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Android Based Indonesian Sign Language Hand Gesture Detection using Transfer Learning Method

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Abstract–People with hearing and speech impairments rely on sign language for daily communication. However, public understanding of the Indonesian Sign Language System (SIBI), particularly its alphabet hand gestures, remains limited, creating communication barriers between deaf individuals and the wider community. This study aims to develop an Android-based application for recognizing SIBI alphabet hand gestures using the Transfer Learning method implemented through Google Teachable Machine. A dataset consisting of 200 images for each SIBI alphabet gesture was collected and used to train the classification model. Several training scenarios were evaluated by varying the Epoch, Batch Size, and Learning Rate parameters to obtain the optimal model. The trained model was then converted into TensorFlow Lite and integrated into an Android application for real-time hand gesture recognition. Experimental results show that the best performance was achieved using Epoch 50, Batch Size 16, and Learning Rate 0.001, producing training and validation accuracy of 1.0 with an error rate close to 0.0. The developed application successfully recognized all tested static SIBI alphabet gestures, demonstrating reliable performance in practical implementation. This study contributes by providing a lightweight Android-based SIBI hand gesture recognition system and experimentally evaluating the influence of training hyperparameters on recognition performance. The proposed approach offers an efficient solution for supporting SIBI learning and improving communication accessibility for deaf or speech-impaired individuals.

Keywords: SIBI; Teachable Machine; Transfer Learning; Deaf; Speech-Impaired

1. INTRODUCTION

Speech-impaired is a condition in humans where there is a loss of the ability to learn reading and writing. This disorder is not caused by physical impairment, but rather by a weakness in the brain's ability to process information received. A brain that is weak in processing information leads to an inability to translate the information it reads, resulting in difficulty in conveying information sent by the brain (L. A. Kumar dkk., 2022). Deaf people are individuals with mild to severe hearing difficulties. Deaf people are individuals diagnosed with deafness, resulting in an inability to hear, thus requiring lip movements from the speaker to communicate (Eldeen & H.G.Yousif, 2021; Vaidya dkk., 2020).

Communication is highly essential for every individual (human being). The purpose of communication is to understand the intentions of others. Research suggests that humans spend at least 75% of their time communicating, whether with themselves (self-talk) or with others. Both of them also have the right to receive education, socialize, and have the right to have fun. To engage in the communication process, they need sign language as a communication tool. Sign language is a language created from lip movements and body language to facilitate communication between both parties in the communication process. Sign language is a crucial language for individuals with disabilities, specifically for the deaf and speech-impaired (Anwar dkk., 2020).

SIBI (*Sistem Isyarat Bahasa Indonesia or* Indonesian Sign Language System) is the official language used by the Ministry of Education in special schools under the Ministry of Education and Culture (Kemendikbud). SIBI consists of 26 letters (24 static handshape letters from A to Z, and 2 dynamic handshape letters, J and Z) and 10 numbers representing digits 0 to 9. The development of this sign language system was pioneered by deaf and speech-impaired individuals through GERKATIN (*Gerakan Kesejahteraan Tunarungu Indonesia* or Indonesian Deaf Welfare Movement), which includes two main systems: SIBI (*Sistem Isyarat Bahasa Indonesia or* Indonesian Sign Language System) and BISINDO (*Berkenalan dengan Sistem Bahasa Isyarat Indonesia* or Introduction to Indonesian Sign Language System). SIBI is a language adopted from American Sign Language (ASL) (Anwar dkk., 2020; Rakun dkk., 2018).

Teachable Machine is a web-based tool created by Google used to create easily applicable classification models in machine learning development. Teachable Machine is accessible and straightforward in its modeling process. The website features three processable features: images, gestures, and sounds. The purpose of creating this website is to simplify the learning process for designers, teachers, and even students in the field of artificial intelligence to create their own models. Teachable Machine uses transfer learning in its learning process (Malahina dkk., 2022).

