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Detection of Hijaiyah Letters Handwritten in Early Childhood Using Yolo V8

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Abstract

This study investigates the effectiveness of the YOLOv8 (You Only Look Once version 8) algorithm in detecting handwritten Hijaiyah letters among early childhood learners. The introduction of technology in early childhood education is essential for enhancing literacy skills, particularly in learning the Arabic alphabet, which is crucial for reading the Quran. This research addresses the challenges faced by educators in assessing children's handwriting, which often lacks consistency and objectivity. A dataset of 3,780 images of handwritten Hijaiyah letters was collected from children at RA BAIPAS Roudlotul Jannah, including various writing styles to ensure the model's robustness. Prior to training, the images underwent preprocessing steps such as resizing, normalization, and data augmentation techniques like rotation and flipping to enhance the quality and diversity of the training data. The YOLOv8 model was trained using an 80-10-10 split for training, validation, and testing datasets. Evaluation metrics such as precision, recall, and mean Average Precision (mAP) were used. The results showed that YOLOv8 achieved an impressive accuracy of 96.08% in detecting handwritten Hijaiyah letters, with high precision and recall rates further validating the model's reliability. This research highlights the potential of integrating advanced object detection algorithms like YOLOv8 into educational practices. By providing real-time feedback, the system can significantly enhance the learning experience for young children, facilitating their understanding and mastery of the Arabic alphabet. Future research should focus on expanding the dataset and refining the model to address handwriting variability challenges and improve accuracy.

Keywords: *Arabic alphabet, early childhood education, handwriting recognition, Hijaiyah letters, object detection, and YOLO.*

I. Introduction

The hijaiyah letter is a letter to arrange 28 words in Arabic with different forms [1]. However, there are other sources that mention it with other numbers. Among them, there are 28 and 30 [2]. Including Lamalif, which some people consider to be a different letter [3]. So that without Lamalif the total number is 29 hijaiyah letters. In addition, the generally accepted count, excludes Lamalif and combines Alif with Hamzah [4]. So some sources dispute this calculation, emphasizing the complexity of the Arabic script [5] . The letter begins with Alif and ends with Ya. Hijaiyah letters are also an integral part of the Quran, both as a basis for reading it and understanding its contents [6]. Therefore, learning, memorizing, and understanding hijaiyah letters is the first stage to be able to read and understand the Quran.

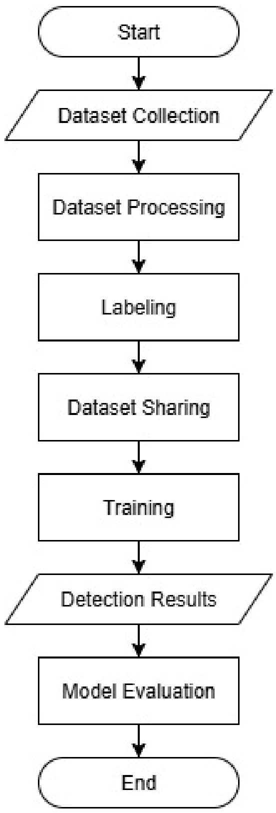
However, not everyone can immediately know and understand the basic science of the Quran, namely hijaiyah letters, especially Early Childhood in kindergarten, namely RA BAIPAS Roudlotul Jannah. They generally do not know the shape, how to read, and how to write all the hijaiyah letters properly and correctly. Understanding the cognitive development stage of children is very important to adjust the teaching method. The learning process involves recognizing letter shapes, understanding simple words, and reading the signs of the letters [7].

Then there are obstacles when what is assessed is the results of children's handwriting work, for example on the object of handwriting hijaiyah letters of the work / work of early childhood. Subjectively humans are able to provide an assessment of the work but there are times when it is less consistent and difficult to determine with certainty the level of similarity of hijaiyah letter handwriting to the hijaiyah letters used as a reference [4]. However, while automated systems can improve accuracy, they may not fully capture the nuances of individual handwriting styles, which remain important in evaluating children's learning progress.

One solution to maximize the learning process and useful for teachers to make it easier to correct the handwriting of the hijaiyah letters of their students is to use object detection [8]. This research tries to develop object detection of hijaiyah letter writing in early childhood, one of which is the application of object detection, especially using the YOLO (You Only Look Once) method, can significantly improve the learning process to recognize hijaiyah letters in early childhood education [9],[15]. The detection system using YOLO is proven to be faster and more accurate to detect an object in an image or image so that it is most suitable if applied to the case taken by the researcher [10]. Using object detection can help teachers in recognizing and distinguishing each of the 30 hijaiyah letters that a person will learn.

