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Development of an Indonesian Sign Language Translation Application with Hand Gesture Detection

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ABSTRACT

Sign language serves as an essential medium of communication for individuals with hearing impairments. However, limited public understanding continues to create barriers between deaf individuals and the broader community. This study aims to develop an AI-based mobile application capable of recognizing and translating Indonesian Sign Language (BISINDO) gestures in real time. The system integrates the YOLOv8 model for gesture detection within a mobile environment. The YOLOv8n model was trained using the BISINDO dataset and evaluated through precision, recall, and mean average precision (mAP) metrics. The model obtained a mAP@50 of 98% under the given experimental settings. These results indicate that the YOLOv8 architecture can be applied to mobile-based real-time gesture recognition and may serve as a foundation for future research on assistive communication technologies.

Keywords: *Indonesian Sign Language, Real-time Gesture Recognition, YOLOv8, Deep Learning, Assistive Technology.*

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INTRODUCTION

Communication accessibility remains one of the most significant challenges for individuals with disabilities, particularly those with hearing and speech impairments. Public awareness of individuals with hearing and speech impairments remains limited, primarily due to communication barriers arising from the use of sign language, which is not widely understood by the general population. People with typical hearing generally rely on spoken language and lip movements, while individuals who are deaf or speech impaired use sign language as a visual medium to communicate. The use of sign language is crucial in facilitating interaction between hearing-impaired individuals and the broader community. (Pradikja et al., 2018).

According to Law No. 8 of 2016 on Persons with Disabilities, people with disabilities in Indonesia are divided into five categories: physical, intellectual, mental, sensory, and multiple disabilities. The Central Bureau of Statistics (BPS) and the Ministry of Social Affairs

(Kementrian Sosial Republik Indonesia, 2020) reported that there were over 22.5 million people with disabilities in Indonesia, which accounted for around 5% of the country's total population. According to the World Federation of the Deaf (WFD), there are around 72 million deaf individuals in the globe, 80 percent of whom reside in developing nations and speak over 300 distinct sign languages. About 223,655 people with hearing impairments and 73,560 people who are both deaf and mute were reported in Indonesia in the 2012 National Socioeconomic Survey (Susenas) (Komisi Nasional Anti Kekerasan Terhadap Perempuan, 2020). These statistics demonstrate how crucial it is to create inclusive communication tools in order to close the gap between non-signers and the deaf community.

Sign language is a visual communication method in which words or letters are represented by body language, facial expressions, and hand gestures. Sistem Isyarat Bahasa Indonesia (SIBI) and Bahasa Isyarat Indonesia (BISINDO) are the two primary sign languages that the deaf community in Indonesia uses most frequently (Pangestu et al., 2024). However, communication barriers between hearing-impaired people and non-signers are sometimes caused by the general public's poor comprehension of sign language.

Numerous investigations have been carried out to create systems for recognizing sign language utilizing a variety of deep learning and computer vision approaches. Using the YOLOv5 algorithm, Permana & Sutopo (2023) created an application for identifying the alphabets in Indonesian Sign Language (SIBI). Although their technology only recognized the alphabet and did not provide real-time translation, it showed encouraging results in detecting static hand movements. However, the lack of dynamic gesture recognition limited its practical usability for real-time communication contexts.

Another study by Arrozaq & Latipah (2024) implemented a computer vision approach to translate SIBI alphabet gestures on Android devices using Convolutional Neural Networks (CNN). The proposed system was capable of identifying gestures from image inputs, yet its detection process was not performed in real time since it relied solely on still images for classification. This highlights the trade-off between model complexity and real-time performance, which remains a challenge for mobile-based implementations.

Similar to this, Pramono et al. (2024) used the CNN approach to create a real-time sign language translation model. The method was not suited for mobile implementation, which limited accessibility for a wider range of users, even if their research accomplished real-time processing in a desktop context. These investigations show that Indonesian sign language translation systems continue to struggle with real-time performance and mobile deployment. By creating an AI-based mobile application utilizing the YOLOv8 model, which offers more recent architectural advancements than earlier methods, this work seeks to overcome these constraints. Their study demonstrated the potential of CNNs for gesture recognition, but the lack of mobile optimization highlights the need for a more lightweight and mobile-oriented detection model.

These studies indicate that challenges in achieving real-time performance and mobile deployment persist in Indonesian sign language translation systems. Previous research primarily focused on recognizing static gestures or performing translation in desktop environments, which limited their practicality for everyday use. Therefore, a research gap remains in developing a real-time and mobile-compatible BISINDO translation system that leverages recent deep learning architectures such as YOLOv8.

Building upon these studies, the present research aims to design a sign language recognition system capable of real-time detection and translation of Indonesian Sign Language gestures on mobile devices. The primary goal is to enhance communication accessibility between the general public and individuals with hearing or speech impairments through the application of an AI-based approach using the YOLOv8 model.

In conclusion, while earlier research has established the groundwork for Indonesian sign language recognition, a fully integrated, real-time, and mobile-compatible system has not yet been developed. By using the YOLOv8 model to improve BISINDO gesture detection's accuracy and responsiveness, our study fills in these gaps. This research focuses on developing a useful, adaptable, and user-friendly mobile application to facilitate inclusive communication, in contrast to previous efforts that were restricted to desktop environments or static picture detection.