Transfer learning is a technique in Machine Learning where a model is generally trained on a larger and more general dataset, and then adapted to fit specific data (Kurhekar dkk., 2019). Transfer learning uses previously learned knowledge to enhance model generalization with less training data (Zhang, Ming, dkk., 2024). In hand gesture recognition, transfer learning can reduce differences in data characteristics across users and acquisition sessions, enabling models to generalize more effectively to new data (Li dkk., 2025). Transfer learning has been successfully

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applied in various domains, including sentiment analysis, text classification, spam detection, and multilingual processing (Weiss dkk., 2016). In speech and language processing, transfer learning is essentially as crucial as diverse, unbalanced, dynamic, and interconnected speech and language, making transfer learning inevitable (Huang dkk., 2016). Transfer learning has also been successfully applied in hand gesture recognition tasks. Transfer learning has been proven to increase gesture recognition accuracy and facilitate real-time applications (Zhang, Liu, dkk., 2024). Compared with conventional Convolutional Neural Network (CNN) models trained from scratch, transfer learning requires fewer training samples, reduces computational cost, shortens training time, and generally provides better generalization performance. These advantages make transfer learning particularly suitable for developing lightweight Android-based hand gesture recognition applications while maintaining high classification accuracy.

Teachable Machine has been applied in various fields, one of which is research conducted by (Harditya, 2020) showing significant results in its application to Indonesian Sign Language (BISINDO), thus warranting consideration as a renewed research topic. Another application was done by (Prasad dkk., 2022), implementing Google Teachable Machine-based Machine Learning in early elementary school children, yielding prediction accuracy of 95.72% and concluding it can be integrated into lightweight mobile web applications and even run on older phones. According to (Camgoz dkk., 2017), researched continuous sign language recognition using transfer learning with SubUNet architecture, achieving top-1 accuracy of 80.3% and top-5 accuracy of 93.9%, marking a 30% improvement over previous studies. Previous studies have shown that transfer learning enhances hand gesture recognition through pre-trained deep learning models (M. Kumar dkk., 2025). Transfer learning was also applied to Arabic sign language recognition using Convolutional Neural Network, researched by (Kamruzzaman, 2020), resulting in enhanced communication for speech-impaired individuals, particularly the deaf, achieving over 90% accuracy and proving effective for practical use. Deep learning-based models such as YOLOv8 have shown promising results in real-time hand gesture recognition tasks (Lian dkk., 2024).

Despite these promising findings, several research gaps remain. Most previous studies focused on BISINDO, Arabic Sign Language, or other international sign language datasets rather than the Indonesian Sign Language System (SIBI). In addition, many existing approaches rely on complex deep learning architectures that require relatively high computational resources, limiting their implementation on lightweight mobile devices. Although Google Teachable Machine has been adopted in several image classification applications, only a limited number of studies have investigated its implementation for SIBI hand gesture recognition. Furthermore, previous studies have primarily emphasized classification accuracy, while the effects of training hyperparameters, including Epoch, Batch Size, and Learning Rate, on model performance have received limited attention. These limitations indicate the need for a lightweight and practical SIBI hand gesture recognition system that systematically evaluates training parameter configurations before deployment on Android devices.

Unlike previous studies, this research focuses on recognizing static alphabet gestures of the Indonesian Sign Language System (SIBI) by utilizing Google Teachable Machine and Transfer Learning. Furthermore, this study evaluates several combinations of Epoch, Batch Size, and Learning Rate to determine the optimal model before deploying it into an Android application using TensorFlow Lite. The main contribution of this research is the development of a lightweight Android-based SIBI hand gesture recognition system by integrating Google Teachable Machine, Transfer Learning, and TensorFlow Lite. Unlike previous studies that primarily focused on recognition accuracy or employed computationally intensive deep learning architectures, this research systematically investigates the influence of Epoch, Batch Size, and Learning Rate on model performance to determine the optimal training configuration. Furthermore, the optimized model is successfully deployed into an Android application capable of performing real-time recognition of static SIBI alphabet gestures. The proposed system not only provides an effective educational tool for learning SIBI but also contributes to improving communication accessibility for deaf and speech-impaired individuals through a practical and efficient mobile application. Therefore, this study proposes an Android-based SIBI hand gesture recognition system using the Transfer Learning method implemented through Google Teachable Machine. Unlike previous studies, this research focuses specifically on recognizing static SIBI alphabet gestures while systematically evaluating the effects of Epoch, Batch Size, and Learning Rate on model performance. The optimized model is then converted into TensorFlow Lite and integrated into an Android application for real-time hand gesture recognition. The proposed system is expected to support SIBI learning and improve communication accessibility for deaf and speech-impaired individuals while providing an efficient and lightweight recognition framework.

