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Personality Recognition Based on Palmistry Using Deep Learning YOLOv5 and YOLO-NAS

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Abstract (10pt)

As an intangible cultural heritage and traditional belief system, palmistry has been conventionally utilized as a medium to understand human personality. However, its interpretation remains subjective and manual, while previous digital studies have been restricted to single-object recognition. This study aims to develop an automated multi-object recognition system for palmistry features, which include palmar lines, mounts, fingers, and hand types, by employing YOLOv5 (anchor-based) and YOLO-NAS (anchor-free) architectures under the constraint of a small-scale dataset. The research phases encompass data selection integrated with data augmentation, bounding box annotation, data splitting, as well as model training and testing evaluated using Mean Average Precision (mAP), precision, and recall metrics. Experimental results demonstrate that YOLOv5 outperforms YOLO-NAS under limited data conditions, achieving a precision of 0.800 and an mAP of 0.846, compared to YOLO-NAS which yields a precision of 0.104 and an mAP of 0.603. Conversely, YOLO-NAS records a higher recall of 0.894. The imbalance between the recall and precision values in YOLO-NAS is primarily influenced by the limited training samples and the implementation of int8 quantization techniques. This study contributes by establishing the efficiency boundaries of deep learning architectures for the digitalization of cultural heritage based on limited datasets.

1. Introduction

Personality is defined as a set of unique characteristics that distinguish one individual from another [1], [2]. Variations in these patterns are driven by the interaction between internal and external factors, encompassing cognitive, emotional, and behavioral aspects influenced by genetic determinants, accumulated experiences, and life course dynamics[3]. A profound understanding of personality types

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significantly contributes to strategic decision-making, including career path selection, determination of effective learning methods, and development of social relationships. By appropriately considering personality aspects, individuals can optimize their potential for success while mitigating the risk of future adverse outcomes.

As an intangible cultural heritage and a universal traditional belief system, the hand is frequently believed to be a representation or map of a person's mind. This tenet serves as a fundamental belief in palmistry, wherein personality characteristics such as traits, potential, strengths, and weaknesses can be identified through pattern recognition on the palm [4]. Palmistry is referred to as a universal language because its system of meaning originates directly from the patterns or marks inherent in human anatomy. Consequently, its interpretation is not influenced by regional, tribal, racial, or national boundaries that differentiate specific human groups. The structures of the hand that contain cultural meaning in palmistry include hand shapes, fingers, nails, mounts (palmar mounds), skin color, and the major lines of the palm.

Research in the field of digital palmistry has advanced to encompass disease identification, personality analysis, and palmar main line detection. Health diagnosis, for instance, has been conducted utilizing Image Matching Techniques [5] and the IPAA (Image Processing and Analysis) Framework [6]. On the other hand, digital image processing and Deep Learning have begun to be applied to recognize personality based on the four elements of hand types (Fire, Water, Air, and Earth) using Convolutional Neural Network (CNN) algorithms [7]. For main line detection requirements, Deep Neural Network (DNN) methods have also been developed through U-Net Segmentation architectures combined with Attention Mechanisms and Context Fusion Models [8]. However, the implementation of Deep Learning in previous studies has generally remained restricted to single-object recognition [9]. Furthermore, conventional CNN-based architectures typically demand computational resources that tend to be complex, thereby frequently presenting technical constraints when implemented on devices with limited hardware specifications [10], [11], [12].

This study explores pattern recognition in palmistry as an alternative means to understand culturally based individual personality characteristics. The selection of hand patterns as the basis for recognition is motivated by their feature characteristics, which have proven to be more stable and consistent compared to facial features or visual image preferences that tended to fluctuate in several previous studies. To overcome the limitations of single-object recognition, this research proposes the development of a simultaneous multi-class recognition system to detect various major palmistry features concurrently. This comparative study approach is implemented using two modern object detection architectures with differing philosophies, namely the anchor-based YOLOv5 and the anchor-free YOLO-NAS, under the performance testing challenge of a small-scale dataset.

