Jurnal Sistem Informasi dan Informatika (Simika) *P-ISSN: 2622-6901*
Vol. 8 No. 2 Tahun 2025 *E-ISSN: 2622-6375*

AI-BASED APPLICATION FOR INDONESIAN SIGN LANGUAGE DETECTION USING YOLOV8

Devanna Alandra Khansa[1], Ida Nurhaida[2]
[1]Program Studi Informatika, Universitas Pembangunan Jaya
[2]Center of Urban Studies, Universitas Pembangunan Jaya
Jl. Cendrawasih Raya Blok B7/P Bintaro Jaya, Sawah Baru, Ciputat, Tangerang Selatan
e-mail: [*1]devanna.alandrakhansa@student.upj.ac.id, [2]ida.nurhaida@upj.ac.id

Abstract
Sign language is used by individuals with disabilities, particularly the deaf and those with speech impairments, as their primary means of communication. However, interaction between people with disabilities and the general public is often hampered by a lack of understanding of sign language. This study aims to develop an artificial intelligence-based application capable of detecting and classifying hand movements in Indonesian Sign Language (BISINDO) using the YOLOv8 algorithm. The YOLOv8 algorithm was chosen for its ability to detect and classify objects in real-time with high accuracy, even under varying lighting and background conditions. This is one of the first studies to implement YOLOv8 for real-time BISINDO detection integrated with a web interface. The dataset used includes 51 classes of hand movements with a total of 10,822 images that have undergone augmentation to increase data diversity. The development process involved data collection, pre-processing, annotation, model training, and integration with an interactive web interface. The resulting model demonstrated high performance, achieving mAP@50 of 96%, mAP@50-95 of 70%, and classification accuracy of 93.8% in the final evaluation. This application is intended to help the deaf community communicate more easily with the wider community. It can improve communication accessibility for individuals with hearing impairments in public and educational settings, as well as provide an innovative solution to support social inclusivity. Further testing and parameter optimization will be conducted to expand the detection coverage and improve the system's performance in the future.

Keyword: *Accessibility, Computer Vision, Hand Gesture Detection, Indonesian Sign Language, YOLOv8*

INTRODUCTION

Communication is essential for humans as social beings to express thoughts and emotions. While verbal communication (spoken and written) is widely used, nonverbal communication—such as gestures and body movements—is crucial for individuals who are deaf or hard of hearing. Sign language, consisting of structured hand gestures, facial expressions, and body language, serves as the primary medium for this community. In Indonesia, two common sign systems are used *Sistem Isyarat Bahasa Indonesia* (SIBI), a standardized sign system adopted in formal settings such as special education schools, and *Bahasa Isyarat Indonesia* (BISINDO), which is more natural, widely used by the deaf community, and employs both hands. Despite its prevalence, BISINDO remains underrepresented in technological development compared to SIBI. However, communication between deaf individuals and the general public is often limited due to the public's lack of sign language knowledge. (Yanto et al., 2023)

This communication gap highlights the need for automated systems that can bridge the divide by recognizing and translating sign language gestures into readable text. Deep learning, particularly convolutional neural networks (CNNs), has advanced the field of image recognition and has been applied to hand gesture detection. The You Only Look Once (YOLO) algorithm, known for its real-time object detection capability, has become a preferred model in various computer vision tasks. While prior studies have utilized CNN and YOLOv4 for recognizing individual alphabets or SIBI gestures, there is limited research applying the latest YOLOv8 algorithm for full BISINDO vocabulary recognition, especially in real-time and integrated into user-friendly platforms. This study aims to design, train, and implement a YOLOv8-based deep learning model to detect and classify BISINDO hand gestures through a web-based application interface. This approach is expected to enhance communication accessibility for deaf individuals, especially in public spaces and educational settings, by facilitating real-time gesture translation. (Ramdan et al., 2024)