2. RESEARCH METHODOLOGY

2.1 PROPOSED RESEARCH FRAMEWORK

This study employed the Transfer Learning method implemented through Google Teachable Machine to develop an Android-based SIBI hand gesture recognition application. The overall research procedure consists of several sequential stages, including dataset collection, image preprocessing, model training, model evaluation, TensorFlow Lite conversion, Android integration, and application testing. The research framework is illustrated in Figure 1.

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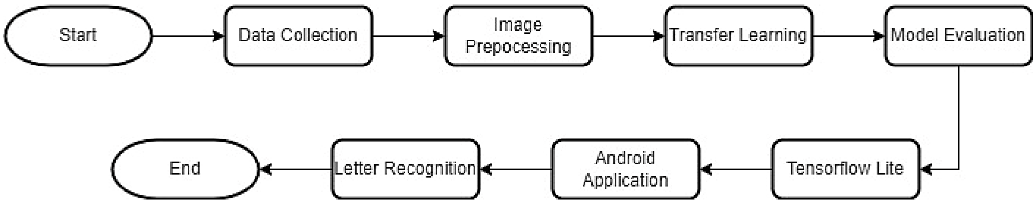


Figure 1. Research Flowchart

As illustrated in Figure 1, the first stage involves collecting SIBI hand gesture images representing each alphabet class. The collected dataset is then organized and uploaded to Google Teachable Machine for transfer learning. Several combinations of Epoch, Batch Size, and Learning Rate are evaluated to obtain the optimal classification model. The best-performing model is exported into TensorFlow Lite format and integrated into an Android application for real-time hand gesture recognition.

2.2 SIBI (Sistem Isyarat Bahasa Indonesia or Indonesian Sign Language System)

Humans communicate with each other using verbal communication. However, not everyone has the ability to communicate verbally; individuals who are deaf and speech-impaired use a language known as sign language. Indonesia has various forms of sign language, but it has a specific system that regulates the standard of sign language in Indonesia, namely Indonesian Sign Language System (SIBI). SIBI is a sign language system used as a means of communication for people with hearing impairments in Indonesia. SIBI follows grammar rules, vocabulary, and sentence structures similar to spoken languages in general. SIBI was developed by hearing individuals, not by deaf individuals. SIBI is equivalent to American Sign Language (ASL) used in the United States (Anggraeni dkk., 2019).

2.3 Deaf

In certain conditions, someone may experience hearing loss, commonly known as deafness. According to data from the World Health Organization (WHO), approximately 466 million people worldwide experience deafness, which accounts for about 6.1% of the global population. In Indonesia, according to the Ministry of Health data in 2018, there are around 3 million people with hearing impairments. Deafness itself is a condition that affects an individual's ability to hear sounds clearly or even results in complete loss of hearing. Deafness can be caused by various factors, such as environmental factors, genetic factors, or age-related factors (Eldeen & H.G.Yousif, 2021; Vaidya dkk., 2020).

2.4 Speech-Impaired

Someone who experiences deafness has a high tendency to also experience speech impairment. There is no exact data on the number of individuals with speech impairment, but according to Ministry of Health data in 2018, there are approximately 3 million people with hearing impairments, including those with speech impairment. Speech impairment itself is a condition where an individual has significant speech disorders, making it difficult or impossible to use spoken language as a means of communication. Speech impairment can be caused by various factors, such as defects in the mouth or throat, neurological or genetic disorders, brain injury, or other medical conditions (Den Hoed & Fisher, 2020).

