Ensemble Deep Learning for Brazil Currency Coin Prediction

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Abstract. In this present fast growing environment the automatic coin reorganization and identification machines has a vital role in all financial allied fields. At present most of coin recognition techniques are depends on physical properties of the coin like length, width, weight etc. Whereas image processing techniques are based on extraction of colour of the coin, edge features of the coin and shape of the coin. For recognition and detection of Brazil currency we have designed Machine Learning, Deep Learning (DL) models in this paper. We have designed various a Machine Learning (ML) models with Convolutional Neural Network for identification and reorganization of Brazil currency. Brazil currency consisting of 5 Centavos, 10 Centavos, 25 Centavos etc. Each of which has different shapes and designs. Different deep learning models are designed and applied ensemble to find the better accuracy. The trained ensemble model is tested on various the datasets which consists of shifting of images, rotation and translated images.

1. Introduction

In this present fast growing environment the automatic coin reorganization and identification machines has a vital role in all financial allied fields. Coin detection/prediction has various applications. These techniques may used in automated toll gates, slot machines, vending machine, coin based certificate printing devices etc. There are 3 different types of traditional coin prediction techniques which use Image Processing, Electromagnetic and Mechanical techniques [1]. In image processing technique the coins are predicted based on the pattern of the coin. The image based coin prediction technique involves basically two steps, the first step is taking the picture of the coin and the second step is to compare it with the reference coin database. The dataset contains images of various coins taken in various angles. After capturing the image of coin, some image processing techniques like Edge detection, DCT, Segmentation, FFT, Gabor Wavelets image subtraction, ANN, SIFT, decision trees, etc. are used to process the image. In the Electromagnetic approach, the material properties to manufacture the coin are considered. So if two coins are made up of the same material then these
Mechanical coin prediction techniques usually based on the physical properties of the coin like weight, height and radius. However, if two coins have the similar physical attributes then this technique fails. Based on features extracted, coins are predicted in various categories. For improving the classification accuracy, ensemble learning can be used. Ensemble Learning (EL) is a different Trending technique in Deep Learning (DL), which utilizes a group of Supervised and Unsupervised learning models to attain enhanced classification results than the fundamental learning algorithms alone. A. U. Tajane et al [1] developed Deep Learning model for recognition of Indian currency coins. Authors have developed own dataset of Indian currency. Authors have used Matlab and Alexnet model.

Chetan et al [2] proposed Side and Rotation invariant coin recognition technique on Indian coins. In their work, the authors have identified the coin in the given image using segmentation. The coin prediction is performed using the radius of coins and based on template matching by the rotating the image. It is observed that the accuracy is ~90%.

Modi et al [3] proposed ANN based automatic coin recognition on Indian coins. In their work, the authors have generated feature vector of image of size 20x20 after preprocessing and pattern averaging the given input image. They have used 70 images of coins and generate 5040 images by different rotations and reported the accuracy ~97%.

Reisert et al [4] proposed a fast technique for coin recognition on CIS benchmark dataset. The authors have used inverse bilinear interpolation to address the small gradient changes in the input images. Further to improve the speed, FFT of feature function is precomputed. The accuracy they achieved is ~97%.

Veena et al [5] used Spatial Gray Level Dependency Matrix and Steerable Pyramid and Laws Mask to extract the features of input images. To increase the performance here we have proposed a new technique. This is a Deep learning based mechanism which uses the Convolutional Neural Network technique.

Nicola Capece et al [6] have implemented deep learning based coin recognition system for mobile devices. They have developed 5 different models for 5 different dataset of Euro coins. Some of the coins have reported the accuracy as 0% and some are reported as 100%. The authors have integrated the machine learning models with Android mobile App.

Imanol Schlag et al [7] developed deep learning model for prediction of ancient roman coins. They have categorize the coins as Very Fine, Fine, Extreme Fine based on the condition of the coins.

2. Methodology

In this present fast growing environment the automatic coin reorganization and identification machines has a vital role in all financial allied fields. Coin recognition is a challenging task. Coin detection/prediction has various applications. These techniques may used in automated toll gates, slot machines, vending machine etc. There are 3 different ways of traditional coin recognition techniques which uses Image Processing, Electromagnetic and Mechanical techniques. In this work for recognition of Brazil coin, we are experimenting with Convolutional Neural Network, a deep learning model. For classification problems, feature extraction is the challenging task. In the advent of Machine
Learning techniques we think coin recognition becomes easier, but feature extraction is a tough task. There are many ML Techniques for recognition of the coin; but how accurate our ML technique recognizing the coin depends on the features extracted with Machine Learning Model. Convolutional Neural Networks (CNN) figure 1 is used to recognize and predict the Brazil coins. Using the handicraft features like color, dimensions for recognition of coin has not given high accuracy. CNN is being used for many applications like Character Recognition [11], traffic signal identification, object prediction etc., Hence we planned to consider the CNN in which the model itself extracts the features and helps in better feature extraction. CNN has multiple pooling layers, convolution layers, fully connected layers, activation functions. In the convolution layer the invariant features will generated by using the filter or kernel applied to the local neighbours. Then the invariant features are passed on to the next layer. The pooling layer is used to reduce the dimension of next convolution layer such that the number of parameters can reduced. The CNN architecture is represented in Figure 2.

