Deep Intelligent System for Precise Coin Identification

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***Abstract*—Precise coin recognition is part of many financial and retail applications, such as vending machines, dispensing machines or any cash-handling systems, as well as numismatic analysis. Most automated systems are problematic in classifying counterfeit coins by traditional means (mechanical or electrical). YOLOv8 is such kind of an algorithm that brags about its efficiency and high accuracy, therefore being innovative. In this regard, this research specifically dwells on the implementation of the YOLOv8 algorithm for coin detection and categorization. The model distinguishes itself from one other with different denominations in coin classification based on distinguishing features such as texture, colour, shape, and others. Due to the involvement of YOLOv8, the proposed model performance is found to be enhanced as it yields precise and accurate results in coin identification. Therefore, this model has the potential to revolutionize across different industries, financial and retail sectors which accept coins as the currency denominations.**

***Index Terms*—YOLOv8, Coins detection, coin identification, coin recognition, intelligent systems,**

I. Introduction

Coins are the most used denomination around the world, they are used in various fields like vending machines, counting machines in banks, payphones, and as currency in business. Coins are cylindrical solids of small heights that are made up of alloys. Coins can be easily faked in many ways, and this could lead to inflation and loss in business. This can be prevented by coin recognition.

The scope of this paper is the detection and recognition of Indian coins. Even though India has many ways of electronic payment, we still use coins for a lot of transactions. Hence, it is essential to detect and recognize counterfeit currencies thereby protecting the Indian economy. Coin recognition can be done using a mechanical method where the parameters such as diameter, thickness and weight of the coin are taken into consideration. However, this method can also be bypassed by using a fake coin of the same material that produces the same electromagnetic field this method is used extensively in counting machines and vending machines while this method is cheap sometimes it could lead to big losses. This paves the way to coin detection using object detection.

Object detection uses images and video streams as inputs and identifies the instances of the object of our interest in our case coins, well it not only does that it also provides the coordinates of the object in the image. There are a lot of parameters for object detection like the cost, the angle of the camera, the deformation of the object etc. In this paper we use

YOLO v8 for the detection and recognition of the coins since it is way more efficient and faster compared to YOLO v5, and its backbone is based on efficiency where it captures high-level features on the coin thereby raising the bars of accuracy in the detection. It also incorporates better data augmentation techniques than YOLO v5. The contributions of this research are described as follows:

1) Utilizing the YOLOv8 deep learning framework in the improvement of Indian coins detection.
2) Improvement in the application of deep learning algorithms for classification of the Indian coins.
3) A comprehensive analysis of performance is performed for the categorization of the Indian coins.

A brief presentation of some of the solutions to this problem that exist in the Literature as well as their limitations are presented in Section II. The proposed methodology in addition to the dataset used is described in Section III. The rest of the paper is organized as follows: Results are given in Section IV with quantitative and qualitative evaluation. Finally, the conclusion is drawn in Section V followed by References.

II. Literature Review

This study focuses on the classification of coins into various categories. To categorize coin images, the proposed approach utilizes a pre-trained YOLOv8 architecture based on Convolutional Neural Networks (CNNs). In this section, we will provide a concise overview of recent research in this field.

In their study [1], Mansoor Roomi and colleagues introduced a model designed for the identification and denomination recognition of Indian coins. Their approach involves several critical steps, including edge detection using the Canny edge algorithm, shape recognition through the Hough transform algorithm, and polar transformation for coin identification in images. If the image indeed contains a coin, they construct a feature map using the Fourier Transform technique, decomposing the image into sine and cosine components. This feature map is then fed into a multi-layered Back-propagation (BP) neural network, which classifies the coin based on its denomination. The model is trained on a dataset comprising 48 images of Indian coins, resulting in an identification rate of approximately 82 %. However, it's important to note that this model has a longer response time due to its multi-stage pre-processing structure.

Li Liu and colleagues [2] presented a novel method for detecting counterfeit coins using image analysis in their study. Using comparisons with a carefully chosen set of prototype images, their method converts coin images into a dissimilarity space described by a prototype vector space. This method measures how different the image under analysis is from the prototype images. Using the Difference of Gaussians detector, each image's local important features are identified, and then they are described using the Scale-Invariant Feature Transform (SIFT) descriptor as part of the dissimilarity computation. Their model is trained using four different datasets.

