Integrate Yolov8 Algorithm For Rupiah Denomination Detection In All-In-One Smart Cane For Visually Impaired

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Abstract

The eyes are crucial tools for human observation and perception, facilitating various tasks in daily life. Individuals, including those with visual impairments or blindness, engage in currency transactions, posing challenges in recognizing notes and preventing mishaps with counterfeit money. Despite government efforts, features like embossing on banknotes have limited effectiveness due to the circulated currency's disheveled condition. Addressing the visually impaired community's needs is imperative. An innovative solution, the "all-in-one smart white cane," integrated with machine learning supports daily activities, enhancing independence for visually impaired individuals. The YOLOv8 algorithm is employed for the precise detection of monetary denominations, subsequently recorded through a camera and seamlessly integrated into a smart cane, resulting in a consolidated device. This device, designed with standout features, excels in detecting Indonesian Rupiah banknote denominations. Detection performance testing, incorporating methods like object rotation, utilized a dataset divided into training (70%), validation (20%), and test (10%) segments. Modifications to contrast and variability rotation are essential in the context of real-time nomination recognition. These adjustments are implemented to ensure accurate and swift identification in dynamic, real-world scenarios. Testing results reveal a 99% average accuracy in recognizing currency note denominations, presenting an effective solution for the visually impaired community.

Keywords: detection, algorithm, smart-white-cane, visually impaired, machine learning

1. INTRODUCTION

Visual impairments represent a significant challenge faced by more than 285 million individuals worldwide, with 39 million among them experiencing blindness and 124 million grappling with low vision, according to data presented by the World Health Organization (WHO) [1]. The substantial population affected underscores the importance of providing special attention to the visually impaired community. Visual impairment is not an isolated ophthalmic condition, but various conditions can cause this visual manifestation [2]. It is crucial to note that despite their visual impairments, they possess the potential to engage in daily activities just like any other individual. Therefore, it is imperative to seek adequate solutions to facilitate their livelihoods.

Financial transactions play a pivotal role in supporting the sustenance of every individual, including the visually impaired community. These transactions encompass purchasing goods, economic activities, and various financial exchanges. Unfortunately, individuals with visual impairments often encounter challenges when engaging in buying and selling, such as confusion in distinguishing currency notes or even the risk of falling victim to counterfeit money.

Bank Indonesia has responded to feedback from the visually impaired community regarding their challenges with physical currency transactions [3]. One of the measures taken is the adjustment of the length differences between currency notes, from the previous 2 millimeters to 5 millimeters. Although this step is positive, many visually impaired individuals still experience discomfort in distinguishing currency denominations based solely on length. Moreover, currency notes in circulation are often not in pristine condition, which can affect the visually impaired's ability to identify their value. To address this issue, Bank Indonesia has introduced tactile features, such as embossed relief, on the sides of currency notes to facilitate denomination recognition.

However, in practice, currency in circulation often lacks uniformity and may show signs of wear and tear. The method still has several weaknesses, namely in terms of memory capacity, physical condition, and the absence of a determinant of honesty in the process of buying and selling goods and services [4]. Previous studies have employed the TCS3200 color sensor to determine the value of banknotes; however, the performance of the system heavily relies on the physical condition of the currency [5]. Conventional image processing methods are less effective in detecting the authenticity of money because of the various types of counterfeit money in circulation [6]. Therefore, the idea of implementing Computer Vision technology, specifically Convolutional Neural Networks (CNN), to facilitate currency denomination recognition has emerged, because CNN can apply to image and text classification [7]. The utilization of machine learning methods for verifying the authenticity of banknotes emerges as an optimal solution, ensuring accurate recognition of currency irrespective of its condition, whether worn or otherwise. This approach enhances the robustness of currency identification [8].

The "All-in-one smart cane" is the latest innovation in the form of a smart cane that incorporates various intelligent features to support the lives of visually impaired individuals. One of the standout features developed is the ability to automatically recognize Indonesian Rupiah denominations. This device is designed to be portable and rechargeable, making it highly practical for carrying anywhere. Furthermore, it utilizes Machine Learning, employing a CNN approach based on the YOLO V8 algorithm.