2. Literature Review

Research on personality identification through image and video media has explored the use of facial objects and aesthetic preferences in images. These studies generally refer to the Big Five Personality theory by implementing various Deep Learning architectures. Specifically, face-based personality recognition utilizes LSTM, VGG16, and AlexNet methods [13], [14], while the Resnet50 architecture is applied for joint analysis of faces and image preferences [14], [15]. However, the use of these two objects has significant weaknesses: facial expressions are temporal and can change with emotional fluctuations. At the same time, aesthetic preferences are often subjective and inconsistent, potentially introducing bias into personality assessments.

The proposed novelty lies in combining various palmistry objects through multiclass recognition and object area detection using a more computationally efficient Deep Learning architecture. The analysis is performed by aligning hand patterns—such as hand type, lines, Mounts, and fingers—with the five basic dimensions in the Big Five Personality framework [1], [2].

Deep Learning's ability to extract knowledge and recognize patterns is effective across complex domains [16], [17], [18], [19], [20], particularly in object identification tasks [21], [22], [23], [24], [25]This study uses the YOLOV5 and YOLO-NAS architectures, which are real-time single-stage object detection methods, to efficiently detect various object classes [26]. As an extension of the YOLO architecture, YOLOV5 offers improved feature quality and accuracy while maintaining lower computational complexity [27]. At the same time, YOLO-NAS provides a more efficient model size, making it suitable for implementation on devices with limited specifications. The effectiveness of these two models has been demonstrated in various studies, particularly in terms of processing speed and flexibility when implemented on devices with limited resources [28], [29], [30]. The integration of these technologies aims to generate personality information from hand patterns (Palmistry) and the Big Five Personality framework using a more efficient multi-class object recognition system.

This study focused on two methods, YOLOv5 and YOLO-NAS, used for palm pattern identification. Besides palms, YOLOv5 has been widely used for object detection. Object detection utilizing the YOLOv5 method is used for the purpose of identifying fungi growing on the surface of various foods [31], detecting defects in solar cells [32], detecting garbage [33], detecting the use of safety helmets by construction workers[34], identifying vehicles in various weather [35], and object detection or detection of safe landing sites (safety support) for Unmanned Aerial Vehicles (UAVs) [36]. The application of YOLOv5 for defect detection in solar cells is enhanced by the Deformable Convolutional CSP Module, the ECA-Net attention mechanism, improved network structure, and the addition of a prediction head to enhance feature extraction, enabling defect detection at various scales. Data quality improvement is achieved through Mosaic and MixUp Scale Fusion, the K-means++ clustering anchor box algorithm, and multi-model integration methods, with model optimization performed via method calls. The performance of the YOLOv5 method for waste detection is supported by training on the PlastOPol dataset (a dataset comprising various types and sizes of annotated waste, with backgrounds such as roads, forests, beaches, and others). The method is still constrained by objects with complex natural backgrounds and very small waste sizes. The performance of YOLOv5 for landing site detection (UAV) is supported by the use of bounding box auto learning, Darknet53 (on CSPDarknet53), bag of freebies, bag of specials, and mosaic data augmentation. The applied YOLOv5 method is also compared with several CNN-based methods, including the previous version of YOLO. The comparison methods used include YOLOv3, YOLOv4, RetinaNet, Faster R-CNN, Mask R-CNN, and EfficientDet-d5. The YOLOv3 and YOLOv4 methods are applied to identify mold on food surfaces, detect defects in solar cells (by adding the SSD and FasterRCNN methods), and detect landing sites for UAVs. RetinaNet, Faster R-CNN, Mask R-CNN, and EfficientDet-d methods were applied for garbage detection. Testing showed the highest accuracy, namely in the use of YOLOv5 with mAP reaching 99.60% for mushroom identification, 89.64% for defects in solar cells (competitive speed with the SSD Method and higher than other methods, reaching 36.24 FPS), 63.3% for landing site detection (UAV), and AP of 84.9% for garbage detection (YOLO-v5s is 4.87 times, 5.31 times, 6.05 times, and 13.38 times faster than RetinaNet, Faster R-CNN, Mask R-CNN and EfficientDet-d5, respectively).

