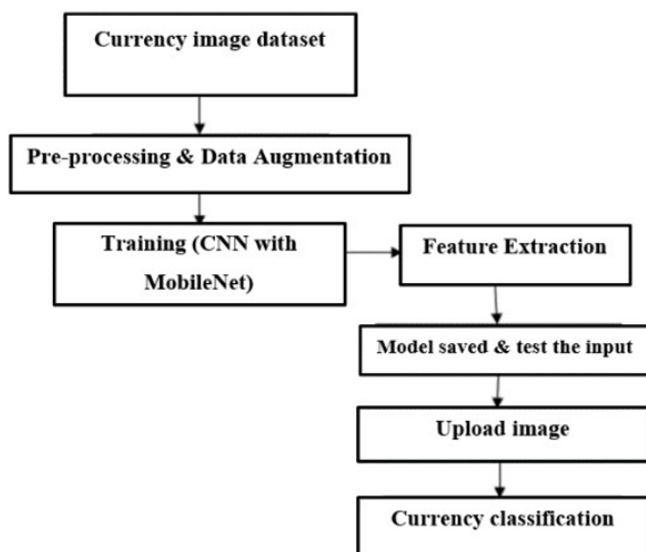
Big Data Analytics and Deep Learning are two high-focus of data science. Big Data has become important as many organizations both public and private have been collecting massive amounts of domain-specific information, which can contain useful information about problems such as national intelligence, cyber security, fraud detection, marketing, and medical informatics. Companies such as Google and Microsoft are analyzing large volumes of data for business analysis and decisions, impacting existing and future technology. Deep Learning algorithms extract high-level, complex abstractions as data representations through a hierarchical learning process. Complex abstractions are learnt at a given level based on relatively simpler abstractions formulated in the preceding level in the hierarchy. A key benefit of Deep Learning is the analysis and learning of massive amounts of unsupervised data, making it a valuable tool for Big Data Analytics where raw data is largely unlabeled and un-categorized. In the present study, we explore how Deep Learning can be utilized for addressing some important problems in Big Data Analytics, including extracting complex patterns from massive volumes of data, semantic indexing, data

tagging, fast information retrieval, and simplifying discriminative tasks. We also investigate some aspects of Deep Learning research that need further exploration to incorporate specific challenges introduced by Big Data Analytics, including streaming data, high-dimensional data, scalability of models, and distributed computing. We conclude by presenting insights into relevant future works by posing some questions, including defining data sampling criteria, domain adaptation modeling, defining criteria for obtaining useful data abstractions, improving semantic indexing, semi-supervised learning, and active learning.

III. Methodology

The Proposed currency system is mainly uses one of the Deep learning techniques CNN based transfer learning (MobileNet) model. This transfer learning method is used to extract the features from the concenter dataset, once after the feature collection the saved model is used to classify and predict the currency types more accurately.

Block Diagram:



IV. Implementation

The project was carried out using the algorithms listed below.

CNN (Convolutional Neural Network):

In deep learning, a convolutional neural network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels that shift over input features and provide translation equivariant responses.

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks makes them prone to overfitting data. Typical ways of regularization, or preventing overfitting, include: penalizing parameters during training (such as weight decay) or trimming connectivity (skipped connections, dropout, etc.) CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme.

The name "convolutional neural network" indicates that the network employs a mathematical operation called convolution. Convolutional networks are a specialized type of neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

APPLICATIONS:

- Image recognition
- Video analysis
- Natural language processing

- Anomaly Detection
- Drug discovery
- Health risk assessment and biomarkers of aging discovery

V. Results and Discussion

The following screenshots are depicted the flow and working process of project.

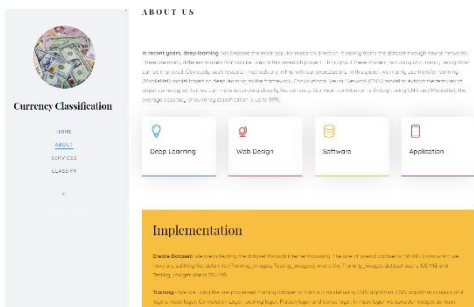
Home:

In this page will display the modules of a project



About project page:

Here display the main theme of project.



