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Research paper

A Deep Learning Approach for Authentication of Original and Non-Original Bank-Issued Gold Coins with Non-Uniform Directions in the Financial Market

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Abstract

In Iran's financial market, the authentication of gold coins is primarily required for transparency, fraud reduction, and proper valuation. Differentiating between bank-issued and non-bank-issued coins poses a challenge, as their appearance is nearly identical. This paper proposes a classification method based on deep learning, consisting of three main components: extracting the region of interest, aligning images using a CNN regressor, and classifying coins with a CNN classifier. The method is tested on a set of 130 coin images (71 coins from banks and 59 coins from non-bank sources) and benchmarked against baseline models that employ feature extraction and SVMs. The proposed method outperforms the baseline with 99% accuracy. The results demonstrate that the model effectively authenticates coins, enabling secure transactions in the gold market.

1. Introduction

A coin is a form of metallic currency commonly produced and issued by a government or an authorized financial authority. Coins are composed of various metals and alloys, such as gold, silver, copper, and other materials. They are used in daily transactions, collecting, and investment activities. Coins serve as standardized monetary units for the purchase and sale of goods and services and are highly valued due to their marketability and divisibility. As a type of metallic currency, coins are issued to facilitate economic exchanges and serve multiple purposes, including everyday transactions, investment, and collection. Coin collecting, recognized as both a hobby and an art form, involves the acquisition of rare and valuable coins of historical and artistic significance. Additionally, coins are often used by enterprises or organizations as symbols or promotional tools. These coins frequently feature various patterns and messages to endorse their brand or products, as exemplified in Figure 1, which displays different types of coins.

Iran produces various coins, including gold, silver, and small change denominations. Small-change coins are made from materials like copper, zinc, and nickel, and their fixed values remain consistent over time. In Iran, for example, 1000 Rials is always the value of a coin bearing that denomination. Conversely, the prices of gold coins fluctuate over time in response to international gold prices.

The value of the coin is determined by the metal used, except for promotional items, which are made for art and are non-denominational. Gold and silver coins, for example, have intrinsic values that are much higher, and their value can change with the market price of the metal.

Artistic coin Promotion coin Rare coin Historical coin Iranian coin

Figure 1. An instance of the variation of coins.

Gold and silver coins, which contain precious metals, can be stored, and their value can increase over time, making them a valuable investment. Because the value of the precious metal remains constant, gold and silver coins can maintain their value and appreciate over time. The nominal value of a coin is the amount set by the issuing government or financial authority, representing the coin's purchasing power in the market. Coins made from precious metals generally have higher value, and the purity and weight of the metal also influence the coin's value.

In Iran, various types of coins circulate, among which the most notable and valuable is the gold coin. This particular coin weighs 8.13598 grams, contains 7.322382 grams of pure gold, has a diameter of 22 millimeters, and a fineness of 900 per thousand. Since various groups in Iran produce gold coins, there are two main categories: coins issued by the Central Bank of Iran and those issued by non-bank entities. Coins issued by the bank (Bcoins) are produced and certified under the supervision of the Central Bank and are valued higher because the bank guarantees their weight, fineness, and packaging. Conversely, non-bank coins (NBcoins) may have issues with weight, fineness, and authenticity. Additionally, some NBcoins are matched with Bcoins in terms of fineness and weight. Table 1 provides a visual comparison between Bcoins and NBcoins. Their similar appearance makes it difficult to distinguish the difference by sight, which requires the expertise of a professional [7-9].

Table 1. Comparison of Bcoin and NBcoin appearance.

Appearance characteristics of Bcoin	Appearance characteristics of NBcoin
One-handed congresses	Non-unilateral congresses
Flat surface	A slightly convex
Uniform thickness	Non-uniform thickness
Organize print	Un-organize print

Sometimes, even experts cannot tell them apart. This difference necessitates the use of appropriate methods and expertise for identification, making it challenging to distinguish or verify them easily. Therefore, there is a need for more precise tools to enable more accurate detection [10-13]. Figure 2 displays samples of Bcoins and NBcoins, indicating that telling these two types of coins apart is difficult.

Figure 2. Right) Bcoin, Left) NBcoin.

The paper is organized as follows: Section 2 investigates recent works. In Section 3, the proposed method is described, and a step-by-step approach to problem-solving is outlined. Section 4 presents the experimental results, including the dataset, performance evaluation, and outcomes. In Section 5, a conclusion is provided, and future directions are discussed.

