Classifying Wheat Cent Pennies Using HOG and Statistical Learning

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***Abstract*—The speed and accuracy of identifying coins is a vital skill for coin collectors. This paper presents a novel approach for classifying wheat cent pennies by date, using statistical learning methods. The focus of this paper is on wheat cent pennies, a subset of U.S. single cent coins from produced from 1909 to 1958. The proposed method extracts distinctive features from high-resolution pre-rotated images of pennies using HOG descriptors. These descriptors are then classified using a linear regression. Experimental results demonstrate the effectiveness of the proposed approach, achieving a relatively high accuracy with a limited dataset, which was limited by the rotation methods used to orient the coins in pre-processing. This research contributes to advancing the automation and accuracy of coin classification techniques, historically done by trained and knowledgeable individuals.**

***Index Terms*— HOG (Histogram of Oriented Gradients), OCR (Optical Character recognition)**

I. INTRODUCTION

WHEAT cent pennies were in production from 1909 to 1958, meaning that there will be a total of 49 unique coins that must be identified. Traditional methods of coin classification rely on manual inspection by experts, which can be time-consuming, subjective, and prone to human error.

This paper proposes an approach to coin classification using advancements made in computer vision and machine learning. Specifically, the scope of this paper is concerned with developing and OCR (Optical Character Recognition) method to recognize the 49 dates mentioned above. This consists of creating an admissible dataset of images, preprocessing the images using HOG (Histogram of Oriented Gradients), and using a Logistic Regression to classify the digit images.

II. PREPARING THE DATASET

The dataset used consisted of groups of coins all placed in one image. Thus, to classify individual coins, the coins must first be separated individually. Separating coins from their background and other coins was done using an HCT (Hough Circle Transform), which identifies circle contours in an image.

Instead of introducing the image of the whole coin into the model, which could introduce unnecessary noise, pre-processing of the images is needed. Firstly, the coin is rotated (rotation is not covered in the scope of this paper but was done using a deep learning method and was also implemented using a landmark matching method with similar accuracy). After rotation, the images can be cropped to focus the image on only the area of interest (i.e. the date).

The images were then processed further by cropping the date images into 4 discrete digit images and labelling the isolated digit images manually. For example, 1925 was separated into 1, 9, 2, and 5 (Fig. 1.).

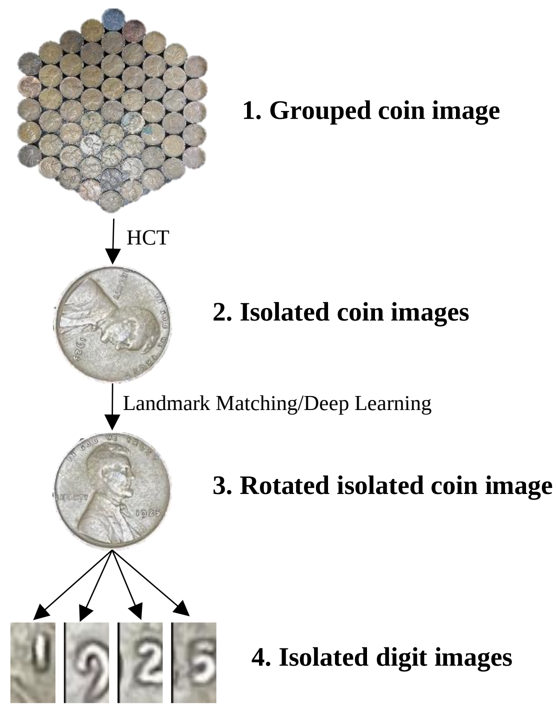

Fig. 1. Processing the dataset of isolated coin digit images.

By isolating digits, the dataset was effectively expanded 4-fold and reduced classification to being across a set of 10. However, it should be noted that the 4-fold expansion of the dataset was comprised of at least 25% nines and 25% ones due to the nature of isolating the digits and the production of wheat cents being between 1909 and 1958. This also implied the date needed to be assembled after classifying each digit on the coin.

Furthermore, by isolating digits, coins of higher rarity that were not found in the previous isolated coin image dataset could be identified, as classification would be done by individual digits instead of wholistically by date.