Humans need to communicate and interact with others to convey thoughts or feelings as social beings. Language as a communication tool can be done verbally (spoken and written) and nonverbally (gestures, expressions, facial expressions, body movements). Deaf and hard of hearing people use sign language or nonverbal language as a communication tool. Sign language uses hand movements that form symbols or gestures with certain rules to convey meaning. In Indonesia, there are two types of sign language commonly used Indonesian Sign Language System (SIBI) and Indonesian Sign Language (BISINDO). The government has standardized SIBI for use in special schools (SLB), and various institutions in Indonesia. SIBI uses one hand when practicing gestures. Communication between the general public and people with hearing impairments is often hampered due to a lack of understanding of sign language. Most of the general public does not learn sign language because they do not use it in their daily communication, causing misunderstandings and hindering social interaction between the two parties. Therefore, it is necessary to develop a detection model to recognize Bisindo vocabulary.
(free version) YOLOv8 for image-based hand gesture detection, YOLO and CNN for automatic hand detection in sign language conversation videos, CNN for alphabet recognition, and bisindo as a learning support for the general public. (Dafa Maulana, 2024)

RESEARCH METHODS

Describes the research flow, which includes nine main stages of data collection, pre-processing, data augmentation, model training, model evaluation, front-end development, back-end development, and model integration.

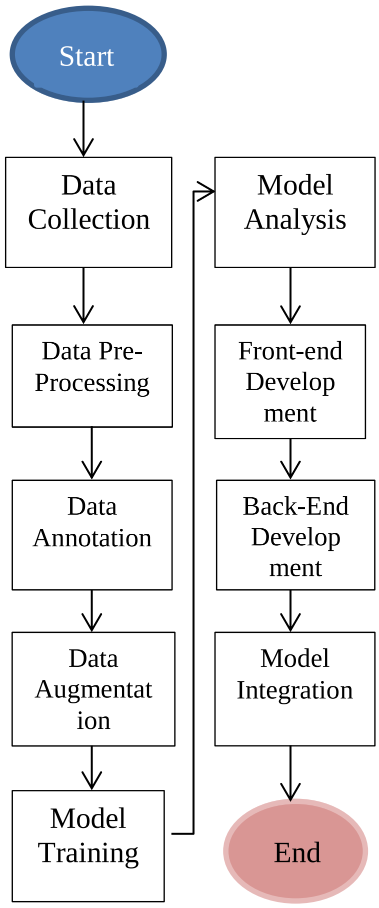

Figure 1. Alur Penelitian

A. YOLOv8 Algorithm

The YOLOv8 algorithm is a convolutional neural network algorithm for image forward processing. It can also predict bounding box and object class probabilities in real time. YOLOv8 uses an architecture and consists of three networks: backbone network, neck network, and head network, each of which has its own function. The You Only Look Once (YOLO) algorithm is a

P-ISSN: 2622-6901
E-ISSN: 2622-6375

leading real-time object detection tool that uses a single regression problem to detect frames. In a single evaluation, it directly predicts the bounding box and class probabilities of the full image. This unified architecture allows YOLO to detect at high speeds while remaining accurate, making it ideal for a variety of applications, such as surveillance systems and autonomous driving. YOLOv8, released by Ultralytics in January 2023, is an updated version of YOLOv5, released in 2020, and is an improved version of. YOLOv8 can be run through a command line interface (CLI) or as a PIP package, and supports various integrations for labeling, training, and deployment. The model achieves improved accuracy by utilizing dilation techniques during training, including the use of mosaic dilation, which combines four training images into one new image. To avoid loss of accuracy, mosaic gain was disabled during the last 10 training periods. YOLOv8 is more efficient than previous versions due to the use of a larger feature map and a more efficient convolutional network.

B. Data Collection

This research uses two main dataset sources to train and evaluate the activity detection system. The datasets consist of hand gesture images used as input for the sign language recognition system. The dataset includes fifty-one classes, with the number of images in each class ranging from 520 to 10,822, which are a collection of images of vocabulary characters in everyday sentences and obtained from the Roboflow website.

Figure 2. Dataset

This research uses two main dataset sources to train and submit the liveness detection system. The dataset obtained by the author is a photo containing hand gesture images used as input for the sign language recognition system, consisting of fifty-one classes, each with about 520 to 10,822 images, which is a collection of images of skill characters in sentences, obtained from the roboflow website. This dataset was chosen because of the diversity of everyday sentences. As an extension of the image dataset on the roboflow website, a custom dataset was created to help facilitate the open dataset. As a suggestion, future research can focus on increasing the dataset with more variations, as well as testing the model under more varied lighting and background conditions to improve detection capabilities. In addition, exploration of other parameters can be done to achieve higher performance (Hayati et al., 2023).