A.U. Tajane and co-authors proposed a method focused on recognizing and categorizing Indian currency images into four denominations: one, two, five, and ten rupees, in their 2018 paper [3]. They employed the pre-trained AlexNet architecture, featuring eight learning layers, including five convolutional layers and three fully connected layers. This deep learning model not only remained theoretical, but was also practically deployed in vending machines using a Raspberry Pi as the controller. Training the deep learning model involved two distinct datasets: standard datasets from various Uniform Resource Locators (URLs) and a custom dataset created by the authors themselves, totaling around 1600 images. The model achieved an impressive accuracy rate of 97 %, accurately categorizing images into four predefined categories.

Anupa and co-authors in [4] introduced an automatic coin counting and sorting machine prototype. This ingenious system was designed using components such as the ARDUINO-UNO, LCD display, and IR sensors. It employed electromagnetic frequency for coin classification. The machine featured a vibrating grill and a dedicated pathway for efficient coin sorting, Along with a load cell for measuring coin weights and facilitating their organized distribution to respective containers. IR sensors played a crucial role in accurately counting coins, and the system provided real-time updates on both the total count and the cumulative value via an LCD display. While this prototype displayed promise, it is important to acknowledge its imperfections and the fact that it may not provide foolproof results.

Nikolay Fonov proposed a coin identification and categorization method created exclusively for USSR coins in their study [5]. "The Multi-Level Counter Propagation Neural Network (ML-CPNN)" was used in this system. In addition, the scientists presented two innovative strategies to improve recognition speed: one for removing the background from coin images and another for identifying the center of the coin by picture rotation. The Deep Learning model was carefully trained using a large dataset of 4000 photos representing 26 different coin varieties. They simplified picture pre-processing in this model by converting the source photos to binary format, cutting them at the edges, center-aligning them, and making them rotation-invariant, removing extraneous features.

Naresh Babu Muppalaneni presented a coin identification and classification model designed for Brazilian coins in his work [6]. The Ensemble Learning Technique was used in this model, which is a popular Deep Learning strategy that combines many supervised and unsupervised learning models to obtain higher classification performance. Four unique Convolutional Neural Network (CNN) models were built in this study, each with its own set of filters and network parameters. These models were trained using a dataset of 3057 photos divided into five categories.

Lina Suhaili Rosidi and her collaborators conducted an investigation into the performance of coin identification models designed for Malaysian currencies, as referenced in [7]. These models were created using pretrained Convolutional Neural Networks (CNNs) like AlexNet, GoogleNet, and MobileNetV2. Among these models, GoogleNet emerged as the top performer, achieving impressive results with a testing. It is worth noting that, at the time of the study, the practical implementation of this model in real-time scenarios on hardware platforms like Raspberry Pi or "Field Programmable Gate Arrays" (FPGA) had not been assessed.

Sarthak Bhardwaj's work [8] developed a model for identifying counterfeit Indian currency that relied heavily on Convolutional Neural Networks (CNN). The method classified notes by comparing the empty regions on them and used both K-NN and CNN to construct a feature vector for each dollar note. The picture was then broken into multiple regions to allow for a thorough examination of its legitimacy, taking into account aspects such as the center number, RBI stamp, color strip, and a visually impaired identification symbol. However, it is important to note that the model was not trained with different corners and augmentations, such as a front, back, front clockwise, front anti-clockwise, back, and back anti-clockwise, which might be a restriction in real-world circumstances.

In their work [9], they created a coin recognition and detection algorithm based on YOLOv5 (You Look Only Once). This model included feature extraction in the backbone of YOLO using "CSPDarkNet (Cross-Stage Partial Networks)" and "PANet (Path Aggregation Network)," and it addressed memory and latency limitations in the neck of YOLO using a Feature Pyramid Network. Notably, feature maps of three distinct scales were constructed in the head of YOLO to enable multi-scale detection, boosting the model's capacity to recognize coins of varied sizes with high accuracy. The suggested model was trained using 525 pictures from four distinct coin classes: one, two, five, and ten rupees.

