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Novel Feature Extraction and Representation for Currency Classification

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ABSTRACT

In an era marked by the rapidly growing levels of international trade and tourism, the accurate recognition of various currency notes has become a necessity. This paper presents research on an image processing technique for classifying the origin of currencies. Individuals are hardly distinguishing between different currencies from various countries. Therefore, it becomes necessary to develop an automated currency recognition system that helps in recognition notes easily, accurately and efficiency. The methodology consists of five stages, which are image acquisition, image pre-processing, feature extraction, classification, and, lastly, results and analysis. The currency image will be pre-processed in grayscale and split into 100x100 blocks at selected regions of interest (ROI) on the currency. Next, binary matrix image features and representations will be extracted. Lastly, the similarity percentage of the binary matrix will be calculated and compared with all currency image matrices. The highest similarity percentage will be chosen as the currency's origin. The proposed algorithm successfully classified the currency and improved the accuracy of currency classification, achieving a 93.4% accuracy rate from the experimental results. The proposed method could be useful for various applications, including financial institutions, security agencies, and automated currency processing machines.

1. Introduction

Any type of money issued by governmental officials in one jurisdiction is known as currency [1]. The currency's importance in facilitating the overall management of countries' economies [2]. Currency notes are an essential aspect of our daily lives and are required for various activities such as investments, business transactions, and marketing. Therefore, the recognition of banknotes becomes a necessity. According to survey all currencies around the world look different [3]. Almost every currency in use around the world has a different appearance and, as a result, different characteristics, for instance, the paper's size, identification marks, colour, pattern, and so on [4].

There are about 180+ currencies worldwide and the necessity for an automatic currency mechanism [5]. In the era of rapidly growing levels of trade between countries and also tourism all over the world, it becomes necessary to recognize each currency note correctly [6,7]. Automatic

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currency recognition systems have become a main source of concern for researchers and developers due to the currency's importance in facilitating the overall management of countries' economies [3]. However, it is not an easy task to differentiate between different currencies and remembering the symbols for each currency is a challenging job that can lead to incorrect recognition [4,8]. And also, it is exceptionally challenging to characterize different coins and notes [5]. Individuals are hardly distinguishing between different currencies from various countries. Therefore, it becomes necessary to develop an automated currency recognition system that helps in recognition notes easily, accurately and efficiency.

In order to ensure the accurate classification of currency origin, a novel feature extraction method for currency classification has been proposed to reduce the inaccuracies in currency quality classification.

The main objective of this research is to accurately classify the currency according to their origin. The study aims to focus on the extraction of currency features and representation that are essential in the classification process. This, in turn, can aid in various applications, including financial transactions, foreign exchange, and counterfeit detection, by ensuring that the currencies are identified correctly.

2. Related Works

In Devi's [9] approach, the image is converted into grayscale for uniformity. This approach focuses on the diagonal vector and compares it with a set of values from the database to identify the currency. Abburu *et al.,* [10] approach identifies the currency origin by template matching, based on empty areas and regions of interest, and then identifies the denomination of the banknote using certain characteristics such as size, colour, and text extraction. This approach achieves an accuracy of almost 93%. In the approach of Tiwari and Dominic [3], banknotes are first converted from BGR to grayscale and then the converted image is checked for binary threshold and pixel value, and the system compares it with the template image. Those approaches [11,12] mainly recognizes India's currency. Rauyani *et al.,* [13] extracted the Region of Interest (ROI), which includes the area where image processing operations and feature extraction operations will be performed. The edges of the currency are detected using Canny's edge detection method. Template matching is used for object detection, which matches required elements in the sample image.

Additionally, some machine learning approaches have been used for classifying the currency origin. Akter *et al*., [14] split the banknote into three channels, filter the channels separately, and then merge them into an RGB picture. A co-occurrence matrix for features such as HSV, edges, and grey levels is computed and saved. This matrix is used to determine the currency's origin by calculating Euclidean distances based on a set of reference values. Zhang [15] proposed a Single Shot MultiBox Detector (SSD) model based on deep learning as the framework, which employs a Convolutional Neural Network (CNN) model to extract the features of paper currency. The recognition of the denomination of the currency, both front and back, is more accurate with the CNN and SSD models.