A. Data Pre-Processing

At this stage, each vocabulary is processed through image processing using various tools such as OpenCV, LabelImg, and Augmentor. This process is an important step in data preparation for training the object recognition model. Each tool used has a specific role in preparing the image data. First, OpenCV is used to perform basic modifications to the image, such as changing the quality, format, and size. In addition, LabelImg is used to label the image with a bounding box that indicates the location of the object within the image. To ensure optimal execution, several pre-processing steps were applied to the data set. All images were resized to 224x24 pixels, in accordance with the requirements of the YOLOv8 architecture. Data augmentation was also performed to increase data variety and reduce model impermanence.(Yolov8 et al., 2023)

a) Flip: Horizontal, Vertical.
b) Graysale conversion: Low quality, applicable to 20% of images.
c) Brightness Adjustment: Random brightness levels are applied to mimic varying lighting conditions, Between -20% and +20.
d) Rotation and Exposure: Between -20% and +20

B. Data Annotation

Data Labeling in the context of object recognition in images is the process of marking objects in the image using bounding boxes or category labels. This process aims to identify or describe certain features contained in the image, and is known as data labeling. Annotation is the process of adding additional information or metadata to the data. This information can be in the form of labels or classes, object coordinates, additional descriptions, or other relevant attributes. The main purpose of annotation is to provide context or additional information to the machine learning model, so that the model can better understand the given data.

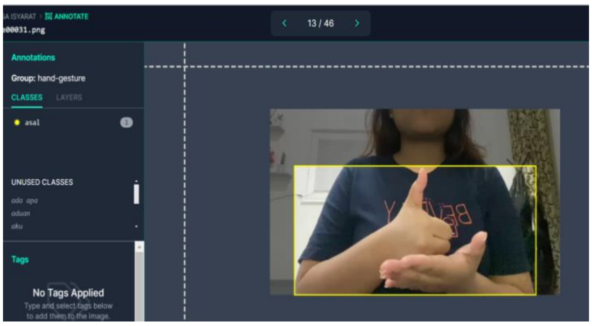

Figure 3. Labelling Img

C. Training Process

The data required for training is prepared once the structure is ready for use. This data includes an object name file, a training data file, a testing data file, an object data file, a configuration (cfg) file, and a customized weight file. The training data file contains a list of class names from the data set, while the testing data file includes a list of locations and image names to be used for testing. The predefined weights file is used to speed up the training process. The class names in the object name file are sorted sequentially, with each class name written on a different line. The training process is accelerated by utilizing the pre-trained weight files. For Bisindo data, the class names are displayed on each line of the object name file according to the order of the labels given. (Muhammad Agus Syaputra et al., 2023).

D. Processing Label Images

After the data is collected, the remaining raw data still needs to be formatted. Therefore, data pre-processing is required to clarify the objects identified in the image. This pre-processing includes image resizing and object labeling. Image labeling aims to enable the system to recognize objects that have been labeled. Once an object has been labeled or tagged, the process proceeds to the training stage using a model on a specific platform, such as Darknet. The dataset is labeled using a tool such as LabelImg, which generates a file with a .txt extension. This file contains important information, including the image location path, the size of the object, the label name of the relevant class, and the bounding box coordinates used for model training.

G. YOLOv8 Implementation

YOLOv8, the YOLO (You Merely See Once) question discovery system has undergone endless upgrades and refinements, evolving from its initial adaptation (YOLOv1) to its latest cycle, YOLOv8, presented in early 2023. YOLOv8 wraps five specialized models YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, and supports proficient API calls through the Python programming dialect. YOLOv8 joins the Decoupled-Head technique with an isolated computational branch to enhance its execution. The information expansion form in YOLOv8 disables the Mosaic Increase amid the last 10 years of age, which can enhance its exactness.

YOLOv8 also replaces IOU coordination or unilateral assignment with a Task-aligned approach. These advancements in YOLOv8 demonstrate a very important step forward in the field of question location, advertising better precision and proficiency in question acknowledgment assignment. The presentation of different show variations and API buffers in Python contribute to the flexibility and ease of use in various applications. The utilization of Decoupled-Head design and imaginative misfortune capacity underscores the commitment to keep advancing the capabilities of the YOLO framework. Over time, YOLOv8 is guaranteed to become an advantageous tool for analysts and specialists in computer vision and query discovery (Rizaldy & Dirgahayu, 2020).