2. Related Work

The importance of coins and their significance in day-to-day transactions are proposed by Prabu, S., et al. [1]. Thus, there is an urgent necessity for automated coin detection and recognition systems. The primary aim of this work is to detect and recognize the different denominations of Indian coins. For this, features such as texture, color, and shape were considered. The popular object detection model YOLOv5 was used for this purpose. Tewari, K. and S. Karn [2] proposed an objective to categorize the different Indian coins based on their values in Indian National Rupees (INR). MATLAB image processing and edge detection were employed to identify coins. Both old and modern coinages are considered in this identification method. Shapes, sizes, surfaces, weights, areas, and centroids, as well as other physical attributes, serve as criteria for grouping coins[1,2].

The illegal trade and theft of coins are significant issues in the illicit antiques market. Image-based recognition of coins and how it could greatly aid in combating this problem is discussed. An overview is provided of recent research on coin classification, exploring whether existing methods can be extended to ancient coins [3]. A trademark is a distinctive sign that gives identity and individuality to products or services. It is necessary to avoid any confusion between trademarks when registering a company's trademark, but with the increase in the number of registrations, manual examination is no longer adequate and prone to errors. Alshowaish, H., Y. Al-Ohali, and A. Al-Nafjan [4] have suggested that deep learning can detect trademark similarity and improve accuracy and efficiency. To conduct the study, this study used VGGNet and ResNet which were pre-trained convolutional neural networks for feature extraction purposes.

The image dataset of Indian coins is a dataset that consists of 6672 images that represent the 53 categories of coins [5]. These images represent the coins of various denominations, including 25 Paisa, 50 Paisa, 1 Rupee, 2 Rupees, 5 Rupees, 10 Rupees, and 20 Rupees coin types. The dataset comprises obverse and reverse images of the coins, captured in various backgrounds and environments. This data fills the gap in the existing coins dataset and gives a larger and more diverse dataset. This dataset comprises images captured in various environments, backgrounds, and angles, offering a current and diverse representation of the Indian coin dataset, which is modern and eclectic.

Accurate coin identification is crucial in domains such as vending machines, self-checkout machines, money exchange systems, and currency studies in financial and retail settings. Traditional automated systems experienced difficulty in detecting counterfeit coins. The authors in [6] proposed the YOLOv8 method for detecting and classifying coins, based on its efficacy and high performance. The strength of the YOLOv8 model lies in its feature-based coin classification, which differentiates between currency denominations based on the texture, color, and shape of the coin features.

Digital images are a principle of representational communication today. Any digital image can be modified using various software to make it difficult to identify the original. Savakar, D.G. and M.R. Hiremath. The authors in [8] give a summary of some methods of image forgery detection. Also provides information about the problems associated with these procedures. Image credibility must be maintained through an effective and efficient procedure of exposing any faked scenes to counterfeit news. Copy-move, splicing, and erasing some parts of an image are among the most challenging issues concerning the falsification of images in digital image processing. With the increasing use of digital images, the number of manipulated and forged images has also risen, thereby increasing their prevalence across various industries, including forensics, journalism, and scientific research.

Fast technological developments have considerably lowered the obstacle to creating realistic images, which poses a significant threat to digital forensics, as traditional methods are time-consuming to use and apply. To address this issue, it has become popular to examine the performance of deep learning techniques for image forgery detection. An investigation into the examination of convolutional neural network (CNN) models as a potential solution for image forgery detection and an evaluation of their performance is presented in [9]. Detecting and identifying fake images are areas where researchers, scientists, and forensic experts are currently working to develop tools. It is an increasingly popular research field in digital image forgery detection. Aiming to provide a comprehensive review of the various tools and techniques used in detecting digital image forgery [23], this paper discusses diverse machine learning approaches, including supervised, non-supervised, and deep learning methods, and outlines the challenges inherent in the current state of affairs.

2. Proposed Method

In this section, the proposed method is demonstrated. It is constructed from three main integrative steps, which are shown in Figure 3.

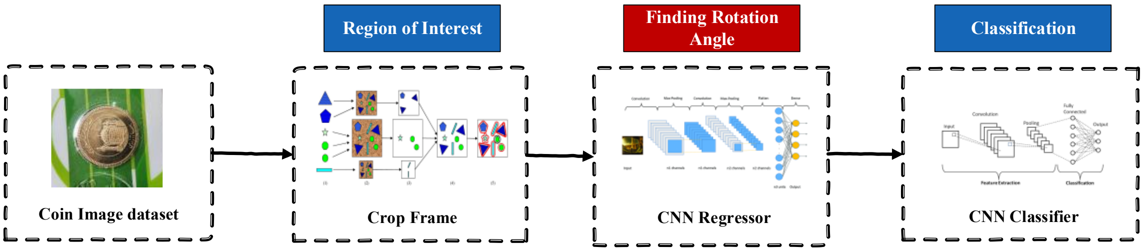

Figure 3. The Schematic of the Proposed Method.