The use of NAS (Neural Architecture Search), also known as YOLO-NAS, in YOLO for image object detection has been discussed in several studies. The object detection studied includes building detection, hand and joint fracture detection, vehicle license plate detection, and fire detection. Building object detection is performed on large-scale satellite imagery using the Hybrid BBD (Buildings boundary detection) method, which is proposed as a remote sensing application, accompanied by geolocation of buildings and their boundaries on Earth [37]. Building detection in the proposed BBD method utilizes the open-source software GeoServer and TileCache to process large amounts of satellite imagery that cannot be analyzed with classical data processing techniques. Deep Learning methods used in the BBD method include YOLOv5, DETR, and YOLO-NAS. SAM is used for segmentation in the BBD technique, and the performance of the RefineNet model is also evaluated. The effectiveness of building and boundary detection is influenced by the initial object detection performance of the Deep Learning method used. The proposed fine-tuning improves the performance of the modified YOLOv5, DETR, YOLO-NAS, and RefineNet models, achieving F1 scores of 0.883, 0.772, 0.975, and 0.932, respectively. The modified YOLO-NAS approach is the one that detects the most objects, with an F1 score of 0.975. The YOLO-NAS-SAM approach for building boundary detection achieves an IoU of 0.912.

3. Method

The proposed personality recognition system comprises several integrated steps, as depicted in Figure 1. The stages in the system development process are as follows:

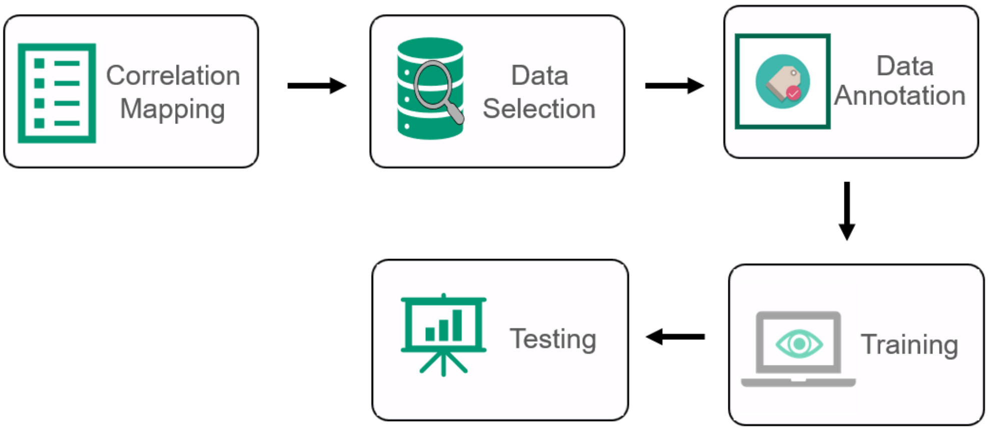

Figure 1. Workflow of the developed palmistry-based personality recognition system

The correlation mapping phase was established to construct a systematic and logical relational framework between the physical features of the palm and human psychological dimensions. In this phase, causal relationships were mapped between specific palmistry objects serving as the classification inputs and the five dimensions of the Big Five Personality Traits, which include Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, as the target outputs.

Data selection was performed to construct a dataset comprising hand types, little fingers, Lower Mars mounts, and hand lines (frequency and Saturn) from human palms. The hand images were sourced from the 11k Hands Dataset [38], the Birjand University Mobile Palmprint Database (BMPD) [39], and the COEP Palm Print Database [40]. This dataset consists of five object categories across 11 classes, totaling 142 images with an aggregate of 608 annotations. These eleven classes encompass Water, Fire, Earth, Air, Low Lower Mars, High Lower Mars, Short Mercury Finger, Long Mercury Finger, Saturn Line, Few Lines, and Many Lines. Finally, several data augmentation techniques, such as vertical and horizontal flips and saturation modifications, were applied to the dataset. For model evaluation, these images were partitioned into an 80:20 ratio, resulting in approximately 114 training samples and 28 test samples. The detailed breakdown of this dataset splitting is presented in Table 1.