A. *Related Research*

1) A. Hermawan, L. Lianata, Junaedi, and A. R. K. Maranto, "Implementasi Machine Learning Sebagai Pengenal Nominal Uang Rupiah dengan Metode YOLOv3,". This research presents an application of currency denomination detection employing the YOLO version 3 (V3) methodology. The investigation involves the development of a mobile application designed for currency denomination detection. Despite achieving commendable accuracy, the device under consideration exhibits limitations, particularly in accessibility for the visually impaired and the complexity of navigation[3].

2) A. K. E. Lapian, S. R. U. A. Sompie, and Pinrolinvic D. K. Manembu, "You Only Look Once (YOLO) Implementation For Signature Pattern Classification,". This study focuses on detecting the authenticity of signatures through the utilization of machine learning techniques. There exists a necessity for the augmentation of datasets and the incorporation of precise signature resolutions to enhance the overall efficacy of the system[9].

3) S. Kudalkar, P. Patil, and N. Shirdhone, "Fake Currency Detection Using Image Processing,". This research endeavors to identify the legitimacy of currency through the application of image processing techniques. The process involves sequential stages, including grayscale conversion, edge detection, segment detection, feature extraction, and comparison. Despite these efforts, the average accuracy in currency recognition remains at 80%[10].

4) A. Bhatia, V. Kedia, A. Shroff, M. Kumar, B. K. Shah, and Aryan, "Fake Currency Detection with Machine Learning Algorithm and Image Processing,". This study employs deep learning for the detection of counterfeit currency. With a dataset comprising approximately 2000 samples, the model achieves a remarkable accuracy of 99.9%. However, the authors posit that further strides are required for real-world implementation, emphasizing the need for substantial additional datasets[11].

5) A. Antre, O. Kalbhor, P. Jagdale, and G. Dhanne, "Fake Currency Detection Using Convolution Neural Network,". This investigation leverages genuine and counterfeit Indian currency for analysis. Preprocessing steps involve the conversion of RGB images to grayscale, accompanied by Gaussian blur application for clarity enhancement. Despite achieving an accuracy rate of 97.72%, the study advocates for the incorporation of additional datasets and further refinement in the methodology[12].

Based on the literature review above, we observe the need for further modifications and optimization to enhance the accuracy level of the Indonesian Rupiah banknote detector.

Additionally, several studies mentioned above still rely on smartphones, which, in our view, may not be widely adopted by the visually impaired; instead, they often use canes. Image capture is conducted using a mobile phone camera, resulting in the partial visibility of currency details [13]. Moreover, all computations are performed on the smartphone, leading to a dependency on its specifications. Our strategy to improve accuracy involves the utilization of the latest YOLO algorithm and use a separate device for computing.

The YOLO (You Only Look Once) algorithm, first proposed by Redmon and his colleagues in 2016, is an object detection algorithm based on regression. YOLO divides the input image into grid cells of a certain size and predicts bounding boxes and class probabilities for each grid cell. By transforming object detection into a regression problem, YOLO can detect objects rapidly and accurately [14].

Hence, this study aims to elucidate how the utilization of CNN technology, specifically YOLO V8, in the development of the "All-in-one smart cane" can effectively address the challenges faced by visually impaired individuals in identifying and distinguishing Indonesian Rupiah denominations efficiently.