In the first step, separating the coin from the background can be achieved through Region of Interest (RoI) extraction. Considering that the coins are not fixed, Step 2 rotates the images to a consistent position. Finally, in step 3, the coins are classified into BCoin and NBCoin.

Step 1: Region of Interest Extraction

An essential aspect of working with dimensional data, particularly images, is to eliminate irrelevant features. It usually causes model disruption, diverting attention from the main features to the background and frame of the images, which is approximately the same in all of the images. To solve this problem, in the ROI process (see Figure 4), the coin object will be separated from the original frame, and the achieved data will be more precise to use for different works, such as image classification and object detection, and help to stabilize the classification model [10, 11].

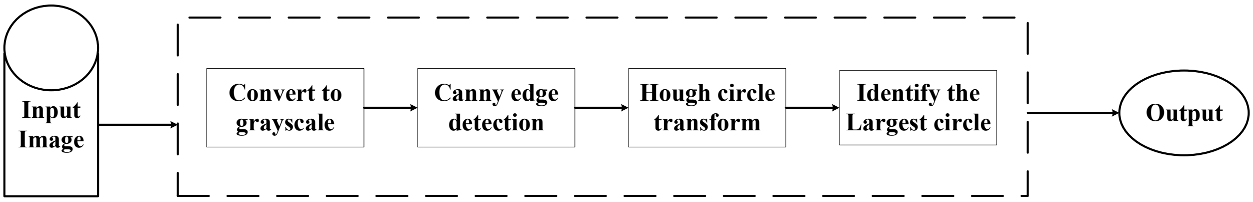

Figure 4. ROI process diagram.

Considering ROI segments have a circular form, the ROI is extracted through four main stages [12].

1) Converting to Grayscale

To simplify the data and enhance the model's ability to distinguish between the two classes, the images are converted to grayscale. By converting the images to grayscale, the dimensionality of the images is significantly reduced, which ultimately speeds up the model's training process. This process also highlights the structural features of the data, such as edges, shapes, and textures, without the distraction of color, which is crucial for a classification task. Considering the existing noise in some images, this process also leads to noise reduction and indirectly enhances the model's performance [13].

The method of converting images to grayscale involves transforming the color image into shades of gray. This is achieved by averaging the intensity values of the RGB channels, resulting in a single intensity value for each pixel. The resultant grayscale image captures the essential structural information while discarding the color data.

2) Canny Edge Detection

In this step, Canny edge detection, a fundamental tool in image processing and computer vision, is used to identify points in an image, often representing object boundaries. It is a multi-stage algorithm that provides a robust and precise method for detecting edges in images [14-16].

The Canny edge detection algorithm begins by applying a Gaussian filter to reduce image noise, smoothing the image and helping to prevent false edge detection caused by noise. This results in a smoother appearance by averaging the intensity of each pixel with its neighbors. Next, the algorithm calculates the intensity gradient of the image using finite difference approximations to compute the gradients in both horizontal and vertical directions. The results are represented in two gradient images (G_x and G_y), which depict the rate of change in intensity in the x and y directions, respectively. The gradient magnitude (G) and direction (θ) are then computed using the following formulas:

$$G = \sqrt{G_x^{\ 2} + G_y^{\ 2}} \tag{1}$$

$$\theta = \arctan(\frac{G_y}{G_x}) \tag{2}$$

The gradient magnitude indicates the strength of the edge, while the direction provides the orientation of the edge.

3) Hough Circle Transform

To detect regular shapes such as lines, circles, and ellipses in images, the Hough circle transform [17] is employed. The Hough circle transform maps points from the image space to a parameter space defined by the circle's parameters.

$$(x-a)^2 + (y-b)^2 = r^2 \tag{3}$$

where a and b is the center of the circle and r is the radius. For each edge point (x, y) in the image, a set of potential circles passing through that point is considered in the parameter space. For each edge point (x, y) and a given radius r, the possible center points (a, b) are computed and voted. For the detection of circles of different sizes, this process is repeated. The peaks in the calculated votes represent a possible circle [18].

4) Identify the Largest Circle

Once all circles are detected, the next step is to identify the largest one. This involves comparing the radii of all detected circles and selecting the one with the maximum radius. The circle with the largest radius is then designated as the ROI. Figure 5 illustrates an example of RoI extraction.