METHOD

According to Judijanto et al. (2024), this study employs a Research and Development (R&D) methodology, which tries to develop or enhance a product through methodical phases of analysis, design, implementation, and assessment. The ADDIE model, which consists of phases for analysis, design, development, implementation, and evaluation, is used in the development process. According to Rayanto et al. (2020), this model offers a structured and interactive framework that guarantees coherence across the whole product development process. The ADDIE model framework used in this study is depicted in Figure 1.

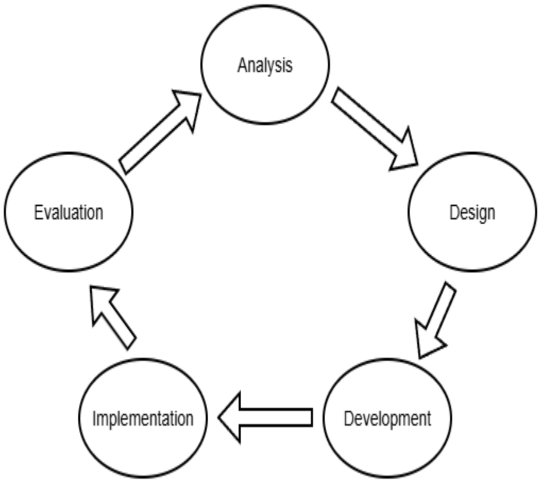


Figure 1: ADDIE

Each phase of the ADDIE model was applied systematically in this research to guide the development of the sign language translation application. The detailed explanation of each phase is described as follows.

1. Analysis

Based on the issues discovered, the analysis phase seeks to establish system requirements and choose the best solution design (Deli & Hendy, 2021). In order to investigate sign language translation technologies and earlier studies on YOLO-based gesture recognition, a survey of the literature was done for this project. The outcomes of this phase form the basis for developing a BISINDO sign language translation system that is mobile based.

2. Design

The design phase involves planning the conceptual and technical framework of the application, including architecture and interface layout (Deli & Hendy, 2021). UML diagrams such as Use Case and Class Diagrams were created to describe the workflow, and a user interface prototype was designed using Figma as a reference before development.

3. Development

The development stage focuses on transforming the design into a functional product (Saleh et al., 2024). At this stage, the YOLOv8 model was trained using the BISINDO dataset and integrated into a mobile application to perform real-time gesture detection. The translation and dictionary modules were also implemented to support instant text output and sign vocabulary access.

4. Implementation

The implementation phase involves testing and deploying the developed system in a real environment (Deli & Hendy, 2021). The application was run on an Android device equipped with a camera to test its ability to detect BISINDO gestures and display real-time translation outputs.

5. Evaluation

The implemented application's performance and functionality are evaluated during the evaluation phase (Deli & Hendy, 2021). To make sure that gesture detection and translation outputs matched the intended BISINDO indications, testing concentrated on usability and conformance concerns. Performance and interface improvements were made using the input received. However, the evaluation phase's acknowledged limitation is its exclusive focus on controlled environment testing; in order to fully evaluate the application's robustness in public use and address external validity, future research should include field testing with a variety of lighting and background conditions.

Data Collection

The BISINDO Sign Language dataset from the Roboflow platform is made freely available for use in this study. The dataset includes 6,433 tagged photos from 38 gesture classes, including 12 typical language signs like "Love," "Sorry," and "Help," as well as 26 letter signs (A-Z). To maximize and assess the performance of the YOLOv8 model, the data were divided into 90% for training (5,823 images) and 10% for validation (610 images). The validity of the training inputs was strengthened by manually spot-checking the labeling quality of the publically accessible dataset to make sure that bounding boxes correctly captured the BISINDO gestures. This was done to assure data reliability.

Data Preprocessing

Before training, all images were resized to 640 × 640 pixels to match the YOLOv8 input format. Several data augmentation techniques including flipping, rotation, brightness adjustment, and scaling were applied to increase dataset diversity. Image annotations were then converted into YOLO format (class ID and normalized bounding boxes) and organized into separate training and validation directories for structured model training.

You Only Look Once (YOLO)

One of the object identification techniques that transformed the detection methodology by approaching it as a regression problem is YOLO. This enables YOLO to estimate the class probabilities associated with each bounding box and spatially separate bounding boxes (Ariansyah, 2024). In particular, YOLO splits an image into many S × S grid cells, each of which is in charge of forecasting confidence ratings and bounding boxes. This procedure is formalized by the following equation:

$$Confidence = \Pr(object) \times IoU^{truth\,pred} \quad (1)$$

In this study, the YOLOv8n model was used for BISINDO gesture recognition, trained for 80 epochs with a batch size of 8 and image resolution of 640×640. Training and validation were performed simultaneously to monitor Precision, Recall, and mAP values as performance indicators.

Mean Avarage Precision

The average value of Average Precision (AP), which measures the area under the precision-recall curve for a single class, is called Mean Average Precision (mAP). To determine mAP, the average value of the Average Precision for each of the current classes is computed. (Pangestu et al., 2024).

$$mAP = \frac{1}{C}\sum_{C=1}^{C} AP_C \quad (2)$$

Precision

Precision is a statistic that describes how accurate the model's positive predictions are given the information supplied. It is determined as the ratio of true positive predictions to the overall number of positive predictions made (Pangestu et al., 2024).

$$Precision = \frac{\sum_{i}^{n} \frac{TPi}{TPi + FPi}}{n} \quad (3)$$

Recall

The model's ability to find pertinent data that fits the query is measured by a metric called recall. Recall, also referred to as sensitivity, quantifies the percentage of pertinent data that is successfully identified relative to the entire quantity of relevant data that is accessible (Pangestu et al., 2024).

$$Recall = \frac{\sum_{i}^{n} \frac{TPi}{TPi + FNi}}{n} \quad (4)$$

FINDING AND DISCUSSION

RESEARCH RESULT

Analysis

The analysis identified that communication barriers between hearing-impaired individuals and the general public occur due to the limited understanding of BISINDO sign language. To address this issue, a system capable of translating BISINDO gestures into text in real time is needed. Therefore, this study proposes the development of a mobile-based BISINDO translation application using the YOLOv8 model to facilitate more inclusive communication.