Chowdhury *et al.,* [16] proposed a method for recognizing the denomination of Indian currency using deep learning and image processing techniques. The banknote is pre-processed before being passed through template matching techniques to identify whether the input banknote is Indian or not. The template matching technique used in this system is Normalized Cross-correlation. If the input banknote is Indian, features such as colour, contrast, correlation, energy, and homogeneity are extracted.

In Bubu *et al.,* [17] approach, the currency is first converted to a grayscale image, and an edge detection process is used to extract the image boundaries. Discontinuities are used to gauge edge detection, which is useful in fields like image segmentation and data extraction. Parameters are then used to check whether the input image matches the degraded image or not. These parameters include PSNR, mean square error, and similarity index. However, this approach only works for some country currencies. In Ramvanshi *et al*., [18] approach, currency images undergo a feature extraction process and are compared with an available dataset. Next, a machine learning algorithm such as SVM, Decision Tree, or Neural Network is used to train the model and improve accuracy [19-22,25].

Unfortunately, currency classification based on computer vision has not yielded many satisfactory results. Distinguishing between different currencies is a difficult task, and remembering the symbols for each currency can be challenging. This can lead to incorrect recognition [4,8].

3. Proposed Solution

In the proposed solution, there are six stages consisting of image acquisition, image pre-processing, feature extraction, classification and lastly results and evaluation.

3.1 Image Acquisition

There are total of 30 images acquired from 6 types of currency. The images were converted into JPEG format. In the stage, images of the currency notes were taken under controlled surroundings with the following factors:

i. High-contrast background compared to the currency paper note;
ii. A constant distance away from the paper note;
iii. An angle of 90° to the ground or parallel to the camera;
iv. Constant light exposure throughout the process.

3.2 Image Pre-Processing

The image will be cropped to minimize redundant background and noises as this will yield better results as shown in Figure 1 and 2. The image will then be resized into 400 × 600. The right side of the image will be focused where this is the unique feature of the paper banknote is located.

Fig. 1. Sample of India Rupees

Fig. 2. Sample of Malaysia Ringgit

3.3 Feature Extraction

The images will be converted to greyscale image in which the colour will be ranging from black to white. The conversion will be crucial as greyscale image is required for edge detection which has only 2 colours, black and white. This process is simply differentiating the foreground and the background and also differentiate the Region of Interest (ROI).

The right side of the front currency image will be focused and further process. To obtain and work on the right side of the image, the following code is used to process the image where *im_w* is the width of the image and *eDetect* is the image after implemented edge detection.

```
im_w=fix(size(eDectect,2)/2);
right = eDetect(:, im_w+1:end, :);
```

The Sample image of China yuan is shown in Figure 3(a). The edges of the image are detected using Canny's edge detection method as Shown in Figure 3(b). Next, novel feature extraction which captures sharp changes in image brightness, edge detection is carried out. This will reflect the sharp intensity changes in the colours of the currency image. This helps classifies object boundaries in the image. The features which are the edges of the unique feature is shown in Figure 3 (c)

(a) (b) (c)

Fig. 3. Sample Image of China Yuan

After the unique feature edges has been extracted, the images will be split into 100x100 block for processing. The code for blockproc is shown as below.

```
h_block=size(right,1)/100;
w_block=size(right,2)/100;
fun=@(theBlockStructure) checkPixel(theBlockStructure);
Testing_Matrix = Blockproc(right, [h_block w_block], fun);
```

The unique features edges are shown in Figure 4.