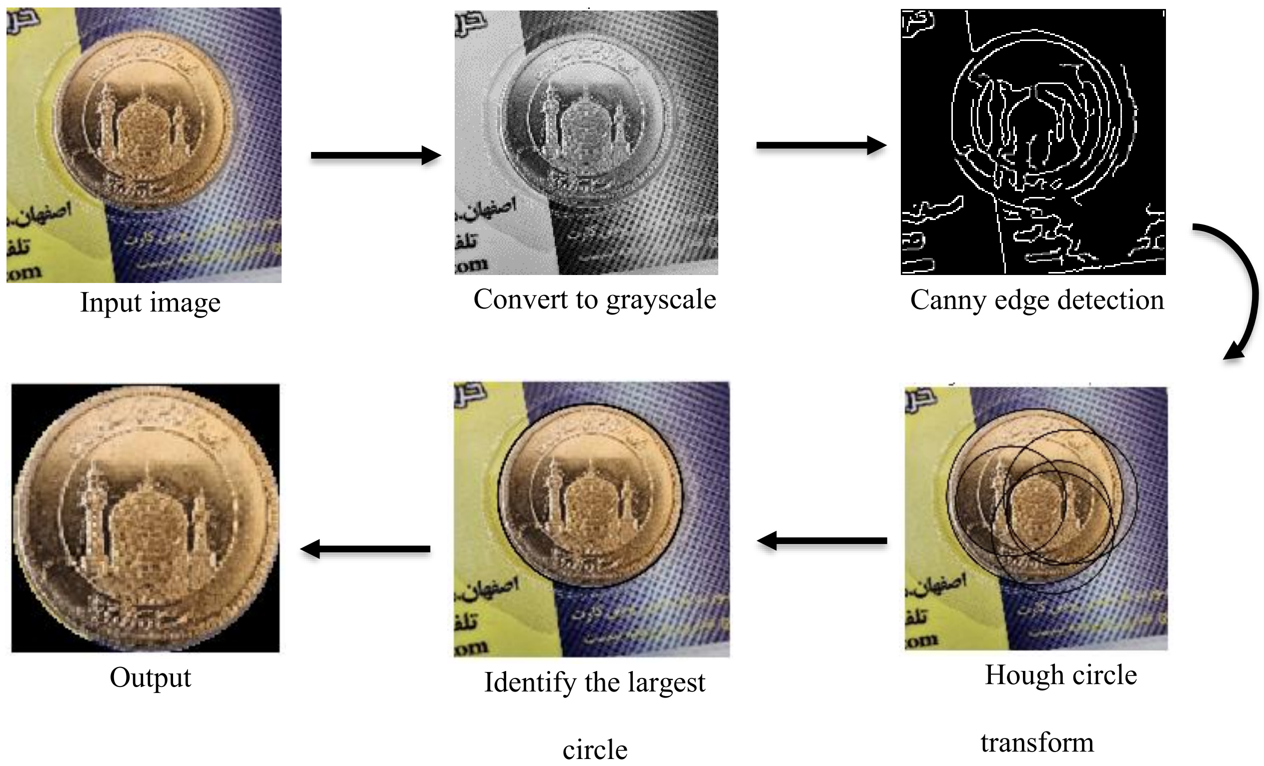

Figure 5. A sample of RoI extraction.

Step 2: Rotating Data to a Fixed Position

When the user wants to take and collect pictures, they may not be in a fixed and constant position, which causes different angles for the images, ranging from 0 to 360 degrees. The angle variation makes the problem more challenging and can complicate subsequent analysis and classification tasks. The main issues arising from the non-standardized position are Inconsistent Feature Representation, Complexity in Preprocessing, and Impact on Model Performance [19]. To solve this issue and improve the reliability of the model, two steps are finding the appropriate angle for each picture and rotating those (see Figure 6).

In the first step, the existing angle target of each image is collected and labeled by an expert and prepared as the input of the model. In this process, the images are rotated to different angles, and the expert identifies which images are positioned at the zero-degree angle. This process is used to make a dataset for training a rotator model and eventually propose a more precise framework.

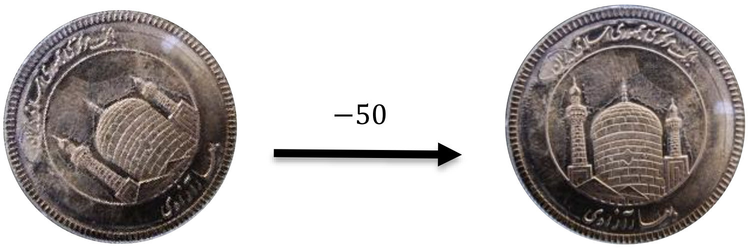

Figure 6. Proposed Rotation Process.