Design

The design phase presents the conceptual and technical framework of the sign language translation application. This includes the system architecture, which illustrates the interaction between the mobile camera, the YOLOv8 detection module, and the translation output. Additionally, UML diagrams such as Use Case and Class Diagrams were created to describe the workflow and relationships among system components. The user interface prototype was also designed to provide a reference for layout and feature placement.

a. System Architecture

The system captures hand gestures through the smartphone camera, processes them using the YOLOv8 model for gesture recognition, and outputs the corresponding text on the device. Figure 2 illustrates this data flow.

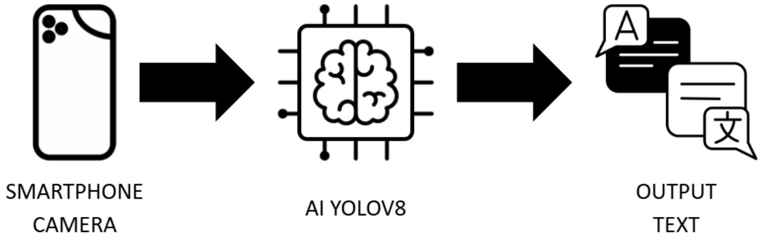


Figure 2: System Architecture

b. Use Case Diagram

The use case diagram highlights the key elements that each actor can access and shows the functional interactions between users and the system. The user and the administrator are the two main characters engaged, as seen in Figure 3.

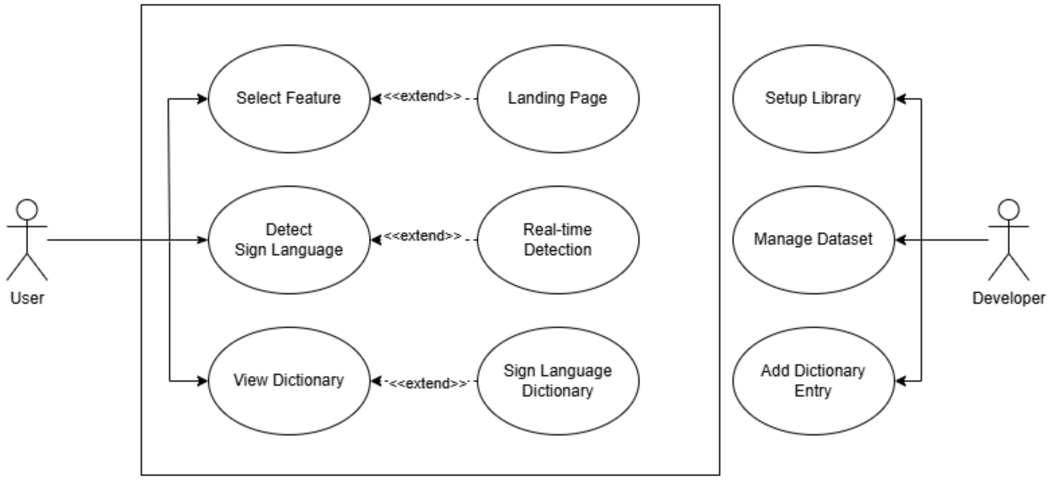


Figure 3: Use Case Diagram

The User can access several main features through the application interface, including select feature, which is further implemented through the landing page; detect sign language, which details the Real-time Detection process; and view dictionary, which extends from the sign language dictionary feature. These use cases represent the core functionalities available to end-users for translating and learning sign gestures.

Meanwhile, the Admin is responsible for system management tasks such as setup library, manage dataset, and add dictionary entry. These administrative use cases ensure that the dataset and dictionary content remain updated and accurate, supporting the overall functionality of the sign language translation system.

c. Class Diagram

The class diagram illustrates the structural design of the BISINDO sign language translation system, showing the relationships and interactions between its main components. As shown in Figure, the User interacts through the UIController, which manages the camera preview and displays translation results. The CameraHandler captures images that are processed by the Preprocessor through resizing and normalization steps. The processed images are analyzed by the SignDetector using the YOLOv8 model, and the Translator converts detection results into meaningful text using data from the DictionaryDatabase. Meanwhile, the Developer is responsible for training the model and updating the dictionary to maintain system accuracy and adaptability.