II. Methods

This chapter will discuss the methods used in the process of detecting children's handwritten hijaiyah letters. This research method is a method used to detect early childhood handwritten hijaiyah letter objects using YOLOV8. This research uses a quantitative approach with an experimental design that aims to test the effectiveness of the Hijaiyah letter detection system. In this research design stage, it is presented in the flowchart illustration in Figure 1. The steps are carried out sequentially in order to get maximum results in writing the final report.



. Figure 1. Research design.
(Source: Personal Preparation)

The image above illustrates the step-by-step process involved in building and training a model to recognize handwritten Hijaiyah letters.

1. **Dataset Retrieval**
   The first step is the retrieval of datasets, which involves taking photographs of early childhood handwritten Hijaiyah letters using a printer scanner. The dataset, consisting of 3,780 images, is categorized into 30 classes, with each class containing 126 images of different Hijaiyah letters. These images serve as the training samples for the system being built.
2. **Data Preprocessing**
   Once the dataset is collected, it goes through a preprocessing stage. During this stage, the images are resized to ensure consistency in dimensions across the entire dataset. This step is critical for optimizing the images and ensuring that they meet the input requirements of the model being trained. Consistent image size allows the model to process and learn from the data efficiently.
3. **Labeling Dataset**
   The next step is labeling the dataset, which involves marking each image with a bounding box using labeling software. This step is essential for training the model to recognize the objects (in this case, Hijaiyah letters) within the images. Each bounding box represents the object in the image, allowing the system to identify and classify it accurately.
4. **Split Dataset**
   After labeling the dataset, the data is divided into three parts: training data, validation data, and testing data. The training data is used to train the model, while the validation data is utilized to evaluate the model's performance during training. The testing data, which has never been seen by the model before, is used to assess the model's ability to generalize and perform accurately on new, unseen data.
5. **Training**
   At this stage, the divided data—training and testing—are accessed through an API in Google Colab. The model is trained using the YOLOv8 algorithm, with accuracy being the primary parameter for evaluating performance. If the initial test results show low accuracy, retraining is performed. This retraining aims to optimize the model to improve its accuracy and overall prediction capability.
6. **Detection Result**
   The detection process begins by feeding the collected images into the system, which uses the YOLOv8 algorithm to analyze the images and recognize objects. The model then marks the detected objects with bounding boxes, providing a clear distinction between the objects and the background. The output of this process is an accuracy score, which reflects how well the model is able to identify the objects within the images.
7. **Model Evaluation**
   Finally, the model's performance is evaluated based on its ability to recognize Hijaiyah letters in previously unseen images. Evaluation metrics include the detection accuracy, inference time, and other relevant parameters that measure the effectiveness of the model. This evaluation ensures that the model performs well in recognizing objects under real-world conditions.

III. Results and Discussions

The results of this study explain the object detection of early childhood handwritten hijaiyah letters using YOLOV8. With this discussion, it can be seen the success in detecting children's handwriting objects. Datasets that have been labeled will be resized and divided into 3 types of data, namely 80% train data, 10% valid data and 10% test data. to facilitate the author in dividing label data quickly without having to sort out one by one [12]. The dataset sharing process is shown in Figure 2.

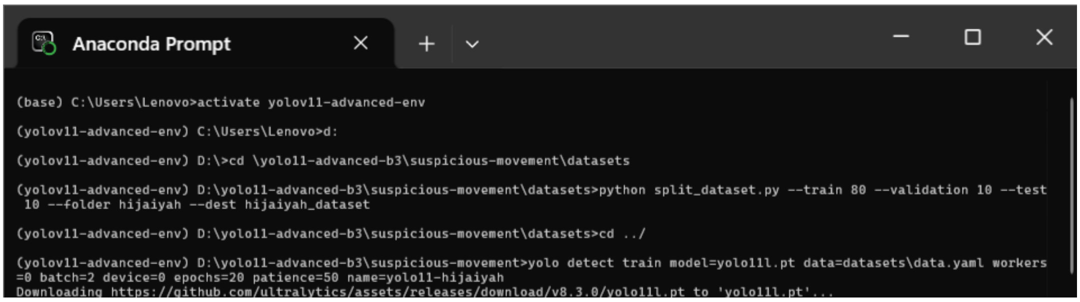


Figure 2. Split dataset Anaconda
(Source: Personal Preparation)

After the installation of the YOLOv8 algorithm system, the training process with the YOLOv8 algorithm uses the model training configuration, namely images with a width resolution of 640 with adjusting height, a total of 50 epochs and 10 batches. The model configuration process can be seen in Figure 3.