Then, a Convolutional Neural Network regressor model is introduced in Figure 7, which is used to predict the angle of each image [20-22]. In step 2, angles found in the CNN model are used to rotate each image to maintain its original angle and align all images to a constant angle. This process helps to place the same features of a class in a fixed position. Also, it prevents model interruption and improves image pattern recognition effectively.

Step 3: Classification

After image data preparation using steps 2 and 3, the final step is to classify between two classes: Bcoin and NBcoin. As the data is an image, several deep-learning methods are suitable for this task, but it is necessary to choose a well-accurate model that can detect different classes of images [23-25].
CNN is one of the most powerful deep-learning algorithms for classifying different types of images very well, by leveraging multiple layers of convolutions, pooling, and non-linear activations. It can automatically learn and generalize complex features from images, making them well-suited for classification [26, 27]. In our study, we employed a CNN with several layers, as demonstrated in Figure 8, to predict complex different classes of images and stabilize the model's performance. The introduced model is well-accurate, considering evaluation metrics, and reliable for tasks requiring a related approach [28].

3. Experiment and Result

In this section, the collected dataset is explained in the first stage. Then, the performance evaluation metrics are introduced. Finally, in the results stage, a comparison between the proposed method and the existing methods and these to the introduced dataset is given.

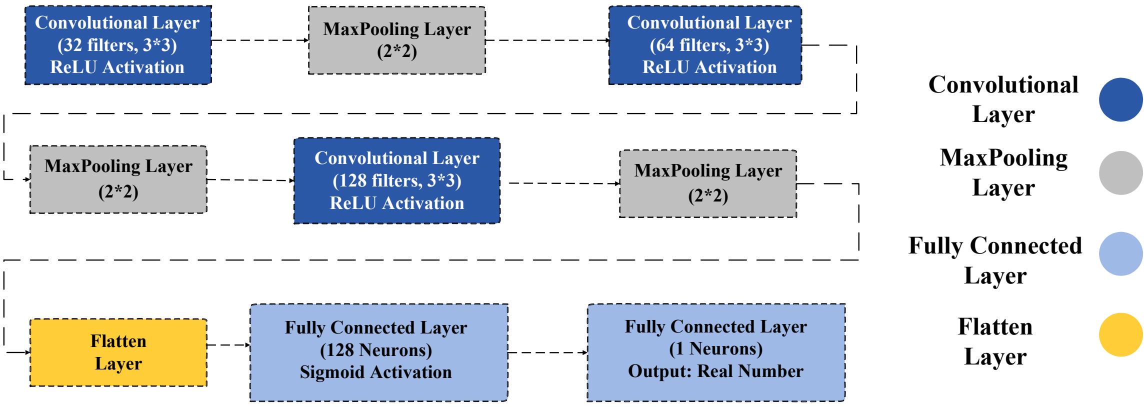

Figure 7. Proposed CNN Regressor Structure.

A. Dataset

In this study, we address a binary classification problem involving the distinction between Bcoin and NBcoin using image data. The dataset consists of 130 images, with 71 belonging to the Bcoin class and 59 to the NBcoin class, and was collected by our team. Each image has dimensions of 200 x 200 pixels and a resolution of 40,000 pixels. In this dataset, each image has its own angle, and all of the images are not in the same order or position. For model training and evaluation, the dataset was partitioned such that 80% of the images were allocated for training, and the remaining 20% were reserved for testing. During the training process, a 10% validation split of the training set was used to assess the quality of training.

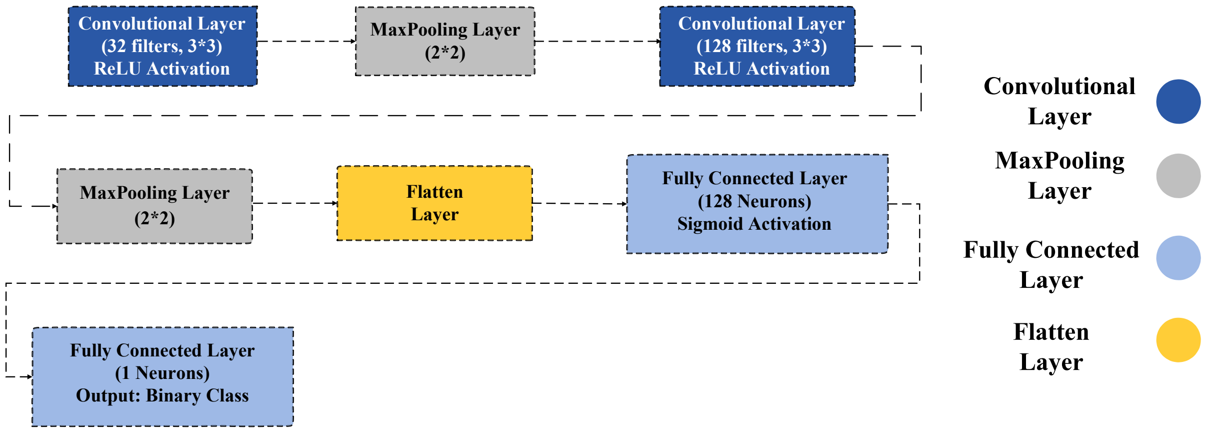

Figure 8. Proposed CNN Classifier Structure.