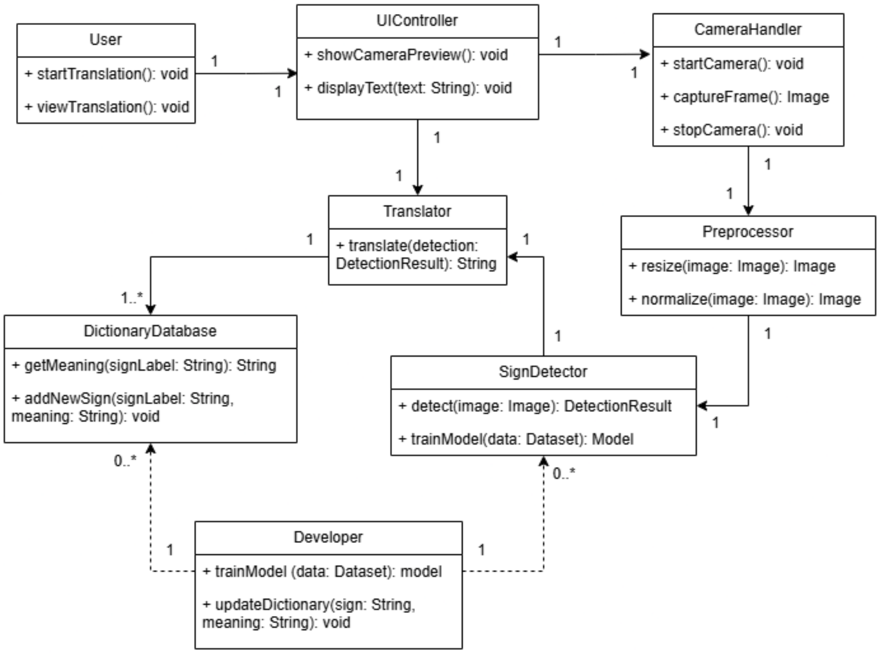

User
+ startTranslation(): void
+ viewTranslation(): void
UIController
+ showCameraPreview(): void
+ displayText(text: String): void
CameraHandler
+ startCamera(): void
+ captureFrame(): Image
+ stopCamera(): void
Translator
+ translate(detection: DetectionResult): String
Preprocessor
+ resize(image: Image): Image
+ normalize(image: Image): Image
DictionaryDatabase
+ getMeaning(signLabel: String): String
+ addNewSign(signLabel: String, meaning: String): void
SignDetector
+ detect(image: Image): DetectionResult
+ trainModel(data: Dataset): Model
Developer
+ trainModel (data: Dataset): model
+ updateDictionary(sign: String, meaning: String): void
1
1..*
0..*

Figure 4: Class Diagram

Development

The main goal of the development phase was to train the YOLOv8n model using the BISINDO sign language dataset. The model was trained for several epochs with the configurations summarized in Table 1. These settings were designed to balance computational cost and recognition capability, allowing the model to be deployed on mobile devices while maintaining acceptable performance.

Table 1: Training Configuration of YOLOv8n Model

Parameter	**Value**
Epochs	80
Batch Size	8
Image Size	640 x 640
Optimizer	SGD
Learning Rate	0.01
Dataset Split	90% Training / 10% Validation

The model's learning progress was tracked during the training process using important performance indicators such box loss, classification loss, distribution focal loss, precision, recall, and mean average precision (mAP). Figure 5 illustrates how training and validation losses steadily declined over the course of the epochs, while precision, recall, and mAP values increased as well. These findings show that the model attained a stable training convergence and progressively learned to identify the unique characteristics of BISINDO hand gestures.

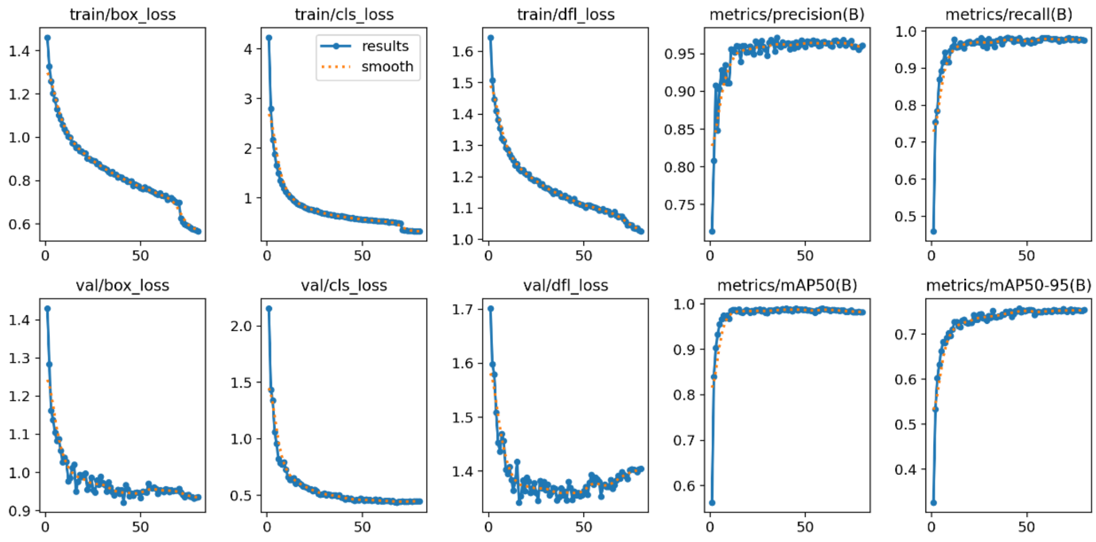
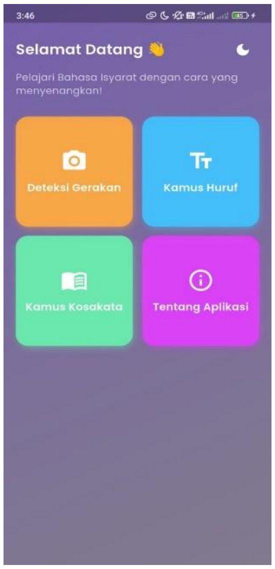


Figure 5: Loss

Implementation

At this implementation stage, the mobile-based sign language translation application was developed using the Flutter framework. The trained YOLOv8 model was integrated into the system to enable real-time BISINDO gesture detection. The application consists of several main interfaces, including the home page, real-time detection page, and sign dictionary page, designed to help users recognize and translate BISINDO gestures directly through the smartphone camera.