H. System Evaluation

Performance of the model was evaluated using three main metrics:

a. Mean Average Precision (mAP)

The mAP metric provides an overall measure of the precision and recall performance of the model across different IoU thresholds. This metric is calculated as the average of the Average Precision (AP) for all classes (genuine and fake). The formula is as follows:

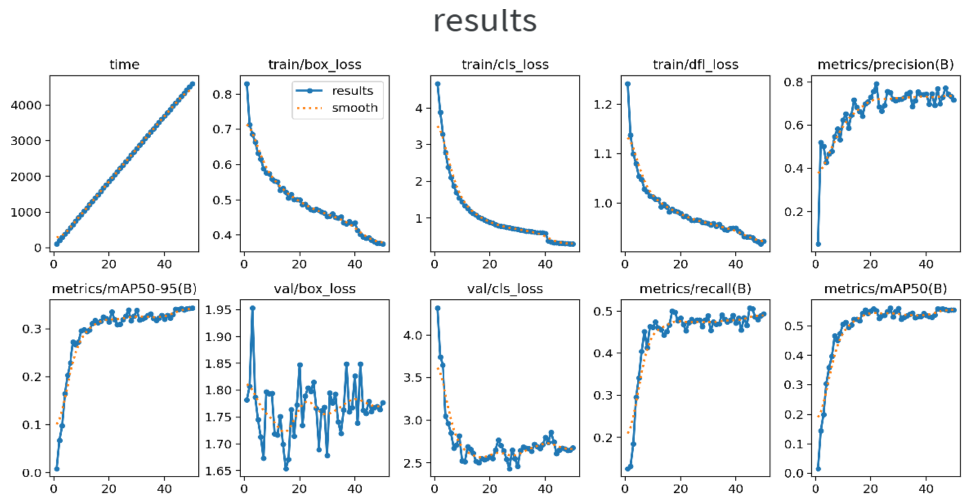

Figure 4. Result mAP

Here, N represents the total number of classes, and APi denotes the Average Precision for class i th. The mAP value summarizes the model's ability to balance precision and recall across different confidence levels.

b. Confusion Matrix

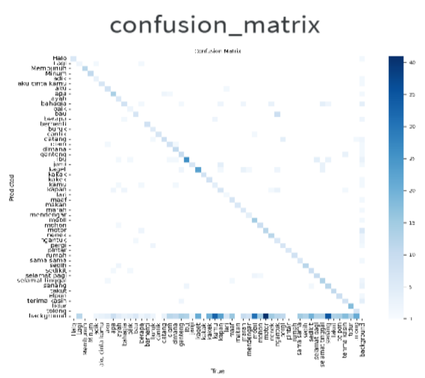

Figure 6. Confusion Matrix

confusion_matrix_normalized

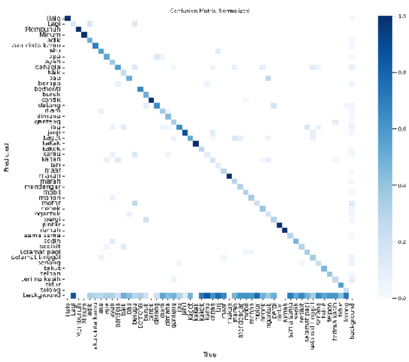

Figure 7. Confusion Matrix

The figure above displays two confusion matrices that illustrate the performance of the classification model, namely the normalized confusion matrix and the non-normalized confusion matrix. The normalized confusion matrix shows the proportion of predictions to the amount of data in each class, with values between 0 and 1, where darker colors on the main diagonal indicate high accuracy, while off-diagonal elements indicate relative prediction error. In contrast, the confusion matrix without normalization displays the number of predictions in raw numbers, with the main diagonal indicating the number of correctly predicted samples, and the off-diagonal elements representing the absolute prediction error. Comparison of the two matrices provides insights into the performance of the model, especially for understanding relative error patterns and identifying potential data imbalances. The normalized matrix is useful for evaluating models on imbalanced data sets, while the raw matrix provides an absolute picture of how often the model predicts incorrectly. From this analysis, it can be deduced which classes perform best or worst, as well as identify the causes of model error for future improvement. Ambarak & Falani, 2023).