Additionally, for further assessment of the proposed method, we evaluated our methodology on the Indian coin dataset [29]. This dataset is organized into classes 1_rupee, 2_rupee, 5_rupee, and invalid, where each classes contain 350 images, and the size of the images is 256×256. To use this dataset for more assessment of the proposed method, we considered a binary class subset of this dataset where invalid is the class of positive and 1_rupee is the negative class. An overall description of used datasets in this study is provided in Table 2.

Table 2. The summary of used datasets in this study.

	Type	Number of samples	Total samples
Iranian coin	Binary	Bcoin: 71 samples, NBCoin: 59 samples	130
Indian Coin	Categorical	Each class: 350 samples	1400

B. Performance Evaluation

The evaluation metric is a key component of any research work, used to measure the performance and effectiveness of methods and models, and how they function on the dataset, particularly across different aspects of the data. The metrics allow researchers to compare various types of models, understand their reliability, and make the best decision to use these methods. In exceptional cases such as classification tasks, it helps to understand the model's ability to correctly identify the classes. In this study, to measure all aspects of the model's ability, mean squared error and mean absolute error are used for the regression phase, while accuracy, precision, recall, and F1-score are used for the classification phase. These metrics emphasize different aspects of the model's performance, such as its ability to avoid false positives (precision), identify all positive instances (recall), and achieve overall correctness (accuracy). In the regression task, several measurements are used to evaluate the results. These metrics assess the performance of regression models, which aim to predict continuous numerical values. They demonstrate the difference between the actual and predicted values and summarize how accurate the model is. Before presenting the regression evaluation metrics, the main materials need to be introduced (see Table 3).

Table 3. Essential variables of the regression phase.

Material	Explain
n	total number of instances
y_i	the actual value of i^{th} instance
$\bar{y}_i$	the predicted value of the i^{th} instance

Mean Squared Error (MSE) is a metric for evaluating the performance of the model in continuous numerical tasks by measuring the average squared difference between the predicted values and the actual values. It is calculated by taking the mean of the squared differences between the predictions and the true values using the following formula:

$$MSE = \frac{1}{n}\sum (y_i - \bar{y}_i)^2 \quad (4)$$

Mean Absolute Error (MAE) is another metric for demonstrating how accurate the model is. It measures the average absolute difference between the predicted values and the actual values. It is calculated by taking the mean of the absolute differences between the predictions and the true values using the following formula:

$$MAE = \frac{1}{n}\sum \left| y_i - \bar{y}_i \right| \quad (5)$$

Before demonstrating the classification evaluation metrics, four main materials need to be introduced for class c (see Table 4).

Table 4. Used Materials

Material	Name	Explain
TP_c	True Positive	The number of instances that were accurately classified as belonging to the class c
TN_c	True Negative	The number of instances that were accurately classified as not belonging to the class c
FP_c	False Positive	The number of instances that were inaccurately classified as belonging to the class c
FN_c	False Negative	The number of instances that were inaccurately classified as not belonging to the class c

Accuracy is one of the most crucial metrics employed in a wide range of scientific works and is commonly used in machine learning and classification problems. It measures the overall correctness of the model's predictions and is calculated by the following formula. It represents the ratio of correct predictions to the total number of predictions and compares the predicted labels to the true labels.

$$Acc_c = \frac{TP_c + TN_c}{TP_c + TN_c + FP_c + FN_c} \tag{6}$$

Precision is the ratio of true positive predictions among all positive predictions. It demonstrates how many predicted labels as positive are truly positive. It is calculated for the class c as below:

$$\Pr e_c = \frac{TP_c}{TP_c + FP_c} \tag{7}$$

To measure the ratio of actual positive instances that the model correctly identified, recall is used. It shows how many of the positive cases in the dataset were captured by the model's predictions. Recall is also known as sensitivity or true positive rate and is calculated as follows:

$$\mathrm{Re}\,call_c = \frac{TP_c}{TP_c + FN_c} \tag{8}$$

The F1-score is the mean of precision and recall, ranging between 0 and 1, and provides a single metric that balances both precision and recall. A high F1 score indicates that the model has both high precision and high recall, meaning it accurately identifies a large portion of the positive instances while minimizing false positives. The formula below shows the calculation of the F1-score for the class c:

$$F1 - score_c = 2 \times \frac{\Pr e_c \times \mathrm{Re}\,call_c}{\Pr e_c + \mathrm{Re}\,call_c} \tag{9}$$

The F1 score is particularly useful in cases where both false positives and false negatives have similar costs or when you want to have a balanced measure of the model's performance.