Selamat Datang 👋

Pelajari Bahasa Isyarat dengan cara yang menyenangkan!

Figure 6: Home Page

The home page serves as the main interface that provides users with access to the application's primary features. It consists of four main menu options: Gesture Detection, which directs users to the real-time BISINDO recognition feature; Alphabet Dictionary and Vocabulary Dictionary, which display lists of sign gestures along with their corresponding meanings; and About Application, which provides information about the system's purpose and functionality. The interface was designed with a straightforward layout to facilitate clear navigation between available features.

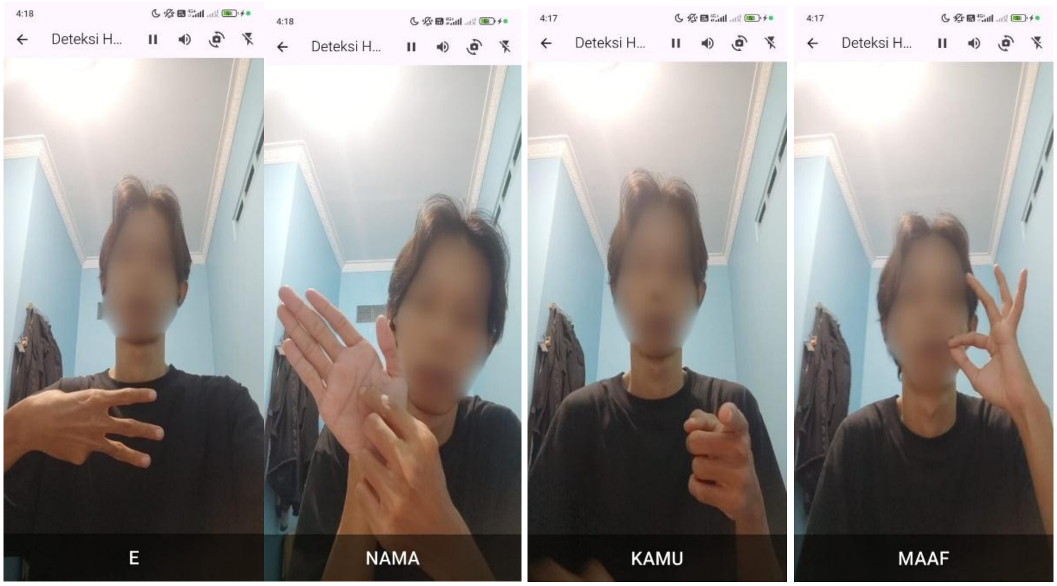
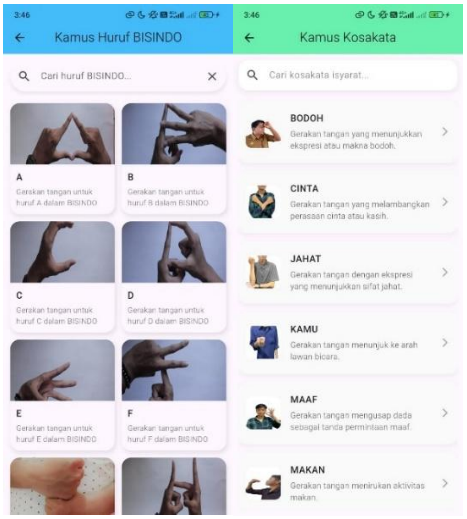


Figure 7: Detection Page

The Gesture Detection page functions as the core feature of the application, enabling real-time recognition of BISINDO hand gestures using the trained YOLOv8 model. Through the smartphone camera, the system detects and classifies hand movements, then instantly displays the recognized sign as corresponding text on the screen. As illustrated in Figure 7, several examples of detection results demonstrate the model's ability to accurately identify various gestures under different lighting and hand orientation conditions, ensuring responsive and reliable translation performance.



A
Gerakan tangan untuk huruf A dalam BISINDO

B
Gerakan tangan untuk huruf B dalam BISINDO

C
Gerakan tangan untuk huruf C dalam BISINDO

D
Gerakan tangan untuk huruf D dalam BISINDO

E
Gerakan tangan untuk huruf E dalam BISINDO

F
Gerakan tangan untuk huruf F dalam BISINDO

BODOH
Gerakan tangan yang menunjukkan ekspresi atau makna bodoh.

CINTA
Gerakan tangan yang melambangkan perasaan cinta atau kasih.

JAHAT
Gerakan tangan dengan ekspresi yang menunjukkan sifat jahat.

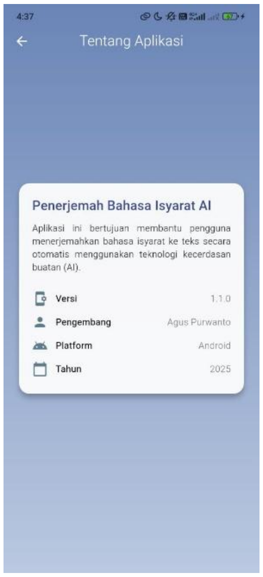
KAMU
Gerakan tangan menunjuk ke arah lawan bicara.

MAAF
Gerakan tangan mengusap dada sebagai tanda permintaan maaf.

MAKAN
Gerakan tangan menirukan aktivitas makan.