Figure 3. Training model YOLOv8
(Source: Personal Preparation)

The results of the evaluation of the YOLOv8 model on the validation set consisting of 378 images showed excellent performance, with an accuracy of 0.973 and a recall of 0.5597. mAP50 reached 0.6129, and mAP 50-95 of 0.4147. The average processing time per image is 4.5 ms for inference, which indicates its reliable real-time detection capabilities. The results of the evaluation of the YOLOv8 model can be seen in Figure 4.

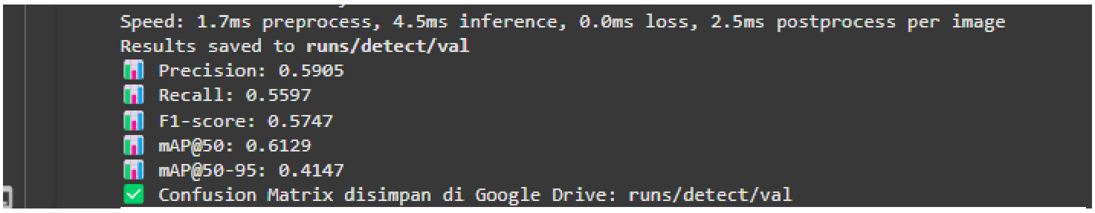


Figure 4. YOLOv8 Evaluation Results
(Source: Personal Preparation)

After the model will be evaluated using test data to measure its overall performance. This involves using evaluation metrics such as Precision, Recall, and mAP to measure how well the model can detect hijaiyah datasets in the image [14]. results as shown in Table 1.

Table 1. Results of the evaluation of the YOLOv8 Model (Source: Personal Preparation)

Class Name	Box(P)	Recall	mAP 50	mAP50-95	Class Name	Box(P)	Recall	mAP 50	mAP50-95
alif	0,947	0,949	0,961	0,766	tha	0,972	1	0,995	0,867
ba'	0,956	0,789	0,943	0,79	dha	0,973	1	0,995	0,783
ta	0,925	1	0,938	0,723	ain	0,997	1	0,995	0,686
tsa	0,92	0,828	0,862	0,622	ghain	0,981	0,938	0,946	0,698
jim	0,984	1	0,995	0,698	fa	0,996	1	0,995	0,778
kha	0,777	1	0,871	0,685	qaf	0,979	1	0,979	0,649
kho	0,99	1	0,995	0,773	kaf	0,92	1	0,979	0,641
dal	0,848	1	0,942	0,705	lam	0,937	0,931	0,934	0,602
dzal	0,764	0,778	0,827	0,616	mim	0,986	1	0,968	0,687
ra	0,981	1	0,938	0,683	nun	0,925	0,867	0,914	0,674
zai	0,939	0,853	0,949	0,742	waw	0,862	0,965	0,968	0,617
sin	0,993	1	0,995	0,78	ha	1	0,964	0,995	0,761
syin	0,981	1	0,995	0,731	lam alif	0,821	1	0,898	0,561
shad	0,974	1	0,995	0,7	hamzah	1	0,925	0,995	0,75
dhad	0,958	0,923	0,95	0,669	ya	0,922	0,984	0,983	0,786

The results of the evaluation of the YOLOv8 model on the validation set consisting of 378 images showed excellent performance, with an accuracy of 0.973 and a recall of 0.5597. mAP50 reached 0.6129, and mAP 50-95 reached 0.4147. The average processing time per image is 4.5 ms for inference, which shows reliable real-time detection capabilities.