2.5 Google Teachable Machine

Google Teachable Machine is a web-based machine learning platform that enables users to develop image, sound, and pose classification models using transfer learning without extensive programming knowledge. The trained model can be exported to TensorFlow Lite and integrated into Android applications (Malahina dkk., 2022).

2.6 Machine Learning

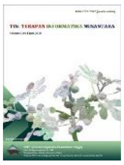
Machine learning is a technology that allows machines to learn from given data without using very clear or detailed instructions. Machine learning enables machines to learn from the data provided by programmers so that they can perform tasks effectively (Gresse Von Wangenheim dkk., 2020).

2.7 Image Processing

Image can be described as a two-dimensional object, such as a picture, photograph, or even a moving image. The transformation process from three dimensions to two dimensions makes the image look different from its original form. Within image processing, there is a technology to recognize these images (Forchhammer dkk., 2022).

2.8 Android Studio

Android Studio is an IDE for Android development introduced by Google at Google I/O 2013. It was designed for developers transitioning from Eclipse IDE and is based on the popular Java IDE, IntelliJ IDEA. Android Studio was chosen for its features that facilitate beginners who want to delve deeper into Android development. While Android Studio can consume a significant amount of RAM on our devices, it can overcome this drawback with several advantages (DiMarzio, 2016; Ribeiro dkk., 2021).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2.9 System Flowchart

The overall workflow of the proposed Android-based SIBI hand gesture recognition application is illustrated in the system flowchart shown in Figure 1. The flowchart describes the sequence of user interactions within the application, beginning with launching the application and accessing the developer information page. Users may then proceed to the main page, where they can upload a hand gesture image for recognition. The system processes the input image and displays the corresponding recognition result. Alternatively, users can exit the application at any stage through the available navigation options.

First, open the application installed on the phone. Then, go to the developer's interface, which contains the group from this study. Next, press the button to proceed to the main page, if you do not wish to continue, you can press the button on the phone to exit the application. If you choose to continue, you will be directed to the main page. There is a while-true loop on the main page. If yes, it will proceed to the next process. If not, press the exit button on the phone to exit the application. Input an image to enter it as data to be detected, and the output will provide the detection results. After this, it will return to the while-true loop on the main page. If you choose not to continue (pressing the exit button on the phone), you will exit the application.

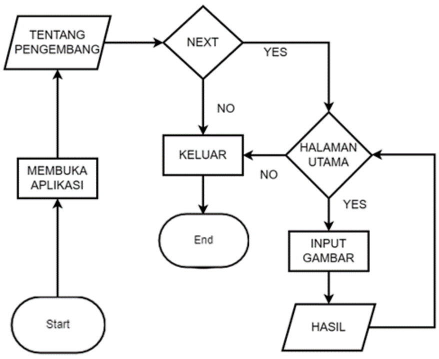
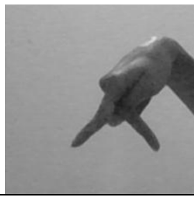


Figure 2. System Flowchart

2.10 Data Collection Technique

The data is in the form of images representing SIBI (*Sistem Isyarat Bahasa Indonesia or* Indonesian Sign Language System) objects for the letters A to Z, except for J and Z, with each letter having 200 images, as in Table 1.

Table 1. Data Collection Alphabet Letters

			
Letter A	Letter B	Letter C	Letter D
			
Letter E	Letter F	Letter G	Letter H
			
Letter I	Letter K	Letter L	Letter M
			

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Letter N	Letter O	Letter P	Letter Q
			
Letter R	Letter S	Letter T	Letter U
			
Letter V	Letter W	Letter X	Letter Y

Table 1 summarizes the image dataset collected for this research. The dataset consists of 4,800 images representing 24 static SIBI alphabet letters, with 200 images assigned to each class. The letters J and Z were excluded because they require dynamic gestures rather than static hand poses. A balanced number of samples was maintained for every class to ensure unbiased model training and improve classification performance. The dataset served as the primary input for the Transfer Learning process implemented through Google Teachable Machine before being deployed into an Android application using TensorFlow Lite.