Figure 8: Dictionary Page

The Alphabet and Vocabulary Dictionaries act as supporting features that help users learn and understand BISINDO gestures interactively. The Alphabet Dictionary provides visual representations of A–Z hand signs, while the Vocabulary Dictionary displays common BISINDO gestures such as "Love," "Sorry," and "Help," each accompanied by a reference image and textual description. These dictionaries complement the detection feature by enhancing user understanding of sign language meanings and usage contexts.



Penerjemah Bahasa Isyarat AI

Aplikasi ini bertujuan membantu pengguna menerjemahkan bahasa isyarat ke teks secara otomatis menggunakan teknologi kecerdasan buatan (AI).

Versi	1.1.0
Pengembang	Agus Purwanto
Platform	Android
Tahun	2025

Figure 9: About Page

Finally, the About Application page provides general information about the application. This page helps users understand the motivation behind the system and its role in supporting communication accessibility for individuals with hearing impairments.

Evaluation

Using the YOLOv8n architecture and training it on the BISINDO sign dataset, the aim of this study was to develop a real-time sign language recognition model. The experiment involved training across 80 epochs, using a batch size of 8, and utilized a dataset comprising 5,823 training and 610 validation images. The model's performance was evaluated using metrics like Mean Average Precision (mAP), Precision, and Recall. Table 2 displays the YOLOv8n model's quantitative performance outcomes from the validation phase.

Table 2: Performance

Metric	Value
Precision	0.959
Recall	0.982
mAP@50	0.986
mAP@50-95	0.756

Table 2 shows that the YOLOv8n model obtained Precision of 0.959 and Recall of 0.982 during validation. The average mAP@50–0.95 score of 0.75 was obtained during validation. Figure 3 illustrates the model’s training process in terms of accuracy and loss across epochs.

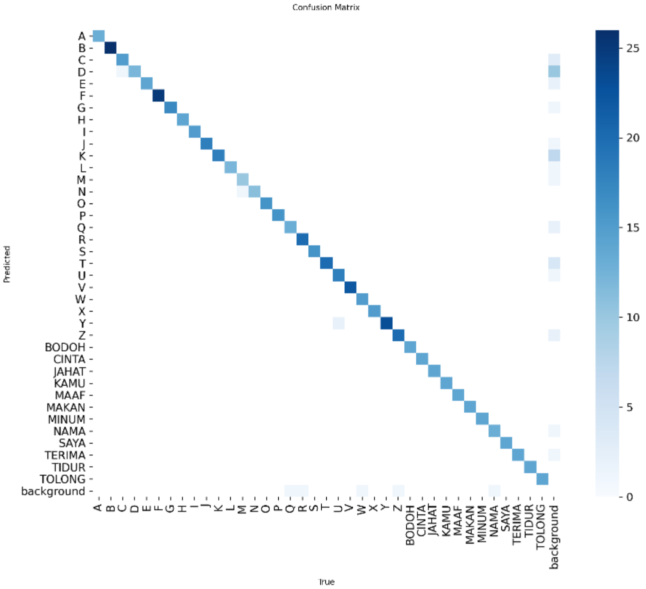


Figure 10: Confusion Matrix

The distribution of accurate and inaccurate predictions for each gesture class is shown in the confusion matrix. Figure 4's normalized confusion matrix makes it easier to see how accurate each label's classification is.

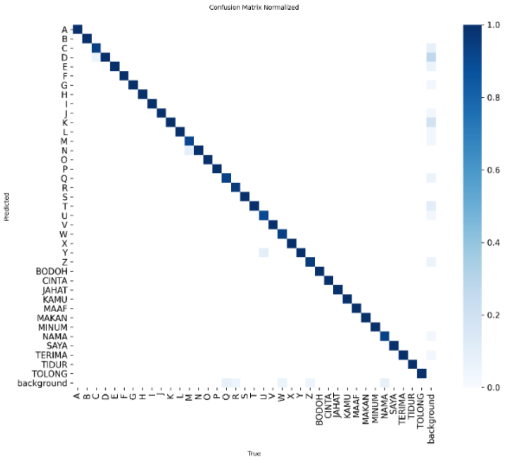


Figure 11: Normalized Confusion Matrix

To further evaluate the model’s classification performance, additional visualizations were generated, including the Precision (P), Recall (R), and F1-score curves, as illustrated in Figures 5–7.