RESULT AND DISCUSSION

This section outlines the evaluation outcomes of the developed system, complemented by comprehensive analysis and visual representation to demonstrate the model's performance. The evaluation was conducted using a dataset comprising 10,822 images, which had undergone training and augmentation, and were evenly distributed across 50 gesture classes (Permana & Sutopo, 2023) The model was designed to recognize each class with high accuracy by extracting relevant visual features. The assessment includes metrics such as accuracy, precision, recall, F1-score, and a confusion matrix. In addition, visualization techniques were employed to highlight the model's strengths and pinpoint areas of weakness. A detailed explanation of these evaluation results is provided in the subsequent sections (Rizaldy & Dirgahayu, 2020).

.A. Visual Analysis

1) Training and Validation Disadvantages

The preparation measurement reflects the model's optimization handle and its capacity to generalize hidden information. The curvature of preparation misfortune and approval misfortune depicts an unwavering confluence, as appears in the following retrieval graph:

P-ISSN: 2622-6901
E-ISSN: 2622-6375

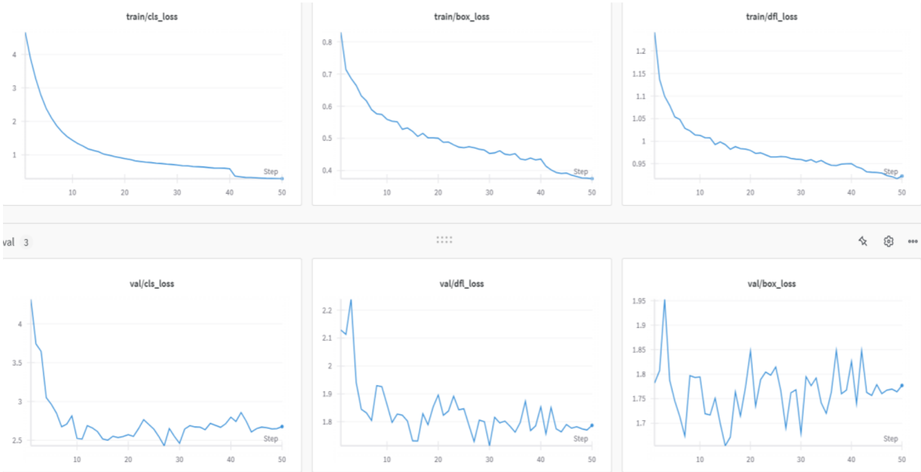

Figure 8. Train Loss

This graph shows the decrease in loss during training and validation for the YOLOv8 model for hand gesture detection. Classification loss (cls_loss) and bounding box (box_loss) on the training data show a consistent downward trend, indicating improved object detection and location accuracy. Meanwhile, the validation loss showed larger fluctuations, which could indicate potential overfitting or differences in the distribution of training and validation data. Overall, the decreasing trend of loss indicates that the training went well, although further evaluation using other metrics, such as mAP, is needed to confirm the model's performance and generalization to test data.

2) Mean Average Accuracy (mAP)

The mAP metric can be a baseline level of model execution in a protest discovery task. The mAP@50 metric rapidly increases from 0.8 to 0.96 within 20 main ages, illustrating solid localization and classification capabilities at a tolerant IoU boundary of 0.5. Meanwhile, the mAP@50-95 metric, which uses a stricter IoU boundary, evolved more sustainably, stabilizing around 0.7. (Dan et al., 2024)