Tabel 1. Data splitting

Palmistry Object	Class	Total	Train	Validation
Hand Type	Water	27	22	5
	Fire	49	39	10
	Earth	46	36	10
	Air	20	17	3
Lower Mars Mount	Low Lower Mars	73	60	13
	High Lower Mars	69	54	15
Line Frequency	Many Lines	99	79	20
	Few Lines	43	35	8
Little Finger	Short Mercury Finger	71	56	15
	Long Mercury Finger	71	58	13
Saturn Line	Saturn	40	33	7

The Image Annotation stage is used to create image labels by marking pixel regions. Each object is marked by creating a pixel region boundary called a bounding box. Annotation is performed for each class of hand object used.

The training phase produces a model capable of recognizing hand patterns based on palmistry. The training uses a deep learning-based object recognition method applied to training data images. The methods used are YOLOV5 and YOLO-NAS. Model training and development were conducted on the Google Colab platform utilizing an NVIDIA T4 GPU. Both the YOLOv5 and YOLO-NAS architectures were initialized with pre-trained weights. The applied hyperparameter configuration consisted of a learning rate of 0.01, a batch size of 16, and a training duration of 300 epochs. The training images are labeled with pattern categories corresponding to palmistry patterns.

The testing phase consists of model testing and application testing. Model testing is conducted using test data generated in the training phase, based on the hand patterns used in this study. The hand recognition results consist of classes and bounding boxes based on the palmistry patterns used. Model testing aims to determine the model's ability to recognize palmistry patterns. The measurement metrics used for evaluation include mAP, Precision, and Recall.|

4. Results and Discussion

This section presents the results obtained from the palmistry object mapping process and discusses their relationship with the Big Five Personality dimensions. The analysis begins with the classification and characterization of palmistry-related hand objects used as input features in this study.

4.1. Mapping of Palmistry Object Data and Big Five Personality

Palm object data used in this study consists of hand type, Mars Mount, little finger, Saturn Line, and Many/Few Lines (fine). Hand type data consists of four classes, namely Water, Fire, Earth, and Air Types. Mars Mount consists of two classes, namely hands with a fairly high Low Mars Mount and a lower Mars Mount. The little finger feature comprises two distinct classes, namely the long and short Mercury fingers. The object data for Saturn Line consists of one class, namely hand data with Saturn Line. Hand Objects related to the frequency of hand lines (many/few) consist of two classes, namely classes with many lines and few lines (fine lines).

The Palmistry-related hand object patterns used in this study are related to the personality dimensions [2] of the Big Five Personality, as shown in Table 2. The hand object patterns [4], consisting of hand type, Mars Mount, little finger, Saturn Line, and hand frequency, are related to five personality dimensions: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. A relationship is formed between each class of Palmistry-related hand objects used with the personality dimensions of the Big Five Personality.

Table 2. Mapping each class (palmistry) with the big five personality

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Fire			+	-	
Water	-	-	-	+	+
Earth	-	+			
Air	+	+	+		
Many Lines	-	-	-	+	+
Few Lines			+		-
Saturn Line		+			
Long Mercury Finger	+				-
Short Mercury Finger	-				+
High Lower Mars		+	+	-	
Low Lower Mars		-	-	+	

Hand patterns for hand-type objects consist of four classes, namely Water, Fire, Earth, and Air, related to the five personality dimensions. Water Hand Type is related to relatively high Agreeableness and Neuroticism personality dimensions, while the personality dimensions of Openness, Conscientiousness, and Extraversion are relatively low. Fire Hand Type is related to relatively high Extraversion personality dimensions and relatively low Agreeableness personality dimensions. Earth Hand Type is related to relatively high Conscientiousness personality and relatively low Openness personality. Air Hand Type is related to relatively high Openness, Conscientiousness, and Extraversion personality and relatively low Neuroticism personality. Patterns for Low Mars Mount Objects consist of two classes, namely High and Low, related to the personality dimensions of Conscientiousness, Extraversion, and Agreeableness. The levels of Conscientiousness and Extraversion are relatively high, while the levels of Agreeableness are relatively low for High Low Mars Mount. The levels of Conscientiousness and Extraversion are relatively low, while the levels of Agreeableness are relatively high for low Low Mars Mount. The pattern for the little finger object is related to the personality dimensions of Openness and Neuroticism. A relatively high level of Openness and a relatively low level of Neuroticism are found for long, little fingers.