Zhen Lei and colleagues [10] presented a high-performance FPGA-based embedded vision system that consumed much less power than standard "Central Processing Unit (CPU)" and "Graphics Processing Unit (GPU)" -based vision systems. This system was created with System Generator and included several coin classification methods such as coin image interference background removal and binarization using XSG in Matlab/Simulink. The conclusion emphasized the benefits of employing FPGA technology, which demonstrated quicker processing and reduced power usage when compared to traditional approaches. The use of a diameter recognition technique reduced hardware complexity, and the FPGA-based recognition algorithm proved to be extremely versatile, allowing for program customization. It was discovered that removing picture backgrounds during the preprocessing step considerably improved classification accuracy.

III. PROPOSED METHOD

This paper proposes an approach to the prediction of Indian currency using the YOLOv8 model for the recognition of objects. This method emerges as a separate direction that makes use of the YOLOv8, and it performs the former models attaining an accuracy of 99.2 % and precision of 99.1 % over validation. Earlier works discussed ensemble learning methods while outperforming with up to 98 % accuracy in predicting Indian currency. Since the experiments had been conducted, such a method delivered outstanding average accuracy - 99.2%.

The well-known new model YOLOv8 is a model of object recognition indeed thanks to ultra-fast speed and great accuracy. The neural network structure comprises of convolution layers 53 in number and cross-stage partial connections facilitating the transfer of information between stages and layers. Several convolutional layers are on the head of YOLOv8 and afterwards fully connected layers. These layers create class probabilities, bounding boxes, and confidence scores of objects detected in an image.

The hyperparameters in our model based on YOLOv8 are widely tuned to improve its performance. Combinations of model parameters need careful tuning to get the best accuracy and precision. The most important applied changes included an increase in the batch size from 8 to 16. After such a change, the model was able to analyze large-sized data batches during the training phase, learning more steadily and effectively. Higher batch sizes, often leading to quicker convergence with increased model generalization during testing, are the main reasons for our improved results accuracy and precision.

A. Dataset

The Indian Coin Image Dataset is a large repository of Indian coin images of high quality, primarily meant for use with computer vision. This dataset includes a few photographs of 4 Indian cash denomination types with the name of a particular class and its occurrence count which is represented in Table 1. So, this dataset may work as an extremely useful approach for the viewpoint task through both coin identification and denomination categorization. The dataset has 1,796 pictures in total with 1,796 JSON files whereby one JSON file is formatted as per the COCO annotation standard. Every photograph in the collection has the same resolution - 256 by 256 pixels, which leaves no chance for misclassification or denomination analysis.

Each photo in the collection avails a medium average size of about 0.07 megapixels (MP) while in quality, each image is constant. Further, the COCO format annotations are provided within the dataset and then those are converted to the text files for each image. This dataset helps us train and test our model effectively. The Indian Coin Image Dataset is, therefore, an invaluable tool set to be used for numerous computer vision applications.

Class label	**Instances**
1 Rupee	657
5 Rupees	509
2 Rupees	447
10 Rupees	183

Fig. 1. Number of images in a class

Thus, it may come in handy for practitioners, developers as well and researchers as a useful tool in the class of picture-related tasks, classification, object identification, and currency denomination recognition among others. The constant picture resolution as well as the wide class variety of the dataset must thus be appreciated to appreciably improve the suitability of the dataset to finally build and evaluate machine learning models using actual Indian coin data.

B. Methodology

The architecture used in this study can be divided into three key components, each of which plays a distinct role.