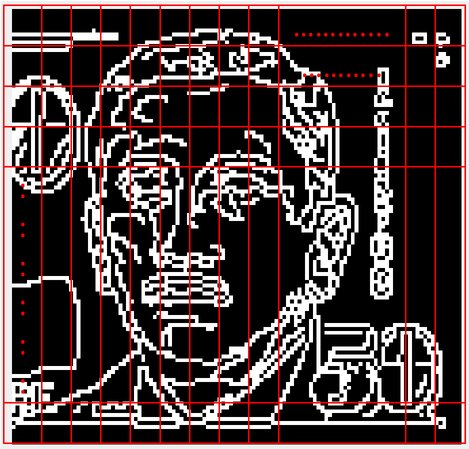

Fig. 4. Sample Singapore Ringgit feature with 100x100 block

For each block in the image, the percentage of white and black pixel in that one particular block will be calculated. Next, the percentage of white pixel in the block, w_*percen* by dividing the sum of *w* in the block by *sop* and multiply by 100. Next, if the number of white pixels *is* more than 10% in that particular block, the block will return value 1 to indicate the block is white. The same applies if the number of white pixels in that particular block is less than 10%, however the value will be return as 0 to indicate that particular block is black. The reason the condition is set to 10% is to eliminate any unwanted noise or unnecessary information in the image to increase the accuracy of the recognition process. The pseudocode for determining either block is white or black is shown as below:

```
function block_out=checkPixel(theBlockStructure)
  w=sum(theBlockStructure.data==1);
  b=sum(theBlockStrucutre.data==0);
  sop=w+b;
    w_percen = (w/sop)*100;
    if (w_percen)>10;
      return_value=1;
    else
      return_value=0;
    end
  block_out=return_value;
end
```

The values will be mapped based on whether the particular square in the gridlines has specific values. If one of the squares in the gridline has more than 10% white pixels, the pixel value of that matrix square will return 1. Vice versa, if the square has more than 10% black pixels, the pixel value of that matrix square will return 0.

The features will be in matrix form = $\mathbf{Image}, \mathbf{I} = \begin{vmatrix} X_{0,0} & \dots\dots\dots & X_{0,m} \\ \vdots & \dots\dots\dots. & \dots\dots. \\ X_{n,0} & \dots\dots\dots. & X_{m,n} \end{vmatrix}$

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where X is either 1 or 0 and m is row of matrix and n is row of column.

3.4 Classification of the Currency Category

The sample image's matrix will be determined by considering four sample images from each currency category. The image matrix extracted will be matched with the sample image's matrix using the following code, where Currency Matrix is the matrix obtained after processing the ideal image, and Testing Matrix is the matrix obtained from the sample image representation. Once the resulting matrix has been obtained, the testing image's matrix with the highest similarity percentage to the sample image matrix will be classified as that sample image's specific origin.

The output will yield the edges of the unique features of the sample banknote, which in this case, are the human facial or symbol of the sample banknote. The currency's country will be classified after matching the edges of the unique features.

The origin of the testing currency is based on the highest percentage obtained after mapping the sample image matrix onto the testing image matrix. The pseudocode for calculating the similarity percentage is shown below:

```
simipercen= Currency_Matrix==Testing_matrix;
h_simi=size(simipercen, 1);
w_simi=size(simipercen, 2);
iwant=sum(simiprcen(:));
percen=iwant/(h_simi*w_simi)*100;
recognition = percen;
```

4. Experiments

There are 30 images acquired from 6 types of currency that will be used for the experiments. The currency will be loaded, and the currency features will be extracted as show in Figure 5. Similarity will be measured, and then the classification of the currency origin will be performed as show in Figure 6.

Fig. 5. Currency features extraction

Fig. 6. Similarity measurement and currency classification

5. Results and Analysis

Table 1 shows the results for the 30 samples, which contain information on the type of currencies, the similarity percentage between currencies for each origin, the currency's origin category, and the respective comments from the proposed solution.

Table 1
Result of currency from proposed solution and manual grading.