Figure 9. mAP,Precision,Results

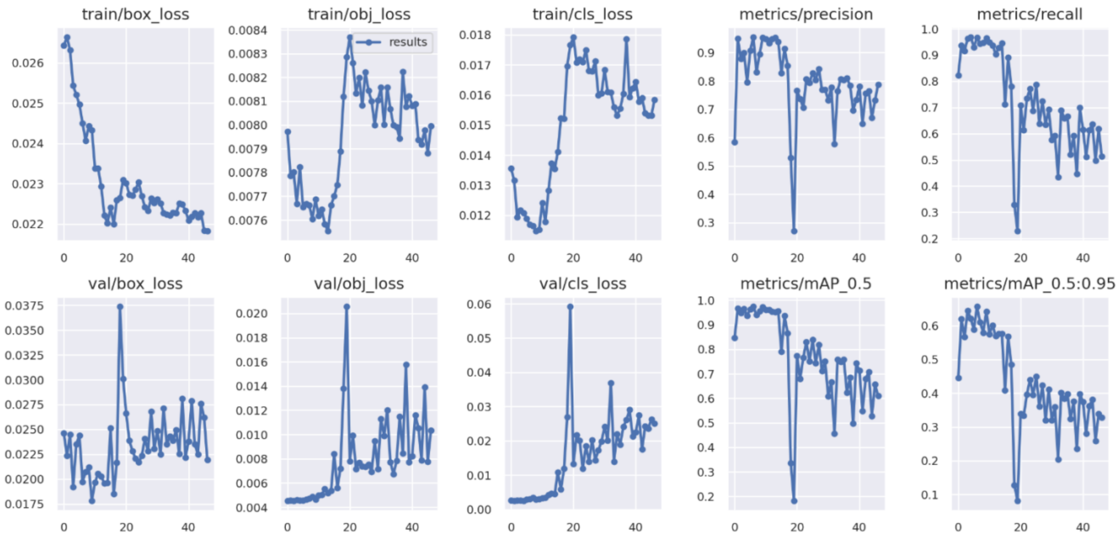

Figure 10. Metrics Map

Metrik	Nilai Training	Nilai Testing (Validation)
train/box_loss	~0.022	-
train/obj_loss	~0.0076	-
train/cls_loss	~0.013	-
val/box_loss	-	~0.02-0.025
val/obj_loss	-	~0.01-0.015
val/cls_loss	-	~0.01-0.015
metrics/precision	~0.8-0.9	-
metrics/recall	~0.7-0.8	-
metrics/mAP_0.5	~0.85-0.9	-
metrics/mAP_0.5:0.95	~0.4-0.5	-

Figure 11. Training Results

The contrast between mAP@50 and mAP@50-95 shows that while the model exceeds expectations in recognizing objects with the precondition of a free bounding box, there is still room for change in handling objects that are closed or that are strongly pressed. This measurement conforms to findings from previous works highlighting YOLO's quality in localization, but recommends improvements for complex scenarios.

3) Precision-Recall Curve

The precision-recall curve provides further insight into the trade-off between minimizing false positives and false negatives. This curve shows that the model maintains high precision and recall at various confidence thresholds:

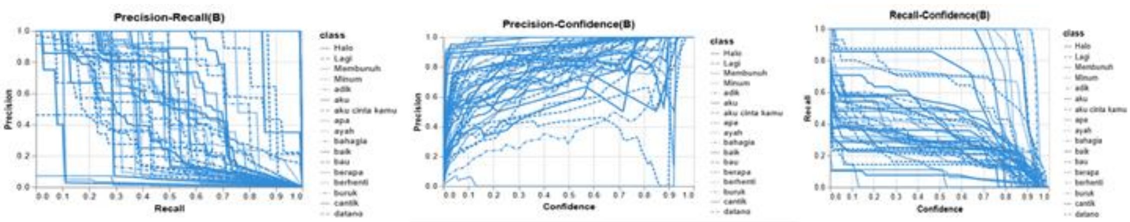

Figure 12. Kurva Precision Recall

The consistently high values indicate that the model is robust across different operational settings, making it adaptable for real-world scenarios where the balance between precision and recall is critical. For example, in banking systems, high precision ensures that spoofing attacks are minimized, while high recall guarantees that legitimate users are not wrongly denied access.