1) **Backbone Network**: In YOLOv8, the importance of backbone network because this is where effective features are supposed to be effective by the input images. Whenever targeting the detection of Indian coins, this network is very significant at feature extraction and incorporates vital visual attributes like texture, shape, and edge details.
   For this purpose, YOLOv8 employs the powerful ResNet-50 architecture as its backbone. ResNet-50 is used for deep convolution neural networks and is pre-trained on a big dataset such as ImageNet. It mainly gives a good starting point to gradually move forward with good object recognition ability. From the given images, the high-level features can be extracted, and given its distinct visual appearance, ResNet-50 assists in the accurate detection as well as recognition of Indian coins. This backbone network forms the initial building block of the YOLOv8 architecture in the process of allowing the subsequent layers to work effectively.
2) **Neck Network**: The Neck Network serves as an interlocutor between the Backbone and the Head Networks, which further plays a main role in ameliorating the feature extraction process for Indian coin detection. The Neck Network is responsible for linking Head's prediction to the feature extraction carried on by the

Backbone. It will see mainly that the corresponding feature maps created by the Backbone are well-tuned and okay for the accurate pinpointing of coins. In doing so, the Neck Network targets two primary concerns.

First, it describes techniques that are used in shrinking feature map sizes while still maintaining that delicate trade-off between computation efficiency and accuracy. Through this process, the YOLOv8 model is made to work fast and effectively in the detection task. Besides, the Neck Network also works to increase the resolution of the rescued features so that it can capture small details and variabilities of the Indian coins. Thus, it is through striking this balance that the Neck Network assists the Head Network in making coin recognition due to its provision of feature maps specialized in the identification of items.

3) **Heads Network**:The topmost layer in the YOLOv8 architecture which predicts what will be found present in the given input images, might be Indian coins too. The discriminative of the various coin types are the subtasks of finding them concerning the Head Network and accurately in the given images. The Head Network makes use of techniques like anchor boxes to help in the precise placement of the detected coins. By classifying the detected object, the network helps determine the type of traced coin and uses scores for the same to assign them. Moreover, to attain more accurate identification of the coin, the Head Network is painstakingly trained with the focus to better the alignment between the ground truth and the expected bounding boxes, which further implies increasing the Intersection Over Union (IOU).

   In addition, this technique comes with non-maximum suppression (NMS) which is fitting in removing bounding box overlap and staying only with the most likely predictions. So, it increases the accuracy and reliability of object detection to a great extent, due to which this technology proves best in distinguishing Indian coins based on a variation having visual characteristics.

In conclusion, the Head Network models make exact predictions of almost all kinds and locations of Indian coins, while the Neck Network directs how feature maps will be refined for accuracy. All these three layers, including the backbone, provide a proper structure that helps the YOLOv8 model properly detect Indian coins

C. Configuration

The YOLOv8 model was fine-tuned in such a way that improves its performance on this particular job of detecting Indian coins by conscious adjustment of batch size and accordingly tweaking of hyperparameters. For that, some of the various parameters set up of the YOLOv8 model were learning rate, momentum, and weight decay.

These changes were done in a way that the model efficiently maximizes the accuracy in choosing the Indian coins out of all of the photos. This change aimed to adjust the size of the groups, which affects the number of photos that are processed simultaneously at a single time step across training. It was decided The batch size for this particular value complies with empirical findings inferring some optimal one for this concrete coin recognition task. The method amounts to completing 50 exercises only by applying the biggest and most accurate form of YOLOv8 architecture, that is, the YOLOv8x structure.

While this particular structure may process relatively slower than the other YOLOv8 variants, accuracy should be of supreme importance for the system under focus. YOLOv8 architecture handles five versions all performing a unique balance between the computational economy and processing speed against the same component which is the accuracy. Least as well as the fastest type, the v8n kind may often resort to giving lesser precision. On the other hand, while the biggest, the v8x version can compromise processing speed for accuracy. The v8s, v8m, and v8l variants fall into the middle ground in terms of precision, speed, and computing effectiveness.