C. Results

In this section, the results achieved on the dataset are presented in two parts: the regression phase and the classification phase. In the first part, the performance of the CNN regressor on the Iranian coin dataset is demonstrated in Table 5. This phase illustrates the difference between the actual and predicted angles of each image and, ultimately, the performance of the rotation process.

Table 5. Performance of the Regression phase on the Iranian coin dataset.

Method	**MSE**	**MAE**
CNN regressor	0.01	0.08

This table highlights the performance of the CNN model in predicting the correct angle for each image, ultimately demonstrating its reliability in the rotation process and accurately positioning the images.

In the second part, Table 6 presents two different insights into image classification. The results of the first insight show the performance of pre-training models in the feature extraction phase and support vector machine (SVM) for the classification phase on the Iranian coin dataset. Additionally, it displays the results of each of the five pre-training models: AlexNet, ResNet18, ResNet34, ResNet50, and GoogleNet, and provides an overview of the votes cast by these five networks. Furthermore, the proposed method is illustrated in this table to highlight the capabilities of the trainable models.

It can be observed that the pre-training models are effective on the introduced dataset and can predict more accurately than the average of the data. Among the baseline models, ResNet34 performed the best, with an accuracy, precision, recall, and F1-score of 0.90 each. AlexNet had the second-highest accuracy of 0.94, with a precision of 0.94, a recall of 0.95, and an F1-score of 0.94. These models exhibit the highest performance compared to other pre-training models. Additionally, to verify the accuracy of the results obtained from these models, a voting technique is employed. Considering the achieved results, the proposed method is introduced to enhance performance and increase the total number of correct predictions. The proposed method achieved the highest performance among all the new techniques, considering evaluation metrics, and provided reliable insights into image classification. Furthermore, to demonstrate the method's effectiveness in classifying Bcoin and NBcoin, a confusion matrix is shown in Figure 9. In general, while the proposed method achieved high accuracy on the available dataset, some limitations were observed. Misclassified samples mainly involved coins with worn surfaces or those photographed under glare conditions, where ROI extraction became less reliable. This indicates that the model is sensitive to variations in surface texture and illumination. Moreover, the dataset was collected under controlled conditions, and robustness under real-world scenarios, such as diverse lighting, partial occlusion, or background clutter, was not evaluated.

Furthermore, we provided more assessments of our methodology in Table 7, which shows the performance of our framework on the Indian coin dataset. As can be seen, the proposed method successfully classified both standard and invalid samples, demonstrating valuable performance across all evaluation metrics. Also, Figure 10 demonstrates the ability of the proposed method in classifying positive and negative classes.

Table 6. Performance of state-of-the-art classifiers compared to the proposed method (The proposed method is evaluated using 5-fold cross-validation) on the Iranian coin dataset.

	Accuracy	Precision	Recall	F1-score
Proposed Method	**0.96 ± 0.02**	**0.98 ± 0.03**	**0.95 ± 0.04**	**0.96 ± 0.03**
Voting	0.87	0.89	0.87	0.88
ResNet18	0.81	0.82	0.81	0.81
ResNet34	0.90	0.90	0.90	0.90
ResNet50	0.56	1.0	0.56	0.72
AlexNet	0.94	0.94	0.95	0.94
GoogleNet	0.51	0.68	0.51	0.57

Table 7. The performance of the proposed method on the Indian coin dataset.

	Accuracy	Precision	Recall	F1-score
Proposed Method	**0.993**	**0.993**	**0.993**	**0.993**
AlexNet	0.950	0.950	0.950	0.950
SVM	0.971	0.972	0.971	0.971
MLP	0.950	0.950	0.950	0.950
LSTM	0.864	0.867	0.860	0.864
GRU	0.971	0.972	0.971	0.971

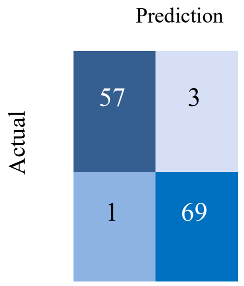

Figure 9. The confusion matrix of the proposed method based on the 5-fold cross-validation on the Iranian coin dataset.