Types of Currencies used of Testing	Similarity Percentage between Testing Image with each of the Ideal Currency Image in Database (%)						Currency's Origin Category	Manual Currency's Origin Category
	Pound	Rupees	Dong	Ringgit	Sing Dollar	Yuan		
Pound	60.6039	52.5882	61.011	72.8352	63.4219	60.9431	Ringgit	Misclassified
Pound	56.3998	51.9608	61.3683	58.0956	61.9333	61.2512	Sing Dollar	Misclassified
Pound	61.6254	51.7864	54.2015	49.4309	57.7503	55.2059	Pound	Ok
Pound	66.5234	51.7864	55.1220	48.3310	58.7301	53.2021	Pound	Ok
Pound	71.8920	51.7864	53.3120	50.2302	57.8901	52.2101	Pound	Ok
Rupees	53.7025	56.7353	51.7851	47.7686	52.7851	51.2562	India	Ok
Rupees	49.5566	55.8491	44.0660	47.6415	47.4151	44.7547	India	Ok
Rupees	55.8347	61.7851	48.8430	49.616	53.3554	50.0000	India	Ok
Rupees	52.7500	59.4815	47.1852	48.6296	47.9444	48.3981	India	Ok
Rupees	51.2908	60.2310	50.2134	49.9092	50.2390	49.2901	India	Ok
Dong	53.333	50.7549	59.9856	52.9149	56.3203	56.9408	Dong	Ok
Dong	54.2442	45.6961	68.1586	61.4483	63.8828	64.4483	Dong	Ok
Dong	53.0228	51.6176	60.8632	53.8547	57.5299	57.4359	Dong	Ok
Dong	54.0216	50.5098	61.0682	54.0758	58.6212	60.3712	Dong	Ok
Dong	52.4782	51.2930	61.9802	53.7820	57.3460	58.8904	Dong	Ok
Ringgit	47.9583	49.9917	45.5250	50.3083	46.1667	42.3500	Ringgit	Ok
Ringgit	57.6557	49.9118	63.2384	74.4126	65.1244	61.4469	Ringgit	Ok
Ringgit	54.3511	48.2647	60.7125	75.4056	63.1623	62.2894	Ringgit	Ok
Ringgit	42.9917	47.0879	41.2444	50.2718	41.3803	40.0214	Ringgit	Ok
Ringgit	52.3948	50.3332	52.8902	70.3461	62.7483	50.4628	Ringgit	Ok
Sing Dollar	52.8333	52.6500	50.4500	49.0917	55.3333	49.8583	Sing Dollar	Ok
Sing Dollar	59.2946	51.0196	53.1397	59.6725	72.6294	64.1941	Sing Dollar	Ok
Sing Dollar	53.5345	50.6034	50.9569	48.0776	58.3362	49.3534	Sing Dollar	Ok
Sing Dollar	55.4467	49.0882	65.4382	60.0144	69.7126	64.2241	Sing Dollar	Ok
Sing Dollar	53.4839	50.3423	55.3827	61.2315	66.3837	59.0937	Sing Dollar	Ok
China Yuan	53.3981	45.6765	67.0232	66.7544	65.1932	67.1245	Yuan	Ok
China Yuan	55.7317	52.3333	61.7986	58.8264	61.3958	63.4861	Yuan	Ok
China Yuan	55.7495	49.5294	64.6108	60.6978	66.5292	67.1131	Yuan	Ok
China Yuan	59.0986	52.4412	63.9418	60.2624	63.8143	65.5566	Yuan	Ok
China Yuan	56.3234	52.3425	62.3423	61.2342	63.3420	65.2349	Yuan	Ok

Table 2 is the summary information based on the testing and experimenting in Table 1. Overall, the experiment was conducted for only 5 currencies. However, one of the currencies could not be recognize easily. The currency that could not be recognize easily, which was the United Kingdom Pound.

Table 2
Accuracy of currency recognized by proposed solution

Currency	Percentage of Currency Recognized (%)
United Kingdom Pound	60.00
India Rupees	100.00
Vietnam Dong	100.00
Malaysia Ringgit	100.00
Singapore Dollar	100.00
China Yuan	100.00

It was later found out that when all the different types of currency were put in the same image as shown in Figure 7, the position of the unique feature, which in this case is the Queen of England's head, is different for each type of United Kingdom Pound. The difference in the position of the unique feature will affect the accuracy as the binary matrix that was yielded from the recognition process may have increased similarity with other countries' currency after undergoing the similarity percentage algorithm.