In contrast, a relatively low level of Openness and a relatively high level of Neuroticism are found for short little fingers. The relationship formed for the pattern on the Saturn Line object is that the Conscientiousness level is relatively high for hands with Saturn Lines, and relatively low for hands without Saturn Lines. The pattern related to the line frequency object consists of the Few Line Class and Many/Fine Lines) is related to the five personality dimensions. The levels of Agreeableness and Neuroticism are relatively high, while the levels of Openness, Conscientiousness, and Extraversion are relatively low for many (fine) lines. The level of Extraversion is relatively high, while the level of Neuroticism is relatively low for a few lines.

4.2. The Image Annotation

The annotation process was based on identifying five distinct hand features: Line Frequency, Hand Type, Saturn Lines, Low Mars Mount, and Little Fingers [41].

Figure 2. Image annotation process result [38]

Figure 2. illustrates an example of these results, specifically displaying the annotations for Line Frequency and the Little Finger. In the visual, the Line Frequency is highlighted directly on the palm, while the Little Finger annotation covers both the tip of the pinky and the uppermost joint of the ring finger.

4.3. Test Result using YOLOv5

The test results obtained using the YOLOv5 Method for all objects (Line Frequency, Saturn Line, Hand Type, Mars Low Mount, and Little Finger) are a precision of 0.8, a recall of 0.767, an mAP50 of 0.846, and an mAP50-95 of 0.563. The evaluation results, in the form of loss graphs (box loss, object loss, and class loss) and metrics (precision, recall, mAP50, and mAP50-95), are shown in Figure 3. The loss rate tends to decrease, while the precision, recall, and mAP rates tend to increase as the number of epochs increases and tend to be stable at 300 epochs. Changes in the measurement results obtained indicate progress or improvement in the learning process.

The confusion matrix obtained from the test results is shown in Figure 4. The highest recognition result was obtained for the Low Mars Mount Object in the Low Mars Mount Class of 0.92. The lowest recognition result was for the Air Class in the Hand Type Object of 0.33. The recognition results for other classes were the Many Lines Class in the Line Frequency Object of 0.90, the Long Little Finger Class for the Mercury Object of 0.82, the Water Class, Earth for the Hand Type Object, the High Low Mars Class for the Low Mars Mount Object of 80%, the Short Little Finger Class for the Little Finger Object of 0.75, the Few Lines Class for the Line Frequency Object of 0.62, the Saturn Class of 0.57, and the Fire Class for the Hand Type of 0.4.