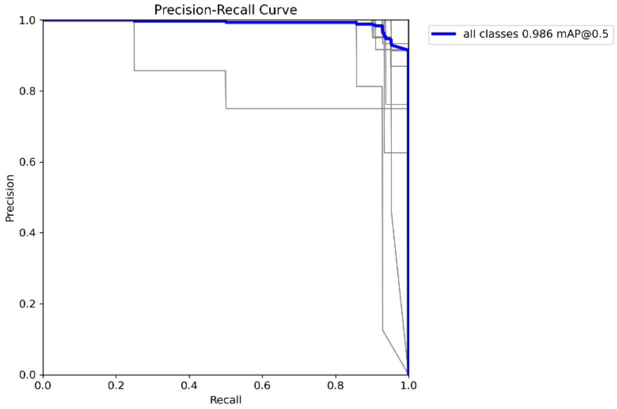


Figure 12: Precision Curve

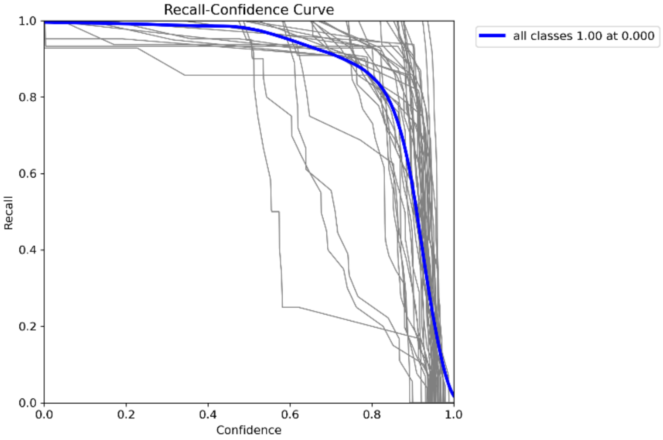


Figure 13: Recall Curve

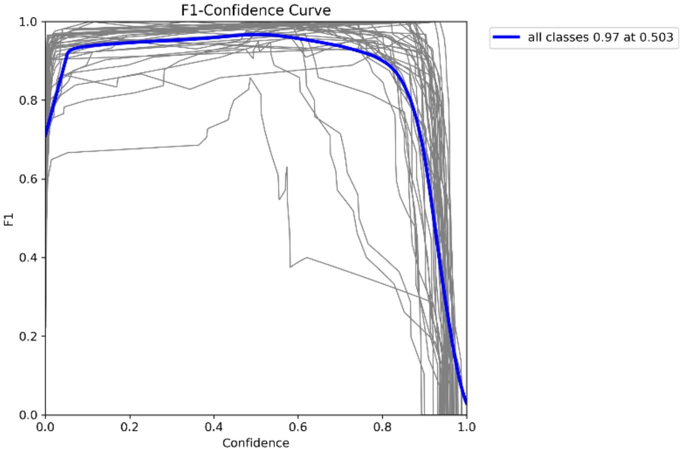


Figure 14: F1-Score Curve

After evaluating the model performance using quantitative metrics, a black-box testing was also conducted to assess the functionality of the mobile application. This testing aimed to ensure that the integration of the YOLOv8n model with the Flutter-based interface operated as intended and that all main features performed correctly.

Table 3: Blackbox Testing

Testing Scenario	Expected Result	Status
User accesses the detection feature from the home page	The detection page opens successfully	Valid
User performs hand gesture in front of the camera	The system detects and displays the corresponding sign translation	Valid
User toggles dark mode	Application switches interface to dark theme	Valid
User searches for a word in the dictionary	Related sign images are displayed	Valid
User activates flash or flips the camera	The camera flash turns on or front/back view switches	Valid

DISCUSSION

The evaluation results show that the YOLOv8n model was able to recognize BISINDO sign motions with high accuracy, as seen by its 0.959 precision, 0.982 recall, and 0.986 mAP@50 score (mAP@50–95 score of 0.756). These findings show that the model can accurately identify and categorize hand gestures in real time with minimal error rates. The majority of gesture classifications were accurately detected with little misclassification, as further confirmed by the confusion matrix display. The YOLOv8 architecture's resilience for intricate hand motion detection tasks, where temporal responsiveness and spatial accuracy are crucial, is confirmed by this result.

Compared to previous studies, the proposed model shows substantial improvements in real-time performance and mobile deployment. Prior research by Permana & Sutopo (2023) who used YOLOv5 for SIBI alphabet recognition, reported an accuracy of 77%. Similarly, Arrozaq & Latipah (2024), utilizing a CNN architecture for SIBI, achieved a peak accuracy of 81.48% under ideal lighting conditions. These studies, which primarily focused on static alphabet recognition, lacked comprehensive real-time detection capabilities. Furthermore, Pramono et al. (2024) developed a CNN-based model for translation, achieving a detection rate of 70.2%, but the system remained limited to desktop platforms, restricting broad user accessibility. In contrast, the present study advances this line of research by integrating the lightweight YOLOv8n into a mobile environment, achieving a mAP@50 of 98.6% and enabling responsive real-time BISINDO gesture recognition directly on portable devices. This integration fundamentally bridges the gap between high accuracy and practical, accessible deployment, a key limitation in existing assistive technology research.

The superior performance of YOLOv8 can be attributed to several architectural advancements. As noted by Hussain (2024), YOLOv8 employs an anchor-free detection mechanism and a C2f module, which together simplify the network structure while improving feature extraction efficiency. These innovations contribute to faster inference and greater accuracy than prior YOLO versions. Furthermore, Abhinand et al. (2024) demonstrated the model's effectiveness on lightweight devices, underscoring YOLOv8's suitability for edge-based and mobile applications. In this study, these design features translated into smooth and responsive real-time detection, validating YOLOv8n's practicality for mobile deployment.

Despite these promising results, several limitations remain. The dataset used in this study includes a limited number of BISINDO gesture categories, which may reduce generalization to more complex or continuous sign sequences. Moreover, while YOLOv8n provides a balance between accuracy and computational efficiency, larger variants (e.g., YOLOv8s or YOLOv8m) could further enhance detection accuracy at the cost of higher resource demands. As emphasized by Goodfellow et al. (2016), model performance in deep learning is significantly influenced by data diversity and hyperparameter tuning. Future work should therefore consider expanding the dataset, optimizing model parameters, and applying compression or quantization techniques to further improve YOLOv8's deployment on low-end mobile devices.

CONCLUSION

This study used the YOLOv8n model to create a real-time Indonesian Sign Language (BISINDO) recognition system. According to the evaluation results, the model performed consistently under the specified dataset and experimental setting, achieving precision of 0.959, recall of 0.982, mAP@50 of 0.986, and mAP@50–95 of 0.756. These results imply that there is room for adaption of the YOLOv8 architecture in mobile-based gesture detection challenges. In order to enhance performance on devices with limited resources and facilitate broader applications in inclusive communication technology, future research may concentrate on broadening the dataset to encompass a greater variety of gestures, signer diversity, and environmental variations. Additionally, optimization techniques like model compression or quantization may be investigated.