The goal of achieving the highest level of accuracy in Indian coin detection led us to select the YOLOv8x structure for our work. The structure's capacity to efficiently train and converge to a good solution within the limits of 50 training epochs further supported it.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Pre-processing

Simulation experiments was done in Python using Ryzen 9 processor with 16 GB RAM and 8GB GPU. The dataset is divided into training, testing, and validation sets and each consists of 80 %, 10 %, and 10 %, respectively. Here are the results obtained from training and validation. In Fig 2, there is a sample dataset and a sample annotated file shown. The dataset consists of 1907 image files and its corresponding 1097 Text files which contain its annotations

```
15 0.570312 0.595703 0.179688 0.105469
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Fig. 2. Sample data and Annotation

B. Training and Validation

Table 3 presents validation findings that shed light on how well our object detection model performs in various classes. Understanding the model's advantages and disadvantages in practical situations depends on these insights.

These are the few metrics which says about training and validation performances are shown. These metrics such as box loss, classification loss, distribution focal loss are shown

Class	Images	Instances	Box(P)	R	mAp50
all	179	179	0.991	0.996	0.992
1	179	66	0.999	0.985	0.995
10	179	19	0.99	1	0.995
2	179	44	0.978	0.997	0.985
5	179	50	0.998	1	0.995

Fig. 3. Number of images in a class

in Figure 4, Pression and recall from Figure 5 are stated to analyse validation performance. The metrics such as mAP50 and mAP50-95 are shown in Figure 6 to analyse the training performance.

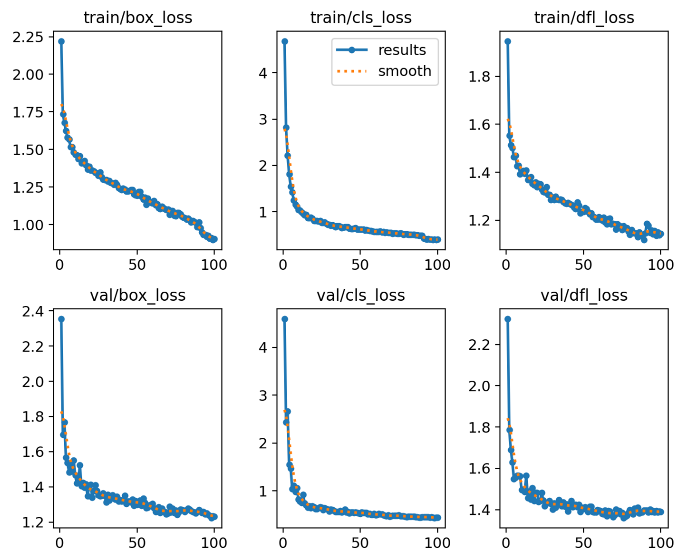

Fig. 4. Loss

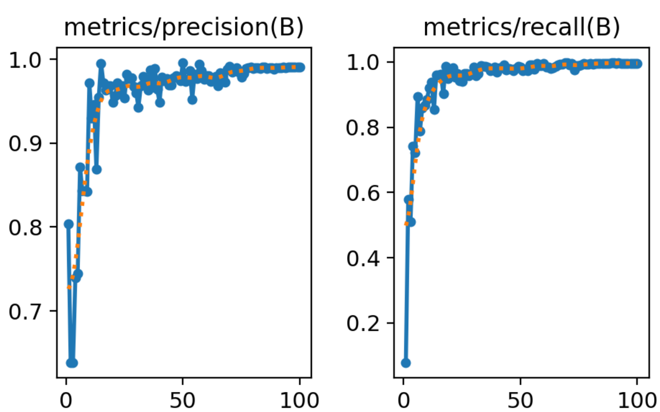

Fig. 5. Pression-Recall

The confusion matrix which is derived from the training data, indicating that the model effectively categorized the Indian coins with minimal loss is shown in Fig 7.

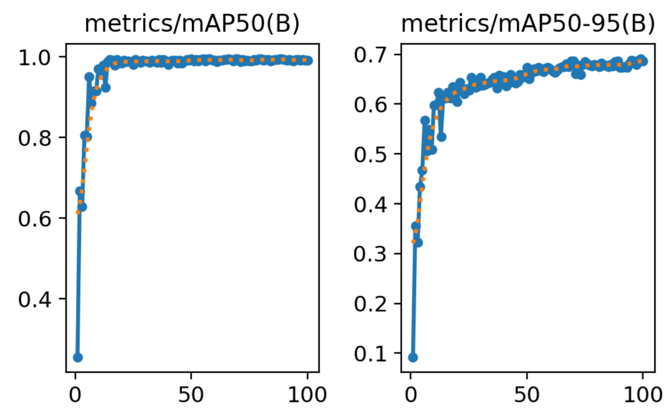

Fig. 6. Accuracy

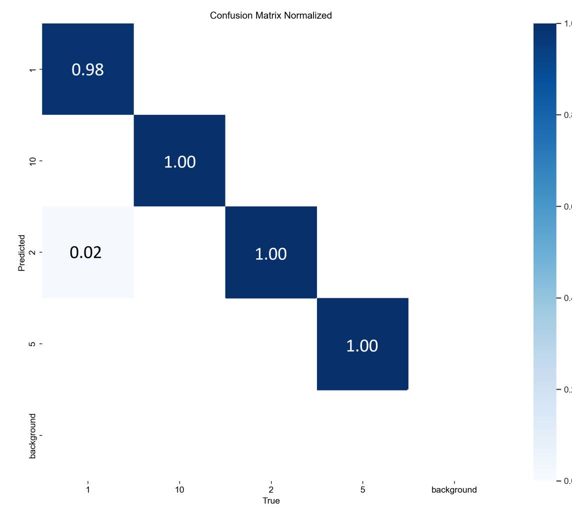

Fig. 7. Confusion Matrix

C. Compare

In Table I, the proposed method is compared with some of the existing methods for categorizing Indian coins which was mentioned in the literature. Out of all the coin detection algorithms described in the literature, it says that the presented model outperforms the existing methods in the classification of Indian coins.

V. Conclusion