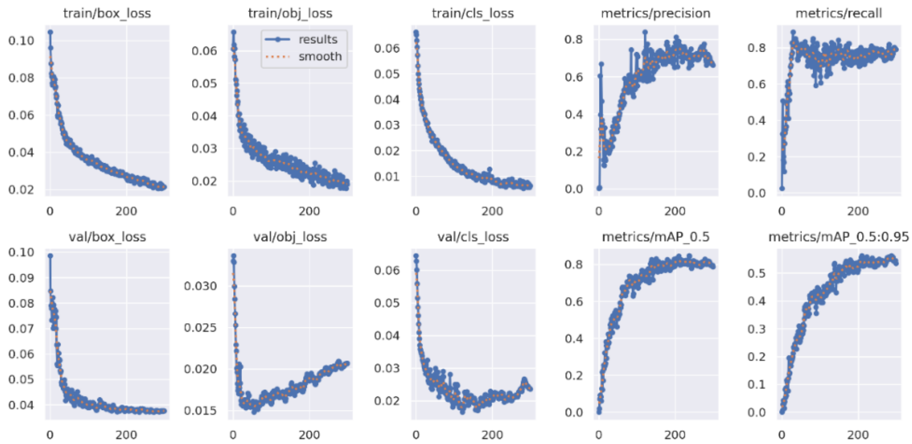

Figure 3. Loss and metric graphs for training and testing on all objects

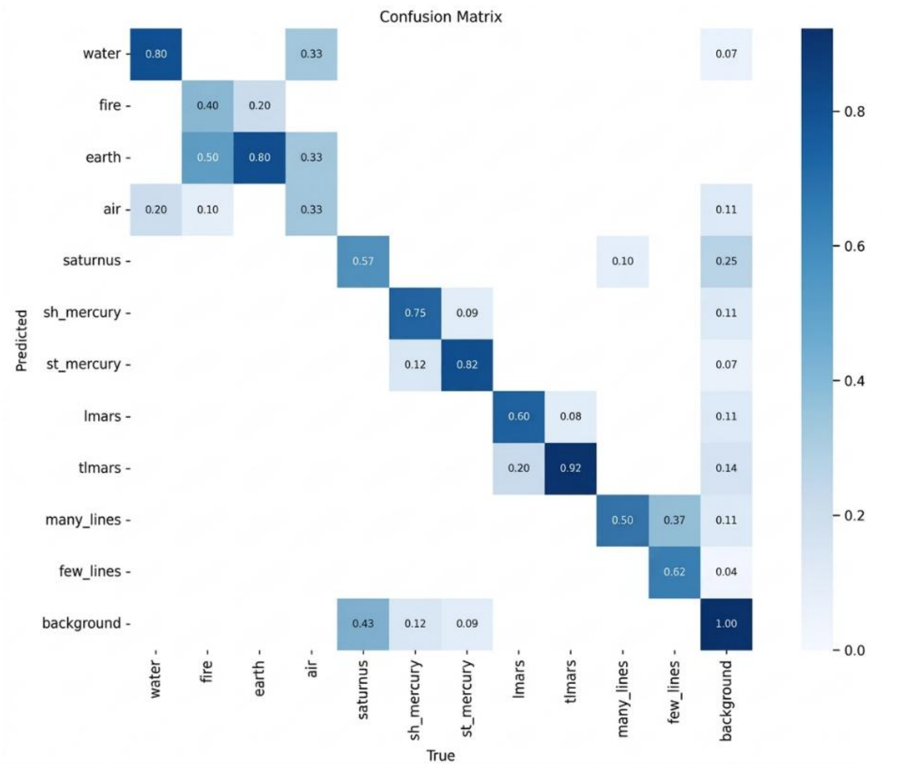

Figure 4. Confusion matrix for testing all object data

The mAP values for each class during model testing using the YOLOv5 method are shown in Figure 5. The mAP value for all classes obtained based on the Precision-Recall Curve reached 0.846. The highest mAP value based on the Precision-Recall Curve was 0.995 for the Water and Air Classes in the Hand Type Object. The test results showed the lowest mAP value for the Short Little Finger Class, which is 0.632.

Other mAP results are Low Mars Low Class of 0.938, A lot of Lines Class of 0.918, Few Lines Class of 0.894, Long Little Finger Class of 0.871, High Mars Low Class of 0.819, Fire Class of 0.742, and Saturn Class of 0.653.