Fig. 7. Different types of United Kingdom Pound

Furthermore, although the proposed algorithm is able to accurately detect the origin of other currencies, the similarity percentage between the tested currencies and all 6 Ideal Currencies is quite low. Testing currencies such as the 10 Indian Rupee, 20 Indian Rupee, 500 Indian Rupee, 20,000 Vietnamese Dong, 5 Malaysian Ringgit, 100 Malaysian Ringgit, 5 Singapore Dollar and 100 Singapore Dollar are accurately recognized as their respective origins, but all of these currencies have a similarity percentage of 60% and below. The low similarity percentage might be due to the conversion of RGB images to grayscale images. Since different colour contrasts will yield different grayscale images, this might severely affect the edges that will be obtained during the Canny Edge Detection algorithm. The binary matrix produced from the recognition process will be affected as well and might be matched to other currencies' binary matrix more accurately than the testing currency's own ideal currency. Another factor that can cause the system to have 100% similarity in the classification of the currency and low similarity percentage between the Testing Image and Ideal Image is the Ideal Image used. The Ideal Image used may affect how the prototype system recognizes the Testing images as the binary matrix produced from the Ideal Image depends on the Ideal Image that was used at that time. If the Ideal Image is changed to test the same Testing Image currency, the similarity percentage will differ in value.

The accuracy of currency origin classification can be calculated using the equation below.

$$Classification\ accuracy = \frac{Total\ number\ of\ correct\ classification}{Total\ number\ of\ experiments\ on\ fruit\ samples} \quad (1)$$

The experiment results achieved accuracy of 93.4%.

6. Conclusions

Addressing the challenge of currency recognition, this paper introduces a successful algorithm for classifying currency origin with an improved accuracy rate. The proposed algorithm is able to classify not only currencies like Pound, Singapore Dollar, China Yuan, Rupees, Dong, and Ringgit Malaysia successfully. The overall result achieved 93.4% accuracy. With this new solution, users can determine the currency origin more effectively and efficiently. The proposed algorithm for currency origin classification has shown promising results in accurately identifying the origin of banknotes. Further development and testing can be carried out to enhance the algorithm's accuracy and applicability to a wider range of currencies and platforms, ultimately providing an efficient and reliable solution for currency recognition. The proposed algorithm also can be deployed in mobile and cloud-based platforms, allowing users to recognise the currency origin easily, anywhere and at any time.

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References
[1] Sodhi, Gurjot Singh, and Jasjot Singh Sodhi. "A Robust Invariant Image-Based Paper-Currency Recognition Based on F-kNN." In *2021 International Conference on Intelligent Technology, System and Service for Internet of Everything (ITSS-IoE)*, pp. 1-6. IEEE, 2021. https://doi.org/10.29304/jqcm.2018.10.1.359

[2] Shaker, Shaimaa H., and Mohammed Gheni Alwan. "Paper Currency Detection based Image Processing Techniques: A review paper." *Journal of AL-Qadisiyah for computer science and mathematics Vol* 10, no. 1 (2018).

[3] Tiwari, Krishna Kant, & Dominic, Praveen."Currency recognition system using image processing". International Journal of Computer Science and Engineering, 7(6), 1-3. (2020). https://doi.org/10.14445/23488387/IJCSE-V7I6P101

[4] Muhamad, Sabat, and Twana Ahmed. "Counterfeit currency recognition using deep learning: A review." (2021).

[5] Bhardwaj, Sarthak, Shivam Vishwakarma, Suneel Kumar, Sagar Jaiswal, and Gauri Katiyar. "Identification of Currency via Image Recognition." In *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, pp. 609-613. IEEE, 2021. https://doi.org/10.1109/ICACITE51222.2021.9404760

[6] Rajan, Georgie V., Dincy M. Panicker, Nisha Elizabeth Chacko, Jayalekshmi Mohan, and V. K. Kavitha. "An extensive study on currency recognition system using image processing." In *2018 Conference on Emerging Devices and Smart Systems (ICEDSS)*, pp. 228-230. IEEE, 2018. https://doi.org/10.1109/ICEDSS.2018.8544310

[7] Sindhu, R., & Verma, P. "Currency Recognition System Using Image Processing". International Journal of Scientific & Engineering Research Volume 11, Issue 4, (2021).

[8] Muhamad, Sabat, and Twana Nasih Ahmed. "Image-Based Processing of Paper Currency Recognition and Fake Identification: A Review." (2021).

[9] Devi, P. Durga, and M. Chandrakala. "Morphological based Segmentation and Recognition of Indian Coins."