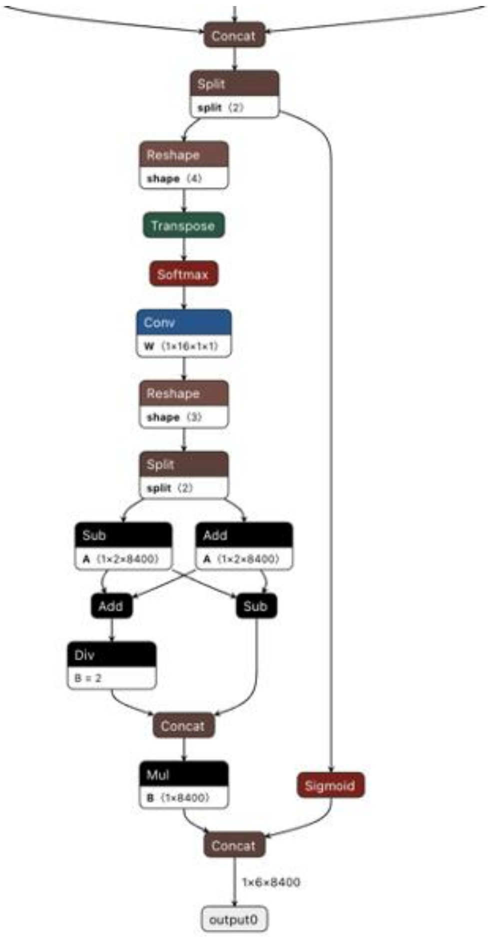

Figure 1 The Detection Head for YOLOv8

The YOLO (You Only Look Once) object detection framework has undergone continuous development and refinement, evolving from its first version (YOLOv1) to its latest iteration, YOLOv8, introduced in early 2023. YOLOv8 encompasses five distinct models: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, and it supports efficient API calls through the Python programming language.

YOLOv8 incorporates a Decoupled-Head architecture with separate computational branches to enhance its performance [15]. Data augmentation processes in YOLOv8 disable Mosaic Augmentation during the final 10 epochs, effectively improving its accuracy. The Classification loss is transformed into VFL Loss, and CIOU Loss is introduced alongside DFL (Distribution Focal Loss) as the regression loss function. YOLOv8 also replaces IOU matching or one-sided allocation with the Task-aligned approach.

These advancements in YOLOv8 represent a significant step forward in the field of object detection, offering enhanced accuracy and efficiency in object recognition tasks. The introduction of multiple model variants and API support in Python further contribute to its versatility and ease of use in various applications. The adoption of the Decoupled-Head architecture and innovative loss functions underscores the commitment to continually improve the YOLO framework's capabilities. As YOLOv8 continues to evolve, it promises to be a valuable tool for researchers and practitioners in computer vision and object detection.

2. RESEARCH METHOD

The stages undertaken in this research encompass data collection, data preparation, data labeling, device design, and testing.

2.1 Data Collection

The data utilized to support this research comprise images of Indonesian Rupiah banknotes issued from 2009 to 2023. These banknotes are categorized into seven denominations: Rp 1,000, Rp 2,000, Rp 5,000, Rp 10,000, Rp 20,000, Rp 50,000, and Rp 100,000. The dataset includes images of both sides of the banknotes, captured from various angles and rotations. In addition to the complete banknote images, the dataset has been modified by cropping only the nominal value areas. This modification was performed to enable the model training phase to better recognize the distinctive characteristics of each denomination.

Figure 2 Sample data rotated and flipped from various sides.

Figure 3 Sample crop yield data from each nominal.

2.2 Data Preparation

The data employed in this research comprise multiple classes. To facilitate data management and labeling, we opted to organize the data into seven distinct folders. Each folder is named based on the number of samples it contains, namely, 1000, 2000, 5000, 10000, 20000, 50000, and 100000.

This categorization process was executed meticulously, ensuring that each data sample corresponds to the quantity indicated by the folder's name. With this approach, we can readily identify and access data with specific sample counts.

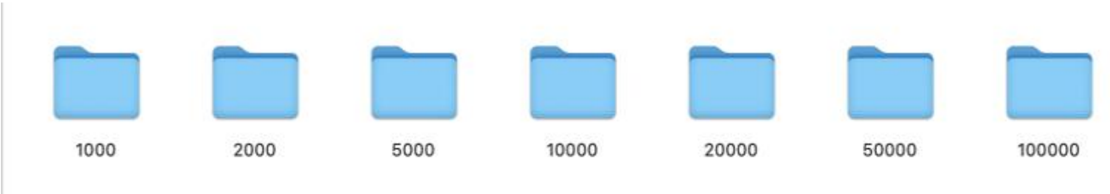

Figure 4 Folder of each image.