This work introduced an elaborative and pioneering method for the detection and identification of Indian coins using the advanced YOLOv8 deep learning model. The proposed work is suitable for deployment in Smart Cities and IoT-driven environments and can be seamlessly integrated into any vending machine. Certainly, the proper identification of coins is one of the important needs for functioning in different financial and retail sectors, and this methodology solved efficiently the acute problem of automation of coin identification processes. The training phase gives an amazing accuracy of 99.2 % and precision of 99.1 percentile, outperforms the previous models, and shines the performance of YOLOv8 in capturing the peculiar characteristics of Indian coins that include texture, color, and shape. This method, in testing, achieves striking accuracy of 98.2%, thus

TABLE I
COMPARISON OF ACCURACY FOR DIFFERENT ALGORITHMS

YEAR	ALGORITHM USED	ACCURACY
2015	Multi-layered BP neural network [1]	82
2018	AlexNet Architecture [3]	97
2021	Multi-Level Counter Propagation Neural Network [5]	99.29
2021	Ensemble learning model consisting of 4 separate models with CNN algorithm by varying filters [6]	87.36
2022	AlexNet, GoogLeNet, and MobileNet [7]	99.2
2022	Tries to improve the embedded system performance with various neural network algorithms [8]	97
2022	YOLOV5 with CSPDarkNet (Feature Map Creation) and Feature Pyramid Network [9]	98.6
Proposed Method	**YOLOv8 with ResNet-50**	**99.2**

reaffirming the robustness and reliability of our model. In summary, this paper carries forward for the blossoming domain of computer vision and has implications indeed to facilitate the identification of coins in order to further the chains of adopters in retailers and application in banks accurately as well as quickly.

One important direction this research will go in the future is comparing and contrasting the YOLOv8 and YOLO NAS models to find the best way to accurately identify and categorize coins. The purpose of this comparative analysis is to evaluate the two models' performance in terms of a number of metrics, including speed, accuracy, and resource efficiency. Through comprehensive experiments and benchmarking tests, the study can determine which model performs better when handling the complexities of Indian coin recognition.

Additionally, the study will explore the real-world effects of applying the selected model, taking into account things like embedded system compatibility and real-time processing requirements.The goal of the study is to make the chosen model as efficient as possible for coin-operated devices, such as vending machines and other systems that need to identify coins. With this method, the selected model is guaranteed to perform well not only in theoretical benchmarks but also in operational settings. This comparative study's results will direct the choice of the best model, opening the door for the creation of a reliable and effective coin identification system with potential uses in a variety of automated settings.

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VI. CONCLUSION