[10] Abburu, Vedasamhitha, Saumya Gupta, S. R. Rimitha, Manjunath Mulimani, and Shashidhar G. Koolagudi. "Currency recognition system using image processing." In *2017 Tenth International Conference on Contemporary Computing (IC3)*, pp. 1-6. IEEE, 2017. https://doi.org/10.1109/IC3.2017.8284300

[11] Garkoti, Pravidhi, Pranshu Mishra, Nitin Rakesh, Mandeep Kaur, and Parma Nand. "Indian Currency Recognition System Using Image Processing Techniques." In *2022 9th International Conference on Computing for Sustainable Global Development (INDIACom)*, pp. 628-631. IEEE, 2022. https://doi.org/10.23919/INDIACom54597.2022.9763134

[12] Gautam, Kalpna. "Indian currency detection using image recognition technique." In *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)*, pp. 1-5. IEEE, 2020. https://doi.org/10.1109/ICCSEA49143.2020.9132955
[13] Rauyani, Ahmad Imam, Muhammad Hamka Ibrahim, and Subuh Pramono. "ROI based Indonesian Paper Currency Recognition Using Canny Edge Detection." *Journal of Electrical, Electronic, Information, and Communication Technology* 2, no. 1 (2020): 5-8. https://doi.org/10.20961/jeeict.2.1.41349
[14] Akter, Jesmin, Muhammad Kamal Hossen, and Md Shahnur Azad Chowdhury. "Bangladeshi paper currency recognition system using supervised learning." In *2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, pp. 1-4. IEEE, 2018. https://doi.org/10.1109/IC4ME2.2018.8465595
[15] Zhang, Qian, and Wei Qi Yan. "Currency detection and recognition based on deep learning." In *2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, pp. 1-6. IEEE, 2018. https://doi.org/10.1109/AVSS.2018.8639124
[16] Chowdhury, Uttoran Roy, Susovan Jana, and Ranjan Parekh. "Automated system for Indian banknote recognition using image processing and deep learning." In *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)*, pp. 1-5. IEEE, 2020. https://doi.org/10.1109/ICCSEA49143.2020.9132850
[17] Babu, P. Ashok, P. Sridhar, and Rajeev Ratna Vallabhuni. "Fake currency recognition system using edge detection." In *2022 Interdisciplinary Research in Technology and Management (IRTM)*, pp. 1-5. IEEE, 2022. https://doi.org/10.1109/IRTM54583.2022.9791547
[18] Ramvanshi, Nayna, Shelke, Harshada, Tile, Damini, Badgujar, Vaishnavi, & Bhadane, S.N. "Currency Recognition System using Image Processing". International Journal of Advanced Research in Science, Communication and Technology (IJARSCT, 2(6). Volume 2, Issue 6, (2022).
[19] Aseffa, Dereje Tekilu, Harish Kalla, and Satyasis Mishra. "Ethiopian banknote recognition using convolutional neural network and its prototype development using embedded platform." *Journal of Sensors* 2022 (2022): 1-18. https://doi.org/10.1155/2022/4505089
[20] Jadhav, Rushikesh, Swaraj Kalbande, Rohan Katkar, Rohan Katta, and Rakhi Bharadwaj. "Currency Recognition using Machine Learning." *International Research Journal of Engineering and Technology (IRJET)* (2022).
[21] Jumma, Laith F. "Real-Time Recognition and Detection of Iraqi Currency Using DNN." *Journal of Scientific Reports* 5, no. 1 (2022): 1-7.
[22] Mane, Pratiksha, AnujaMulik, Inamdar, Saniya, Hire, D.H. (2020). "Currency Identification Using CNN". International Journal of Interdisciplinary Innovative Research &Development (IJIIRD) ISSN: 2456-236X Vol. 05 Special Issue 01.
[23] Gonzalez, Rafael C., and Richard E. Woods. "Digital Image Processing, Hoboken." *NJ: Pearson* (2018).
[24] Mandankandy, Arun, and K. E. Kannammal. "Fake currency detection: A survey." *Gedrag en Organisatie* 33, no. 4 (2020): 622-638. https://doi.org/10.37896/GOR33.04/072
[25] Yadav, R. K., Pulkit Valecha, and Shaivya Paliwal. "Counterfeit currency detection using supervised machine learning algorithms." In *Machine Learning for Predictive Analysis: Proceedings of ICTIS 2020*, pp. 173-178. Springer Singapore, 2021. https://doi.org/10.1007/978-981-15-7106-0_17