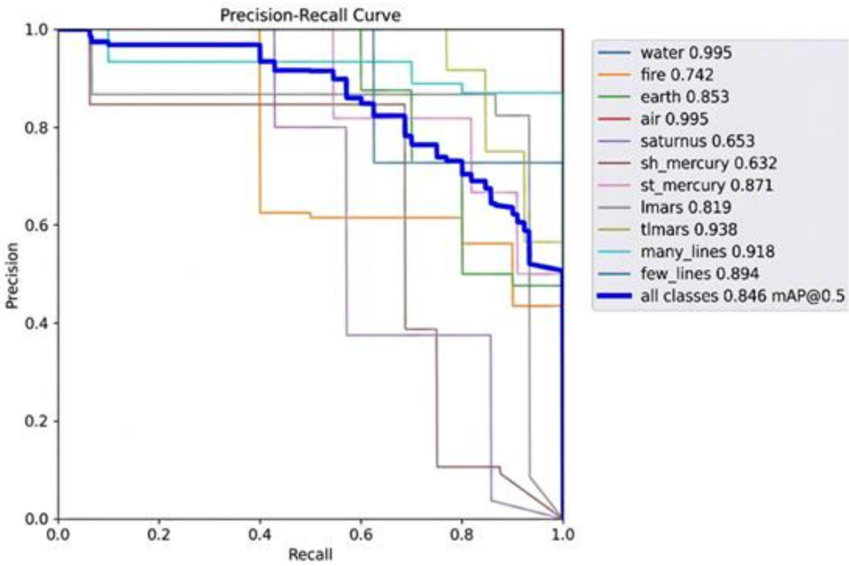

Figure 5. Precision-Recall Curve graph for each class and overall for all objects.

4.4. Comparison of Test Results Using YOLOv5 and YOLO-NAS

Hand object pattern recognition was also performed using the YOLO-NAS method. Figure 6. shows the test results obtained using the YOLO-NAS method. The results were an mAP value of 0.603, Precision 0.104, and Recall 0.894. Comparison of mAP values obtained using the YOLOv5 and YOLO-NAS methods can be seen in Figure 7.