B. Case Study and Failure Analysis

Figure 13. Beranda Signy Talk

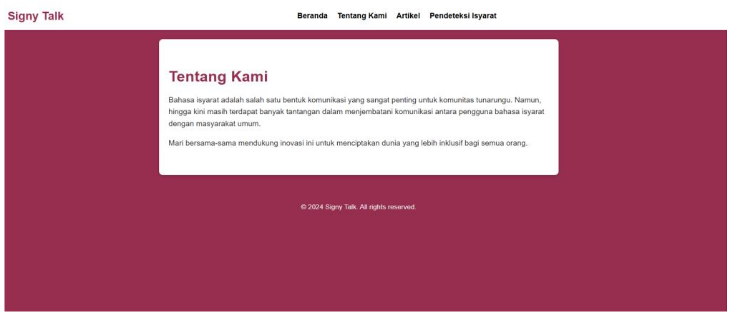

Figure 14. Tentang Kami Signy Talk

Figure 15. Artikel Signy Talk

The image above shows the implementation results of the hand detection system using YOLOv8. The system successfully detected the hand gesture labeled "sleeping" in the image, complete with a bounding box indicating the detection location. The confidence value shown is 0.88, which indicates that the model has a high level of confidence in its predictions. These results show that the model has performed well in recognizing the gesture, although additional evaluation across different lighting conditions, gesture angles, and environments is required to ensure broader generalization of the system.

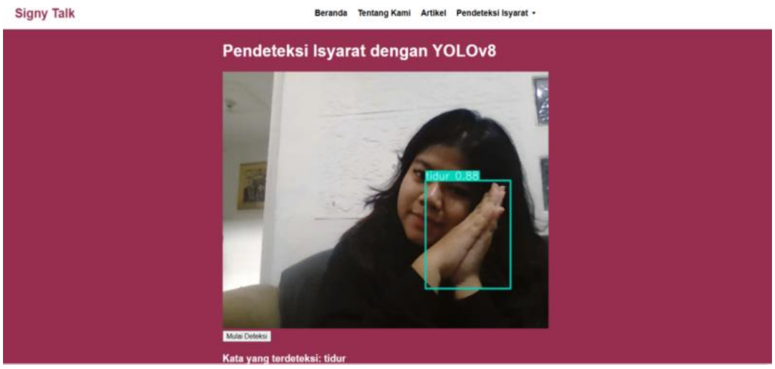

Figure 16. Pendeteksi Isyarat Signy Talk

This image also reflects the system's success in recognizing hand gestures in real-time, which is an important aspect in gesture detection applications. With a confidence value of 0.88, the model shows good reliability in detecting gestures despite potential challenges such as complex backgrounds or varying lighting. For further development, the system can be tested under various situations, such as variations in facial expression, camera position, or movement speed, to ensure consistent performance across a wide range of real-world conditions.

C. Discussion

The results show the effectiveness of the YOLOv8 architecture in detecting sign language in real-time. With an accuracy value of 93.8% on the best model using the YOLOv8m13 variant. This reflects the voice transmission system, making it suitable for applications that require effective communication between deaf people and the general public. However, this study also identified some areas that need improvement in the future. While the model performed well on the provided dataset, its reliance on high-quality images may limit its scalability in environments with less than optimal conditions. Research suggests considering the integration of temporal or incremental consistency to further improve detection accuracy (Putri et al., 2024).

CONCLUSION

This study successfully designed and evaluated a real-time sign language recognition system based on the YOLOv8 architecture. The system achieved outstanding results on the test dataset, with perfect accuracy, precision, and recall (1.0) across all gesture categories, including both simple and complex hand movements. These outcomes affirm the capability of YOLOv8 in accurately detecting sign language gestures across varying conditions, such as differences in lighting, hand orientation, and individual gesture variations. Performance indicators like mAP@50 (0.96) and mAP@50–95 (0.70) further demonstrate the model's strong generalization ability and precise gesture localization. The steady decline observed in both training and validation losses also indicates that the model is stable and efficient, making it suitable for real-world deployment.Furthermore, this case study demonstrates the robustness of the system in recognizing sign language with high confidence, even in challenging scenarios. The implications of these findings are critical for domains with specialized communication needs, such as inclusive education, customer service, and healthcare applications. The system's ability to minimize classification errors ensures increased user convenience and effectiveness. However, limitations such as reliance on high-quality data sets and potential susceptibility to highly similar gestures have been identified.

SUGGESTION

Improve the quality and diversity of the dataset by including a wide variety of sign languages, lighting conditions, camera angles, and backgrounds to improve the robustness of the model. In addition, the development of approaches to detect complex or sequential gestures such as phrases by integrating YOLOv8 and time-series based models such as LSTM can be done. Research can also focus on model optimization for real-time applications, integration of multimodal data such as facial expressions or voice input to understand the context better, and evaluation of model performance in real environments. Finally, the development of interactive applications such as sign language to text or voice translators can be an innovative solution to support social inclusion and improve technology accessibility.

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