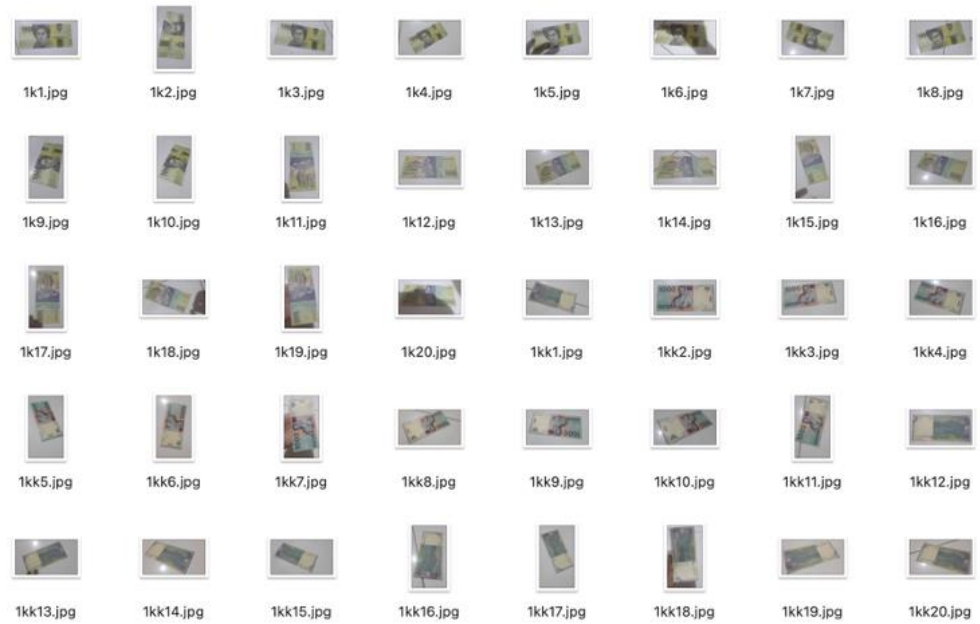

Figure 5 Sample dataset image.

2.3 Data Labeling

The labeling process was carried out manually, commencing with the identification of the object to be detected, which in this case, is currency within the images. Each image was analyzed individually. The regions containing currency within the images were recognized and enclosed within bounding boxes to distinguish them from the background. This process was executed meticulously to ensure that the desired currency objects were accurately encompassed within the bounding boxes.

After identifying and enclosing the currency objects within bounding boxes, the subsequent step involved labeling these objects. The labels assigned had to accurately represent the class of the detected object, which, in this context, is "currency." Each bounding box within the image was labeled as "currency" to signify that the object within it was the currency to be detected.

The outcome of the labeling process resulted in annotation files in the .txt format, conforming to the format required by YOLOv8. Each .txt file contained the coordinates of the bounding box and the label "currency" for each detected currency object within the image. This format was utilized in training the YOLOv8 object detection model.

Figure 6 Dataset labeling process.

Following the labeling process, the next step involved data preprocessing. At this stage, the dataset was divided into three folders: "train," "test," and "valid." The division was carried out using a scheme of 70% for the "train" folder, 20% for the "valid" folder, and 10% for the "test" folder. Data within the "train" folder, known as the training set, was used for training the model using the pre-trained YOLOv8 model. Subsequently, the data in the "valid" folder, referred to as the validation set, was employed to evaluate the performance of the created model. Lastly, the data within the "test" folder, designated as the testing set, served the purpose of testing the performance of the developed model.

2.4 Design and Device Development

2.4.1. Physical Design

The design of this device encompasses the use of a conventional folding cane for the visually impaired, onto which an acrylic case is mounted at the top to accommodate electronic components. The case is made transparent to allow visualization of the electronic devices contained within.

2.4.2 Electronic Components

- 10,000mAh 5V, 2.4A Power Bank: Utilized to provide power to the entire system and attached auxiliary devices.
- NVIDIA Jetson Nano: A mini-computer equipped with AI processing capabilities, used for object recognition and navigation.
- 720p 30fps HD Webcam: Employed to capture images and videos of the user's surrounding environment.
- Micro Speaker: Used as an audio output for recognizing Indonesian Rupiah currency denominations.

Figure 7 Jetson Nano: The mini-computer

2.4.3 3D Visualization

To streamline the design process and visualize how all components would be integrated into the casing, we employed 3D design software. This aided in spatial planning and establishing connectivity among the components.