Services:

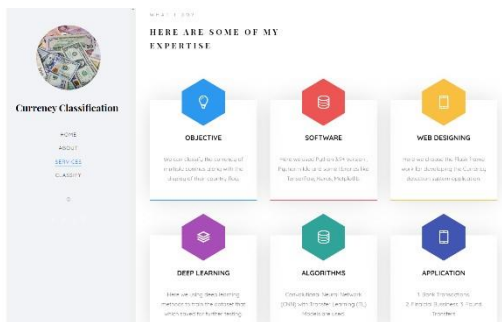
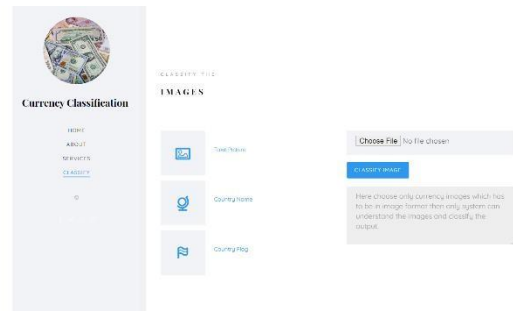


Image Upload page:

Here image files can be uploaded to classify whether the image which class it is.



View uploaded Image information:

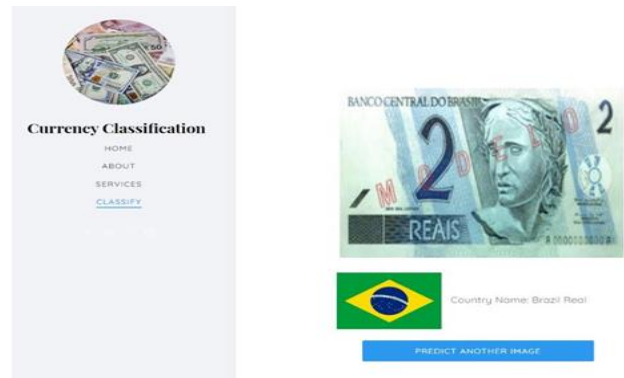
Here model classify the image is "American Dollar".



Here model classify the image is "Australia Dollar".



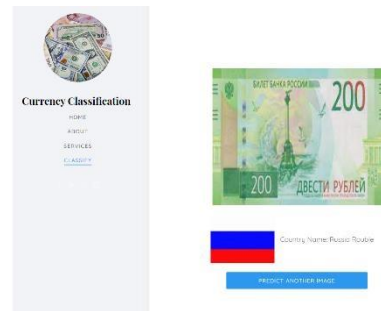
Here model classify the image is "Brazil Real".



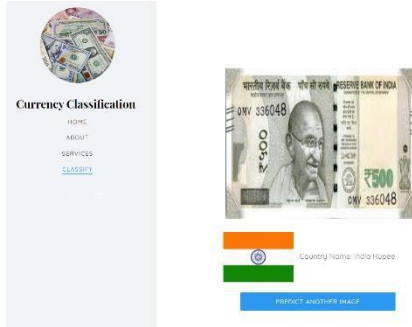
Here model classify the image is “China Yuan ”.



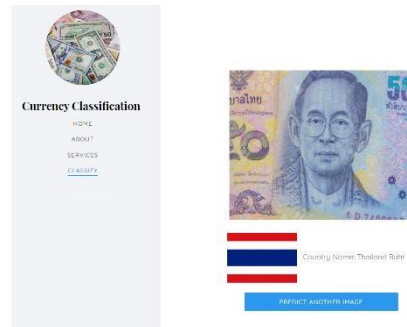
Here model classify the image is “Russia Rouble”.



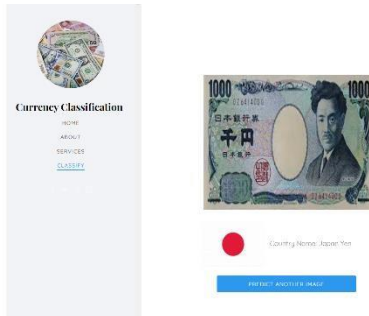
Here model classify the image is “India Rupee”.



Here model classify the image is “Thailand Baht”.



Here model classify the image is “Japan Yen”.



VI. Conclusion

Here model classify the image is “Malaysia Ringgit”.



Here model classify the image is “Philippines Peso”.



The main purpose of this paper is to carry out currency detection. In fact, it includes the denomination of currency. We trained the CNN with MobileNet model, tested different currency images. We have also received satisfactory results. We chose to create a CNN model as a feature extractor. After feature extraction for our currency recognition training. Finally, the trained model could reach 99% accuracy, which shows that our dataset has been fully trained. From the loss function, we see that our model does not have over fitting during the training process. The final research results are satisfactory, the accuracy is very high. The accuracy of the recognition will decrease slightly, but because the dataset is fully trained, the experiments of currency recognition can still be conducted well.

VII. REFERENCES

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Cite this article as :

P. Kavya Sree, Dr. J. Srinivasan, "Currency Classification System Using Deep Learning", *International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT)*, ISSN : 2456-3307, Volume 8 Issue 4, pp. 287-293, July-August 2022.
Journal URL : <https://ijsrcseit.com/CSEIT228448>