2.11 Test Scenario

Teachable Machine, the values of epoch, batch size, and learning rate can be adjusted to create combinations that yield an optimal accuracy level, ensuring good data training results and accurate predictions. The values of the parameters epoch, batch size, and learning rate to be tested are shown in Table 2.

Table 2. Test Scenario

EPOCH	*BATCH SIZE*	*LEARNING RATE*
50	16	0.01
50	16	0.001
50	32	0.01
50	32	0.001
100	16	0.01
100	16	0.001
100	32	0.01
100	32	0.001

Table 2 describes the experimental design used to determine the optimal training configuration for the proposed Transfer Learning model. Three key hyperparameters, namely Epoch, Batch Size, and Learning Rate, were systematically varied to investigate their impact on model performance. The experiments consisted of two Epoch values (50 and 100), two Batch Size values (16 and 32), and two Learning Rate values (0.01 and 0.001), generating a total of eight training scenarios. Each scenario was independently trained and evaluated using the same image dataset to ensure a fair comparison. The resulting performance metrics were analyzed to identify the parameter combination that achieved the highest recognition accuracy and the lowest training error before the model was exported to TensorFlow Lite for Android implementation.

3. RESULT AND DISCUSSION

3.1 Research Result

The overall workflow of the proposed Android-based application is illustrated in Figure 1. The flowchart presents the sequence of processes performed by the system during hand gesture recognition. The test results from the scenarios conducted with variations in epoch, batch size, and learning rate can be seen in Figure 3 to Figure 10.

The performance of the first experimental scenario is presented in Figure 3(a). This experiment was conducted using an Epoch of 50, Batch Size of 16, and Learning Rate of 0.01 to evaluate the learning behavior of the proposed model. Figure 3(b) presents the performance of the second experimental scenario using an Epoch of 50, Batch Size of 16, and Learning Rate of 0.001. The obtained accuracy and loss curves are analyzed to evaluate the effectiveness of the selected training parameters.

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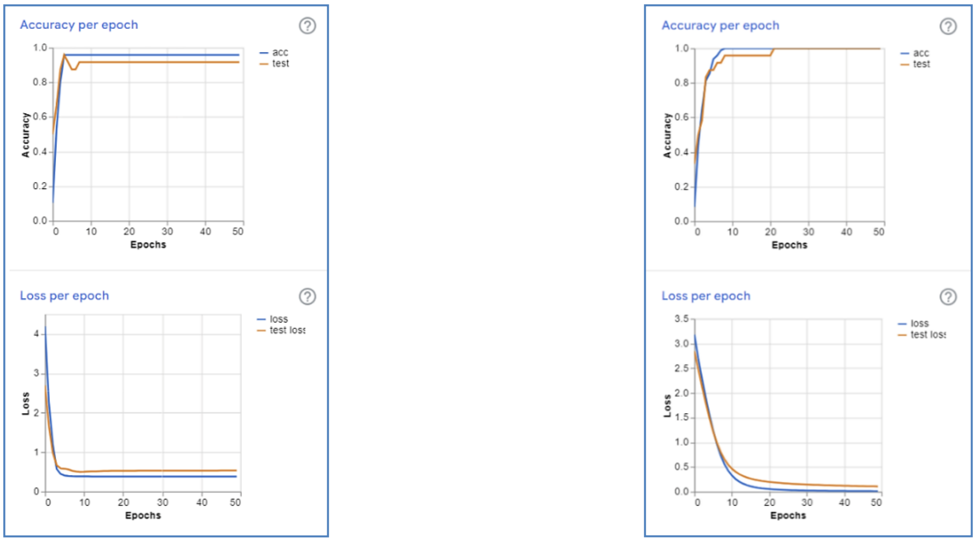
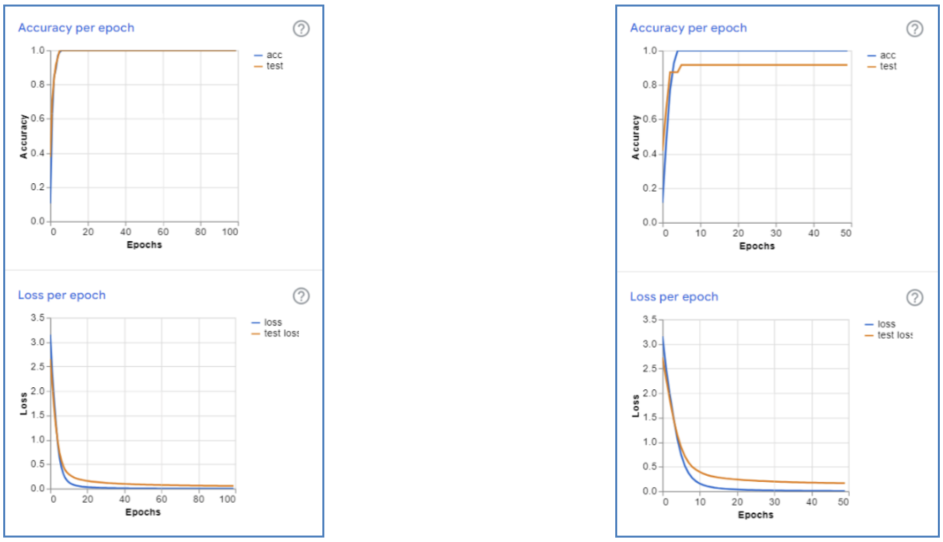