Figure 8 3D Model Design

2.5 Device Testing

Performance testing was conducted to evaluate the effectiveness of the "All-in-One Smart White Cane," specifically employing the YOLOv8 (You Only Look One Level 8) algorithm. This assessment aimed to gauge the device's ability to facilitate the mobility of visually impaired individuals. Key parameters measured in these tests encompassed the exceptionally quick response time required by the YOLOv8 algorithm within the device to detect objects in the user's vicinity, along with the accuracy of object recognition. The results derived from these tests not only provide insights into the device's overall performance but also highlight the YOLOv8 algorithm's efficiency, particularly its swift response time, in enhancing the mobility and safety of users with special needs.

Figure 9 Webcam Detects Nominal Money

3. RESULT AND DISCUSSION

In the Rupiah banknote nominal detection system, various adjustments are applied to the dataset, including contrast adjustments and changes in object orientation variations. This process indirectly results in an increased dataset following the adjustments. Contrast adjustment is performed using histogram equalization. The results and discussion in the journal can elaborate on how these adjustments impact the performance of the detection system, enhance accuracy, and provide detailed insights into the effects of changes in orientation variations on detection outcomes.

Figure 10 Adjusting Contrast And Variability of Image Orientation

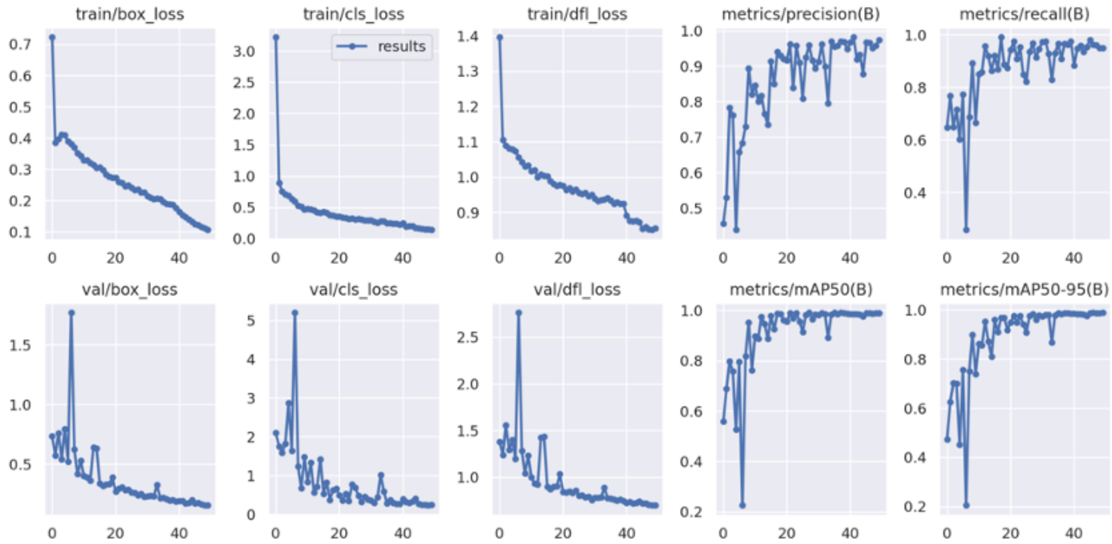

Figure 11 Training results using the YOLOv8 model

In this research, training was conducted using a pre-trained model from YOLOv8s with the configuration of epochs = 30 and optimizer = SGD. The image above illustrates the training results using the YOLOv8 model. It is evident that the recall metric shows improvement starting from epoch 20 onwards, while precision remains relatively stable between epochs 20 to 40.

In this study, the performance evaluation of the Rupiah currency detection model using YOLOv8 is elucidated through various metrics. Box Loss measures the accuracy of predicting bounding boxes, crucial in determining the location and size of the detected currency denomination. Class Loss assesses the model's ability to predict object classes, representing different currency denominations in this context. DFL Loss gauges how well the model predicts the probability distribution of objects, particularly in detecting the likelihood of accurately identifying currency denominations. Graphs illustrate that the values of Box Loss, Class Loss, and DFL Loss tend to decrease with increasing epochs, indicating an improvement in the model's performance in predicting the location, type, and probability of currency detection. Precision and recall also exhibit improvement with increasing epochs, indicating that the model continues to learn and enhance the accuracy of object detection. Additionally, the values of mAP50 and mAP50-95 consistently show improvement in detection performance, even for small-sized objects or in complex environments. These findings depict that YOLOv8 holds practical potential for assisting visually impaired individuals in accurately identifying currency denominations with high precision.