III. PREPROCESSING USING HISTOGRAM OF ORIENTED GRADIENTS

In the proposed methodology for classifying wheat cent pennies, HOG is employed as a feature descriptor on the isolated digit images. The HOG descriptor works by dividing the image into small spatial regions called cells and computing the histogram of gradient orientations within each cell (3 x 3 cells were used in this model). The gradients G were calculated by combining the magnitude and angle from the images, using the following formula:

$$G_x(r,c) = I(r,c+1) - I(r,c-1)$$
$$G_y(r,c) = I(r-1,c) - I(r+1,c)$$

Where I refers to the image and r, c refer to rows and columns respectively.

$$Magnitude = \sqrt{{G_x}^2 + {G_y}^2}$$
$$Angle = \left| tan^{-1}\left({G_y}/{G_x} \right) \right|$$

After the gradient is determined, the gradient matrices can be divided into blocks. For all blocks in the isolated digit image a 9-point histogram is developed. This is done by dividing 9 separate bins from the 180-degree potential, using the following formulas:

$$n = 9$$
$$\Delta\theta = 180°/n$$

Where n is the number of bins and $\Delta\theta$ is the step size of the bins.

$$Bin\ Boundaries: [\Delta\theta \cdot j, \Delta\theta \cdot (j+1)]$$
$$C_j = \Delta\theta(j + 0.5)$$

Where j is the bin number (0-9) and C_j is the center of the bin.

The values of the histogram are then calculated for each bin.

$$V_j = \mu \cdot \left(\frac{\theta}{\Delta\theta} - \frac{1}{2} \right)$$
$$V_{j+1} = \mu \cdot \left(\frac{\theta - C_j}{\Delta\theta} \right)$$

These values are then clubbed together and normalized to achieve our result.

These histograms capture the local gradient, providing a representation of the significant texture and shape characteristics of the digit (Fig.2.).

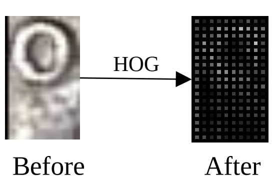

Fig. 2. Preprocessing using HOG.

These characteristics encapsulate information about the edge and gradient distributions within the digit images and reduce the isolated digit images size and noise, enabling effective discrimination between different digit classes when used as the input of a statistical learning classifier.

IV. Classification of Digits using Logistic Regression

A multi-class logistic regression is then employed to classify the preprocessed, feature extracted isolated digit images produced from the original grouped coin images. Logistic regression is a widely used classification algorithm that models the probability of an outcome based on one or more predictor variables. The logistic regression used in this application classifies the preprocessed isolated digit images into the categories representing digits 0 through 9.

In the training phase, a manually labeled dataset of 2866 was created but after pruning the dataset for class imbalances only 854 of those images were used in the training of the dataset (Fig.3.).

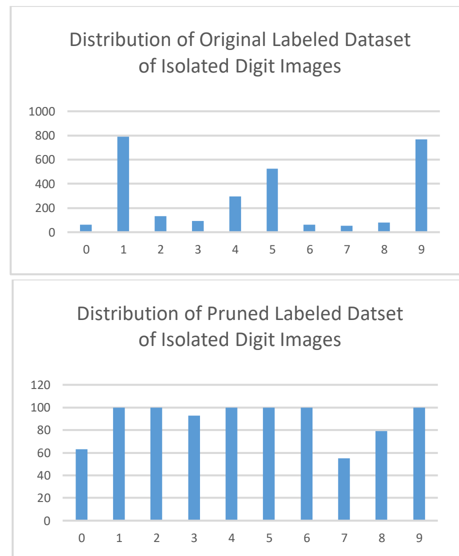

Fig. 3. Dataset distribution before (above) and after (below) pruning imbalances.

An 80/20 training split was utilized in training the dataset. After training, the model yielded an overall accuracy result of 92%.

It should be noted that the accuracy of the logistic regression could be significantly improved with more precise rotation as the rotation method used in this paper yielded a result of ~95% in the range of +/-2 degrees, but this work was done as part of a larger coin detection project and thus rotation of the coin was neglected for a larger rotationally invariant deep learning method using a pretrained ResNet-50 architecture. Still this method of classification still shows lots of promise (if rotation can be more precise) given it is not very memory intensive when compared to the larger pretrained neural network approach.

V. Conclusion

In this paper, a novel approach for classifying wheat cent pennies using Histogram of Oriented Gradients (HOG) and statistical learning methods was presented. This methodology leverages both computer vision techniques and machine learning algorithms to automate the classification process and improve accuracy in identifying wheat cent pennies. The results of this paper demonstrate the effectiveness of the proposed approach, achieving relatively high accuracy rates in digit classification tasks given the limitations of accurate coin rotation in preprocessing. Furthermore, the use of HOG for feature extraction and isolation of digits this method was also robust to illumination and coin conditions, this was especially apparent for the classification of the 1943 steel penny which saw no significant drop in relative accuracy when compared to classic copper pennies.

In conclusion, the proposed methodology offers a promising avenue for improving the efficiency and reliability of coin classification. Future research directions may involve exploring additional feature extraction techniques, growing and optimizing datasets, and optimizing model parameters.

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