(a) (b)

Figure 3. Result: (a) Epoch 50, Batch Size 16, Learning Rate 0,01 and (b) Result Epoch: 50, Batch Size: 16, Learning Rate: 0.001

Figure 3(a) illustrates the training and validation accuracy as well as the loss curves obtained using Epoch 50, Batch Size 16, and Learning Rate 0.01. The accuracy rapidly increased during the early epochs and reached approximately 1.0, indicating that the model successfully learned the SIBI hand gesture patterns. Meanwhile, both training and validation loss decreased significantly and stabilized near zero, demonstrating a stable learning process with minimal prediction error. Figure 3(b) shows the experimental results obtained using the same Epoch and Batch Size while reducing the Learning Rate to 0.001. Compared with Figure 3(b), the model converged more smoothly and produced lower validation loss, indicating improved model generalization.

The third and fourth experimental scenarios are presented in Figures 4(a) and 4(b). These experiments were conducted using an Epoch of 50 and a Batch Size of 32 while varying the Learning Rate values to evaluate their influence on the training performance of the proposed Transfer Learning model.



(a) (b)

Figure 4. Result: (a) Epoch 50, Batch Size 32, Learning Rate 0,01 and (b) Epoch 50, Batch Size 32, Learning Rate 0,001

Figure 4(a) illustrates the training and validation performance obtained using Epoch 50, Batch Size 32, and Learning Rate 0.01. The accuracy curves increase rapidly during the initial training epochs and stabilize near 1.0, indicating that the model successfully learned the characteristics of the SIBI hand gesture dataset. In addition, the training and validation loss decrease significantly and approach zero, demonstrating stable convergence with minimal prediction error throughout the training process. Figure 4(b) presents the experimental results using Epoch 50, Batch Size 32, and Learning Rate 0.001. Compared with Figure 4(a), the lower learning rate produces a smoother convergence