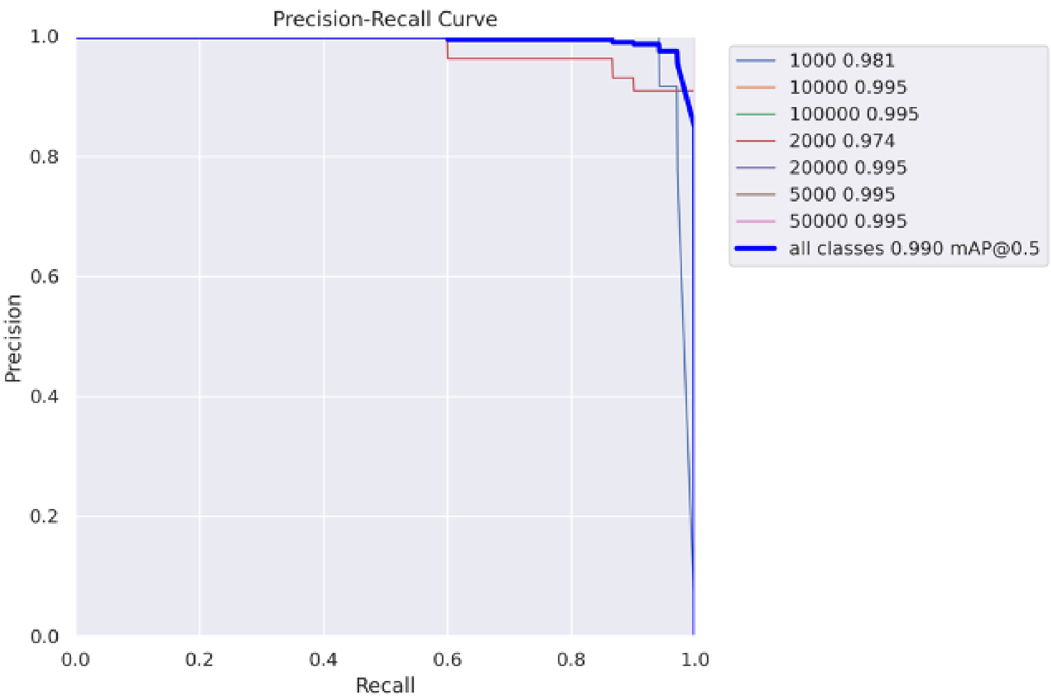

Figure 12 Precision-Recall (PR) Curve

The Precision-Recall (PR) curve is a visual tool used for evaluating the performance of a classification model, especially when dealing with imbalanced datasets. The PR curve depicts how precision and recall change as the model's decision threshold is adjusted. In this study, the PR Curve on the validation set demonstrates an overall average value of 99%, with the highest values observed in classes 10,000, 100,000, 20,000, 5,000, and 50,000 at 99.5%, and the lowest value in the 2,000 class at 97.4%.

These evaluation metrics provide insights into the model's ability to effectively classify and recognize different Indonesian Rupiah currency denominations. The PR curve, in particular, illustrates the model's precision and recall performance across various currency classes, highlighting its robustness and accuracy in handling imbalanced datasets.

4. CONCLUSION

The YOLOv8 model proves to be well-suited for training on Indonesian Rupiah currency datasets and can be implemented into a white cane device, creating a novel product that aids visually impaired individuals in recognizing currency denominations by providing auditory feedback. With the utilization of adequate datasets and careful training, this model delivers accurate results. However, while YOLOv8 excels in currency detection, it still faces challenges when dealing with backgrounds that closely resemble the currency's color. This suggests that further improvements in image processing or pre-detection processing may be necessary to reduce identification errors. The performance of the YOLOv8 model in terms of accuracy can be enhanced through various methods such as fine-tuning, data augmentation, or exploring more advanced model architectures. Continuous testing and model refinement will remain interesting areas of research.

The integration of YOLOv8 into a white cane device opens up possibilities for greater independence and empowerment for the visually impaired community. As technology continues to advance, refining this solution will contribute to improving the quality of life for individuals with visual impairments.

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