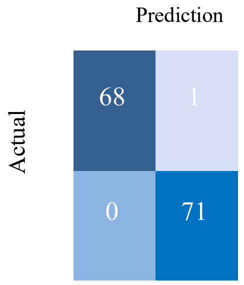

Figure 10. The confusion matrix of the proposed method based on the 5-fold cross-validation on the Indian coin dataset.

4. Conclusion

In this study, we addressed the problem of differentiating bank-issued gold coins (Bcoins) from non-bank-issued gold coins (NBcoins) in Iran, a task with significant practical relevance. We proposed a deep learning-based method that combines a CNN regressor for image rotation estimation with a CNN classifier for coin identification. On a dataset of 130 coin images, our approach achieved an accuracy of 0.99, outperforming benchmark methods such as ResNet34 (0.90) and AlexNet (0.94). These results highlight the potential of our process for accurately classifying coins in controlled settings.

In addition, the inclusion of rotation correction and ROI extraction demonstrated the ability to reduce errors arising from differences in coin orientation and background noise, thus addressing some common challenges in automated coin recognition. Nevertheless, we acknowledge several limitations. The current evaluation was conducted on a relatively small dataset captured under controlled conditions, without testing robustness to real-world variations such as diverse lighting, occlusion, or user-generated imagery. Furthermore, our analysis revealed that misclassifications were most common in cases of highly similar coin designs and surface wear, identifying areas for future improvement. In conclusion, while our method shows strong promise and competitive accuracy within the available dataset, further work is required to validate its robustness in real-world deployment scenarios. Future directions include expanding the dataset, incorporating data augmentation to simulate real-world conditions, and performing pilot deployment studies to assess usability in operational environments.

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یک رویکرد مبتنی بر یادگیری عمیق برای احراز اصالت سکه‌های طلای بانکی اصل و غیراصل با جهت‌گیری‌های غیریکنواخت در بازار مالی

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چکیده:

در بازار مالی ایران، احراز اصالت سکه‌های طلا به‌منظور افزایش شفافیت، کاهش تقلب و تعیین دقیق ارزش از اهمیت بالایی برخوردار است. با توجه به شباهت ظاهری بسیار زیاد سکه‌های صادرشده توسط بانک مرکزی و سکه‌های غیر بانکی، تمایز میان آن‌ها حتی برای کارشناسان نیز دشوار است. در این پژوهش، یک چارچوب مبتنی بر یادگیری عمیق برای تفکیک سکه‌های بانکی و غیر بانکی ارائه شده است. روش پیشنهادی شامل سه مرحله یکپارچه است: استخراج ناحیه موردنظر به‌منظور حذف پس‌زمینه و تمرکز بر ساختار سکه، هم‌ترازسازی تصاویر از طریق برآورد زاویه چرخش با استفاده از یک شبکه عصبی کانولوشنی در قالب مدل رگرسیون و در نهایت طبقه‌بندی تصاویر با بهره‌گیری از یک شبکه عصبی کانولوشنی آموزش‌پذیر. مجموعه‌داده مورد استفاده شامل ۱۳۰ تصویر سکه (۷۱ سکه بانکی و ۵۹ سکه غیر بانکی) با زوایا و شرایط مختلف تصویربرداری است. عملکرد مرحله رگرسیون با معیارهای میانگین مربعات خطا و میانگین قدرمطلق خطا و مرحله طبقه‌بندی با معیارهای دقت، صحت، بازخوانی و امتیاز F1 سنجیده شده است. نتایج نشان می‌دهد روش پیشنهادی در مجموعه‌داده سکه‌های ایرانی به دقت ۰.۹۶ ±۰.۰۲ دست یافته و نسبت به مدل‌های پایه عملکرد بهتری ارائه می‌دهد. همچنین ارزیابی تکمیلی بر روی مجموعه‌داده سکه‌های هندی دقت ۰.۹۹۳ را نشان می‌دهد که بیانگر توان تعمیم‌پذیری مناسب چارچوب پیشنهادی است. این یافته‌ها حاکی از آن است که ترکیب استخراج ناحیه موردنظر، تصحیح زاویه چرخش و طبقه‌بندی مبتنی بر یادگیری عمیق می‌تواند راهکاری مؤثر و قابل اعتماد برای احراز اصالت سکه‌های طلا فراهم آورد، هرچند گسترش مجموعه‌داده و بررسی مقاومت مدل در برابر تغییرات نوری و فرسایش سطح سکه به‌عنوان مسیرهای آتی پیشنهاد می‌شود.

کلمات کلیدی: شبکه‌های عصبی پیچشی، پردازش تصویر، تشخیص سکه، تشخیص تقلب.