REFERENCES

Abhinand, K., Nair, A. B., Dhananjay, C., Hamza, H., MohammedFawaz, J., RahmaFahim, K., & AnoopV., S. (2024). Malayalam Sign Language Identification using Finetuned YOLOv8 and Computer Vision Techniques. *ArXiv*, *abs/2405.06702*. https://api.semanticscholar.org/CorpusID:269757552

Ariansyah, D. S. (2024). PENDETEKSI KATA DALAM BAHASA ISYARAT MENGGUNAKAN ALGORITMA YOLO VERSI 8. *Jurnal Informatika Dan Teknik Elektro Terapan*, *12*(3). https://doi.org/10.23960/jitet.v12i3.4904

Arrozaq, A. G., & Latipah. (2024). Implementasi Computer Vision untuk Terjemahkan Abjad Bahasa Isyarat SIBI pada Aplikasi Android. *Jurnal Teknologi Dan Sistem Informasi Bisnis*, *6*(2), 297–303. https://doi.org/10.47233/jteksis.v6i2.1260

Deli, & Hendy. (2021). Perancangan Strategi Kreatif Rebranding Program Sarjana Sistem Informasi dengan Menggunakan Metode ADDIE. *Jurnal Ilmiah Teknologi Informasi Terapan*, *8*(1).

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press. https://books.google.co.id/books?id=omivDQAAQBAJ

Hussain, M. (2024). YOLOv5, YOLOv8 and YOLOv10: The Go-To Detectors for Real-time Vision. *ArXiv*, *abs/2407.02988*. https://api.semanticscholar.org/CorpusID:270924280

Judijanto, L., Muhammadiah, M., Utami, R. N., Suhirman, L., Laka, L., Boari, Y., Lembang, S. T., Wattimena, F. Y., Astriawati, N., & Laksono, R. D. (2024). *Metodologi Research and Development: Teori dan Penerapan Metodologi RnD*. PT. Sonpedia Publishing Indonesia. https://books.google.co.id/books?id=y3INEQAAQBAJ

Kementrian Sosial Republik Indonesia. (2020, October 26). *Kemensos Dorong Aksesibilitas Informasi Ramah Penyandang Disabilitas*. Kementrian Sosial Republik Indonesia. https://kemensos.go.id/kemensos-dorong-aksesibilitas-informasi-ramah-penyandang-disabilitas

Komisi Nasional Anti Kekerasan Terhadap Perempuan. (2020, September 24). *Siaran Pers Komnas Perempuan: Pekan Tuli Internasional dan Hari Bahasa Isyarat Internasional (23 -29 September 2020)*. Komisi Nasional Anti Kekerasan Terhadap Perempuan. https://komnasperempuan.go.id/siaran-pers-detail/siaran-pers-komnas-perempuan-pekan-tuli-internasional-dan-hari-bahasa-isyarat-internasional-23-29-september-2020

Pramono, I. M., Niswati, imatun, & Agustina, A. (2024). MODEL PENERJEMAH BAHASA ISYARAT INDONESIA DENGAN METODE CONVOLUTIONAL NEURAL NETWORK (CNN). *Seminar Nasional Riset Dan Inovasi Teknologi*.

Pangestu, A. B., Muttaqin, M. R., & Sunandar, M. A. (2024). SISTEM DETEKSI BAHASA ISYARAT INDONESIA (BISINDO) MENGGUNAKAN ALGORITMA YOU ONLY LOOK ONCE (YOLO)v8. *JATI (Jurnal Mahasiswa Teknik Informatika)*. https://api.semanticscholar.org/CorpusID:273829519

Permana, D., & Sutopo, J. (2023). APLIKASI PENGENALAN ABJAD SISTEM ISYARAT BAHASA INDONESIA (SIBI) DENGAN ALGORITMA YOLOv5 MOBILE APPLICATION ALPHABET RECOGNITION OF INDONESIAN LANGUAGE SIGN SYSTEM (SIBI) USING YOLOv5 ALGORITHM. *Jurnal Simantec*, *11*, 230–231. https://doi.org/10.21107/simantec.v11i2.19783

Pradikja, M., Tolle, H., & Brata, K. (2018). Pengembangan Aplikasi Pembelajaran Bahasa Isyarat Berbasis Android Tablet. *Jurnal Pengembangan Teknologi Informasi & Ilmu Komputer*, *2*, 2548–2964.

Rayanto, Y. H., Rokhmawan, T., & Maulana, M. Z. A. S. (2020). *PENELITIAN PENGEMBANGAN MODEL ADDIE DAN R2D2: TEORI & PRAKTEK*. Lembaga Academic & Research Institute. https://books.google.co.id/books?id=pJHcDwAAQBAJ

Saleh, F., Owon, R. A. S., Muhammadiah, M., Palip, R. E. A., Launingtia, I. G. A. N., & Leu, Y. Y. M. (2024). *INOVASI PEMBELAJARAN BAHASA TEORI DAN PRAKTIK* (N. Mayasari & P. A.-V. Maqfirah, Eds.; Pertama). CV WIDINA MEDIA UTAMA. https://repository.penerbitwidina.com/publications/569648/inovasi-pembelajaran-bahasa-teori-dan-praktik#cite