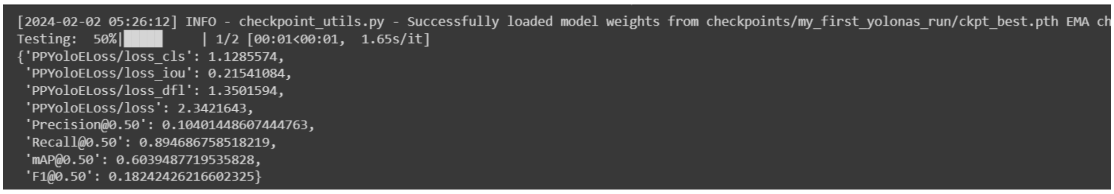
```
[2024-02-02 05:26:12] INFO - checkpoint_utils.py - Successfully loaded model weights from checkpoints/my_first_yolonas_run/ckpt_best.pth EMA ch
Testing:  50%|█████     | 1/2 [00:01<00:01,  1.65s/it]
{'PPYoloELoss/loss_cls': 1.1285574,
 'PPYoloELoss/loss_iou': 0.21541084,
 'PPYoloELoss/loss_dfl': 1.3501594,
 'PPYoloELoss/loss': 2.3421643,
 'Precision@0.50': 0.10401448607444763,
 'Recall@0.50': 0.894686758518219,
 'mAP@0.50': 0.6039487719535828,
 'F1@0.50': 0.18242426216602325}
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Figure 6. YOLO-NAS method test results

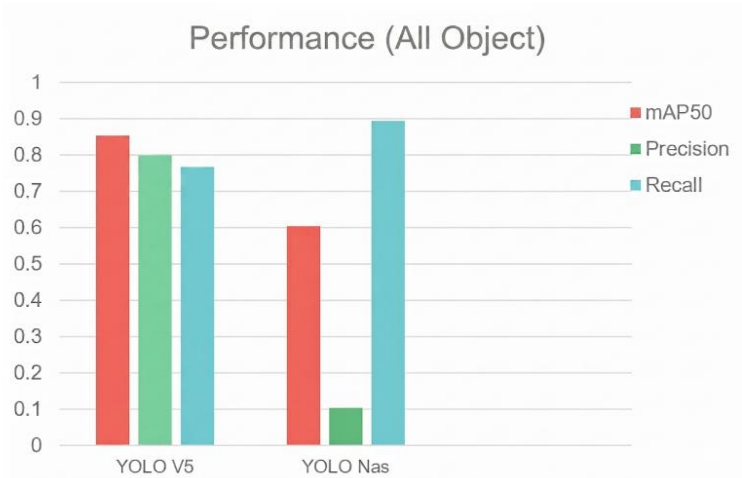

Figure 7. Comparison of test results of YOLOv5 and YOLO-NAS methods

YOLOv5 demonstrates significantly superior overall performance, with an mAP50 value of around 0.85. This indicates excellent and consistent overall detection capability (both localization and object classification) at an Intersection over Union (IoU) threshold of 0.5. YOLO-NAS recorded a lower mAP50, around 0.60. This significant decrease in average accuracy is directly influenced by the extreme imbalance between their Precision and Recall values.

In terms of Precision, YOLOv5 has a high precision level of 0.80. This value indicates that when YOLOv5 predicts the presence of an object, the probability of the prediction being correct reaches 80%. The case of false positives (incorrectly detecting the background or another class as the target object) is relatively low. YOLO-NAS experienced a very drastic performance decline in this aspect, with a precision value of only around 0.10. This indicates very high false-positive interference. This model very often predicts detections that actually do not exist or incorrectly classifies objects. In terms of Recall, YOLO-NAS outperforms YOLOv5, with a score of around 0.89 compared to YOLOv5's 0.77. The Recall value of 89% indicates that YOLO-NAS is highly sensitive and can find almost all target objects in the test dataset (minimizing false negatives and missed objects).

The phenomenon of metric-value disparity in YOLO-NAS (very high Recall but very low Precision) offers an interesting technical picture to analyze. The imbalance in the results is influenced by the use of the Quantization Technique in YOLO-NAS, which transforms model weights to int8 with lower precision, thereby reducing model size and processing/inference time, but can also decrease Precision. The YOLO-NAS model in this test acted very sensitively in making bounding box predictions. Because its main priority was not to miss any objects (resulting in high Recall), this model ultimately lowered its internal confidence threshold. As a result, many empty or noisy areas were incorrectly detected as objects, directly reducing the Precision to 10%. YOLOv5 managed to maintain excellent harmonization between Precision (80%) and Recall (77%). This balance makes the F1-Score (harmonic mean of Precision and Recall) of YOLOv5 far exceed that of YOLO-NAS, resulting in a solid mAP50 of 0.85.

5. Conclusion

Personality recognition in this study is carried out based on Palmistry and Big Five Personality object recognition. The methods used are YOLOv5 and YOLO-NAS. Objects are recognized in a multi-class manner, accompanied by object area localization. The method is implemented by first mapping Palmistry object data and Big Five Personality, and then the annotation stage is used to create image labels by marking pixel regions. After the testing process, YOLOv5 shows the best overall performance, especially on all objects, with an mAP50 of 0.85 and a Recall of 0.77. Although YOLO-NAS achieves the highest Recall of 0.89 on the same dataset, this is not linear, with a very low Precision of 0.10. The success of this detailed palm feature recognition and localization sets a more objective standard for identifying structural traits that previously relied on subjective human expertise.

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Credit Authorship Contribution Statement

In this research article, the author's contributions are as follows: Conceptualization, **Dwi Rusjayanthi** and **Darma Putra**; methodology, **Dwi Rusjayanthi**; software, **Dwi Rusjayanthi**, **Oka Sudana**; validation, **Dwi Rusjayanthi** and **Oka Sudana**; formal analysis, **Dwi Rusjayanthi**, **Oka Sudana**; investigation, **Darma Putra**, **Made Sudarma** and **Oka Sudana**; resources, **Dwi Rusjayanthi**; data curation, **Dwi Rusjayanthi** and **Darma Putra**; writing—original draft preparation, **Dwi Rusjayanthi**, **I Made Sunia Raharja**; writing—review and editing, **Dwi Rusjayanthi**, **Made Sudarma** and **Oka Sudana**; visualization, **Dwi Rusjayanthi**; supervision, **Darma Putra**, **Made Sudarma** and **Oka Sudana**; project administration, **Dwi Rusjayanthi**; funding acquisition, **Dwi Rusjayanthi**.

Declaration Of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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