![Figure 2](image-url) Feature extraction and pooling layers, Fully connected layer and classified outputs after voting (Dropouts) in CNN

2.1. Convolution Layer

CNN is like Neural Networks where all the neurons in one layer connects to neurons in the next layer. The input to the CNN is a two dimensional image. Unlike neural networks, the neurons in one layer may not connect with all other neurons in CNN. CNN has become fast and accurate because of sharing of weights between the two layers. The functioning of CNN is present in the Figure 5. The output of the convolution layer is dot product of image pixel values with kernel (weights). If the Kernel size is NxN and input image size is MxM then the final output after convolution with stride 1 is (M-N+1) * (M-N+1).

2.2. Pooling Layer

The importance of the pooling layer is to minimize the convolute image size to the next convolution layer also as to reduce the parameters to calculate in the training process. Pooling also helps in learning the transformations due to translation and rotation. Pooling layer has to include in between the two convolution layers. There are different ways of applying pooling like Max Pooling, Average Pooling as shown in fig 6 etc.. The method for Max Pooling with size 2x2 is presented in the Figure 5. The filter chosen is 2x2, the output each 2x2 matrix of convoluted images is consider for applying pooling, it is maximum of each 2x2 matrix in the convoluted image. The input for pooling layer is output of convolution layer. In pooling layer if the Kernel size is NxN and input image size is MxM then the resultant output reduces by 1/N times.
2.3. **Fully Connected Layer**

Fully Connected (FC) layer helps in classification. The key purpose of FC layer is learning with non-linear function flatten. It means all the neurons in the preceding layer connected to all the neurons in the FC Layer.

2.4. **Evaluation Criterion**

The key goal of this paper is to recognize the Brazil coins through Deep learning Ensemble after classification scheme on the images acquired from multiparameters like, weight, size and adding multiple filters for each model and calculate the accuracy and loss of the model. A confusion matrix is a ML technique to calculate the performance of the classifier on set of test data where true values will be known as shown in fig 4. Let TP denote true positive, let FP denote false positive, let TN denote true negative, and let FN denote false negative.

2.5. **Ensemble Learning**

Ensemble Learning (EL) is a different Trending technique in Deep Learning (DL), which utilizes a group of Supervised and Unsupervised learning models to attain enhanced classification results than the fundamental learning algorithms alone. Ensemble Learning can be largely grouped into three types as follows:

- **Bootstrap aggregating**, also called bagging in fig 6, and proposed by Breiman [9] is a machine learning ensemble meta-algorithm intended to get better the stability and accuracy of machine learning algorithms used in regression and statistical classification. It also decreases the variance and assist in avoiding of overfitting. The random forest [10] algorithm is an instance of bagging, which groups a set of random decision trees to obtain high accuracy.

- **Boosting** refers to a family of ensemble algorithms which transform a weak classifier to strong classifier. Boosting in fig: 7 is an ensemble method for improving the model predictions of any given learning algorithm. The idea of boosting is to train weak learners sequentially, each trying to correct its predecessor. The Adaboost still is the most broadly implementation of boosting.

- **Bucket of models** is an ensemble learning technique in which a selection algorithm of utilized to selects the best model in a group of various models. Mostly it approaches through cross-validation.

The architecture for ensemble model of deep learning is represented in Figure 5.
Figure 5: The Frame work of our Deep CNN Ensemble Model

Figure 6: Bagging Ensemble

Figure 7: Boosting the weaker classifier
3. Results and Discussion

For recognition of Brazil coin, we employed Convolutional Neural Network, a deep learning model. In this paper we have used the dataset [12] of Brazil coins, which contains 3057. Brazil currency consisting of 5 Centavos, 10 Centavos, 25 Centavos etc.,. Each of which has different shapes and designs. To avoid the manual cropping of coin, we have used automated cropping technique with boundary detection which resulting clear and visible coins of 1662. We divide the dataset into train set of 1187 and test set of 475. We have designed four different CNN models by varying the filters, network dimensions. Training and Testing of Brazil coin images using CNN is performed on NVIDIA Quadro P2000 machine. We tested the Brazil coins on multiple models by using varying filters and network dimensions at layer of the model on feature extracted of the coin images. Results of various models are shown in Table-1 and in table 2 the Confusion Matrix of the ensemble model is presented. The confusion matrix represents the classification results. We got ~87.36% of accuracy which is more than the accuracy given by the models with handicrafts features. Model 1 is able to predict all 1 Real coins and the error rate more in classifying 10 centavos. In Model 2 and Model-3 the error rate is more and misclassifies many coins. Model-4 is able to predict all 1 Real coins and the error rate observed is less in classifying other coins. The architecture of four models and their accuracy, train, test loss is represented in figures 8-19.