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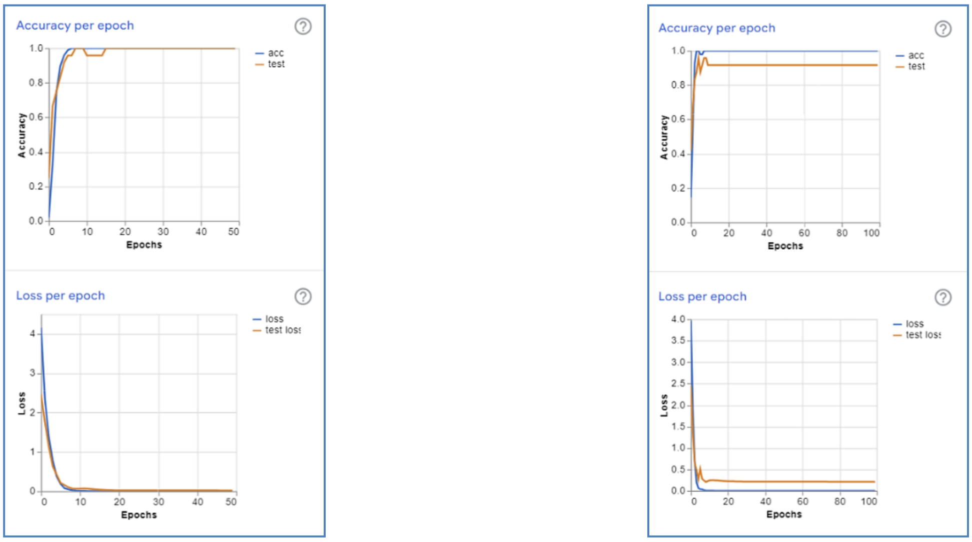
process while maintaining high training and validation accuracy. The loss curves gradually decrease and remain close to zero, indicating that the selected parameter configuration provides effective model optimization and good generalization capability.

Figures 5(a) and 5(b) present the fifth and sixth experimental scenarios. In these experiments, the Epoch value was increased to 100 while maintaining a Batch Size of 16 to investigate the effect of different Learning Rate values on the model performance.

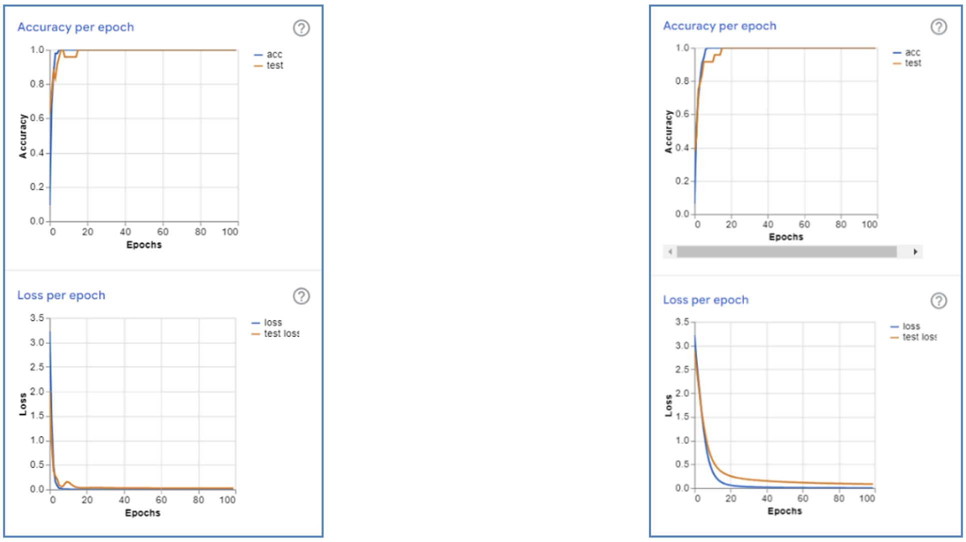


(a) (b)

Figure 5. Result: 5(a) Epoch 100, Batch Size 16, Learning Rate 0,01 and 5(b) Epoch 100, Batch Size 16, Learning Rate 0,001

Figure 5(a) shows the training performance achieved using Epoch 100, Batch Size 16, and Learning Rate 0.01. The accuracy reaches approximately 1.0 after several training epochs and remains stable throughout the training process. Similarly, both training and validation loss decrease rapidly to values close to zero, indicating that the model converges efficiently without significant fluctuations. Figure 5(b) illustrates the experimental results obtained using Epoch 100, Batch Size 16, and Learning Rate 0.001. The model demonstrates consistent learning behaviour, achieving high accuracy while maintaining a very low loss value. Compared with Figure 5(a), the smaller learning rate provides a more gradual optimization process, contributing to improved training stability and reliable classification performance.