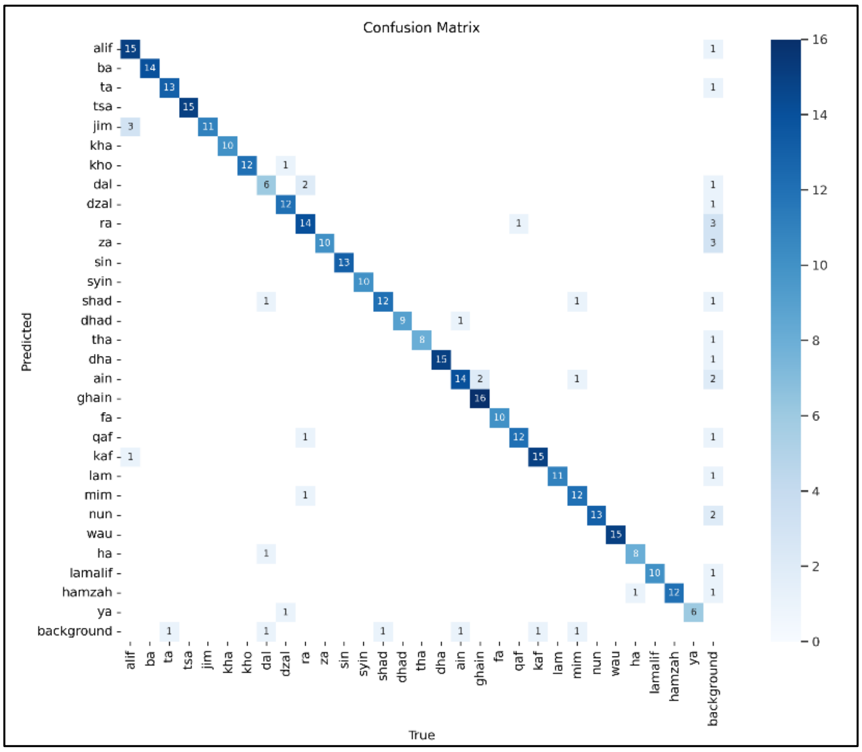
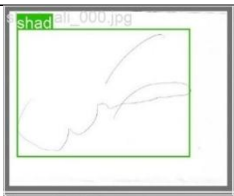
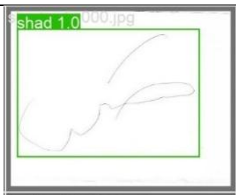
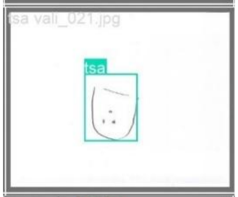
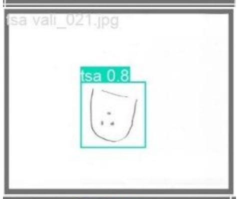
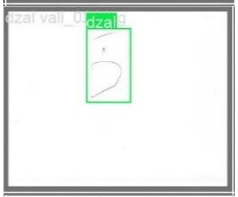
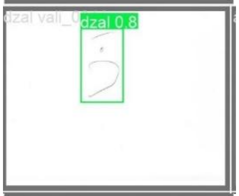
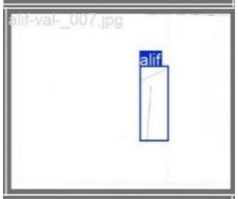
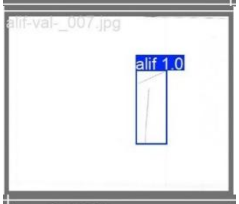
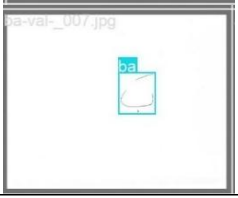
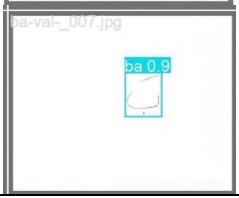


Figure 5. Precision-Recall Curve
(Source: Personal Preparation)

From Figure 5. It can be seen that the level of accuracy is quite good, even until someone touches the number 16 which means very accurate, for example the letter Ghain. The detection of hijaiyah letters using YOLOv8 went well and the accuracy value was quite high. In **Table 2.** Explain the results of the hijaiyah letter detection test

Table 2. Test Results (Source: Personal Preparation)

Test Data	Dataset Class	Detection Results	Level of Certainty
	Shad		1.0
	Tsa		0.8
	Dzal		0.8
	Alif		1.0
	Ba		0.9

IV. Conclusions

The application process for the detection of hijaiyah letters written by early childhood used YOLOv8 with a lancer and succeeded in accurately detecting the presence of breeders. The dataset used consisted of 3790 images on hijaiyah letters which were divided into 30 classes. This dataset is divided into 3 parts: training data (80%), validation (10%), and testing (10%) [12].

Detection using the YOLO model yielded an accurate accuracy of 0.9608 drawn from the mAP50 results, 0.973 precision, and 0.98 recalls. The graph shows a precision average value (mAP) of 0.962 for all classes. This presentation shows that the real-time object detection system using YOLOv8 provides accurate and reliable results when tested.

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