Table 1: Accuracy of various models for prediction of Brazil coins

| Model    | Accuracy |
|----------|----------|
| Model-1  | 79.79%   |
| Model-2  | 78.73%   |
| Model-3  | 78.31%   |
| Model-4  | 82.52%   |
| Ensemble | 87.36%   |

Table 2: Confusion matrix of the Ensemble Model

| Prediction | 1 Real | 50 centavos | 25 centavos | 10 centavos | 5 centavos |
|------------|--------|-------------|-------------|-------------|------------|
| Actual     |        |             |             |             |            |
| 1 Real     | 83     | 0           | 0           | 0           | 0          |
| 50 centavos| 0      | 75          | 1           | 0           | 7          |
| 25 centavos| 8      | 2           | 65          | 1           | 7          |
| 10 centavos| 0      | 0           | 9           | 64          | 10         |
| 5 centavos | 0      | 0           | 6           | 9           | 128        |
Figure 9: Accuracy of Model 1

Figure 10: Loss for Model 1

Figure 11: Model 2 Trained on data set

Figure 12: Accuracy of Model 2

Figure 13: Loss for Model 2
Figure 14: Model 3 Trained on data set

Figure 15: Accuracy of Model 3

Figure 16: Loss for Model 3

Figure 17: Model 4 Trained on data set

Figure 18. Accuracy of Model 4

Figure 19. Loss for Model 4
4. Conclusion

Convolutional Neural Networks (CNN) is used to recognize and predict the Brazil coins. Using the handicraft features like color, dimensions for recognition of coin has not given high accuracy. In our work we consider Brazil currency coins of 5 Centavos, 10 Centavos, 25 Centavos etc. Each of which has different shapes and designs. For recognition of Brazil coin, we employed Convolutional Neural Network, a deep learning model. We have designed four different CNN models by varying the filters, network dimensions. Different deep learning models are designed and applied ensemble learning to find the better accuracy. Ensemble Learning (EL) is a different Trending technique in Deep Learning (DL), which utilizes a group of Supervised and Unsupervised learning models to attain enhanced classification results. We got ~87.36% of accuracy which is more than the accuracy given by the models with handicrafts features.

5. Future Scope

We will have to analyze why and where the prediction is failing. To increase the accuracy, in future we will adopt the LSTM and capsule network to handle the orientation.

Conflict of Interest: There is no conflict of interest.

6. References

1. A. U. Tajane, J. M. Patil, A. S. Shahane, P. A. Dhulekar, S. T. Gandhe and G. M. Phade, "Deep Learning Based Indian Currency Coin Recognition," 2018 International Conference On Advances in Communication and Computing Technology (ICACCT), Sangamner, 2018, pp. 130-134, doi: 10.1109/ICACCT.2018.8529467.

2. Chetan B.V., Vijaya P.A. (2013) A Robust Method of Image Based Coin Recognition. In: Kumar M. A., R. S., Kumar T. (eds) Proceedings of International Conference on Advances in Computing. Advances in Intelligent Systems and Computing, vol 174. Springer, New Delhi

3. Modi, Shatrughan, and Dr Bawa. "Automated coin recognition system using ANN." arXiv preprint arXiv:1312.6615 (2013).

4. Reisert, Marco, Olaf Ronneberger, and Hans Burkhardt. "A fast and reliable coin recognition system." Joint Pattern Recognition Symposium. Springer, Berlin, Heidelberg, 2007.

5. Veena H. N., Muruganandam M., and T. Senthilkumaran " Coin recognition using texture feature based on SPLM and SGLDM algorithm" AIP Conference Proceedings 2039, 020047 (2018); https://doi.org/10.1063/1.5079006

6. N. Capece, U. Erra and A. V. Ciliberto, "Implementation of a Coin Recognition System for Mobile Devices with Deep Learning," 2016 12th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Naples, 2016, pp. 186-192, doi: 10.1109/SITIS.2016.37.

7. Schlag, Imanol, and OgnjenAranjelovic. "Ancient Roman coin recognition in the wild using deep learning based recognition of artistically depicted face profiles." Proceedings of the IEEE International Conference on Computer Vision Workshops. 2017.

8. Z.-H. Zhou, “ Ensemble learning,” in Encyclopedia Biometrics, S. Z. Li and A. Jain, Eds. New York, NY, USA: Springer, 2015, pp. 411–416.

9. L. Breiman, “Bagging predictors,” Stat. Dept. Univ. California, Oakland, CA, USA, Tech. Rep. 421, 1994.

10. T. K. Ho, “Random decision forests,” in Proc. 3rd Int. Conf. Document Anal. Recognit., vol. 1. Aug. 1995, pp. 278–282.

11. N. B. Muppalaneni, "Handwritten Telugu Compound Character Prediction using Convolutional Neural Network," 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, 2020, pp. 1-4, doi: 10.1109/ic-ETITE47903.2020.349.

12. Luis Moneda, David Yonekura, EloáGuedes, "Brazilian Coin Detection Dataset", IEEE Dataport, 2020. [Online]. Available: http://dx.doi.org/10.21227/kj4c-y809. Accessed: Jun. 30, 2020.