The final experimental scenarios are illustrated in Figures 6(a) and 6(b). These experiments evaluate the model using the maximum Epoch value (100) combined with a Batch Size of 32 under two different Learning Rate settings to determine the most suitable parameter configuration.



(a) (b)

Figure 6. Result Epoch 100, Batch Size 32, Learning Rate 0,01 and 6(b) Epoch 100, Batch Size 32, Learning Rate 0,001

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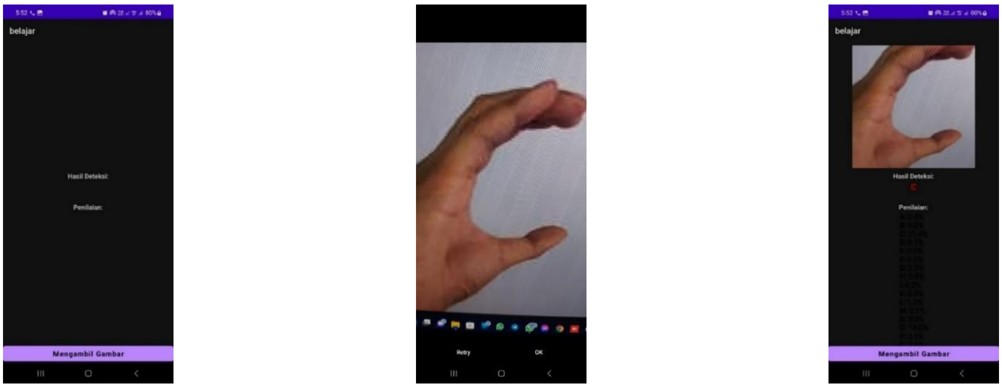
Figure 6(a) presents the training results obtained using Epoch 100, Batch Size 32, and Learning Rate 0.01. The model achieves high training and validation accuracy within a few epochs, while the corresponding loss curves rapidly decrease and stabilize near zero. These results indicate that the model effectively learns the SIBI hand gesture patterns with stable convergence throughout the training process. Figure 6(b) shows the performance of the proposed model using Epoch 100, Batch Size 32, and Learning Rate 0.001. The accuracy curves remain consistently close to 1.0, whereas the training and validation loss gradually decrease until reaching values close to zero. Overall, this configuration demonstrates reliable learning performance and confirms that the proposed Transfer Learning approach is capable of accurately recognizing SIBI hand gesture images.

From the test results of the 8 scenarios with variations in Epoch, Batch Size, and Learning Rate, it was found that the best test result was in the second scenario with Epoch: 50, Batch Size: 16, and Learning Rate: 0.001. The best test had a high accuracy rate and test graph, both at a value of 1.0. It also had a low error rate and test error graph, both close to 0.0, as shown in Figure 3(b).

3.2 Implementation Results

The implementation results of the proposed Android application are presented in Figures 7. These figures illustrate the main user interface, the image capture process, and the recognition result generated by the developed SIBI hand gesture recognition system.



(a) (b) (b)

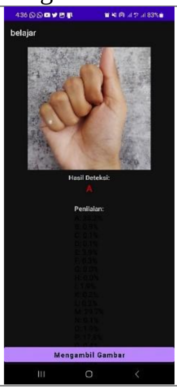
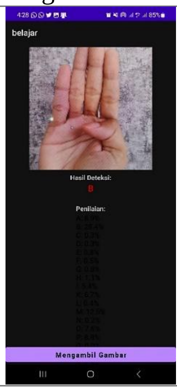
Figure 7. (a) Application main page, (b) Shooting view, and (c) Display of image capture results

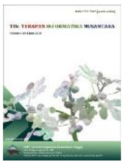
Figure 7(a) shows the main page of the application. On this page, the application's name is displayed in the top left corner, along with the image detection template above the detection result text, and the detection result and evaluation template. Figure 7(b). shows the camera interface for capturing gesture or hand movement images to be converted into letters. After capturing the gesture or hand movement image, there is an option to retake the photo by pressing the Retry button, and if the photo is satisfactory, proceed by pressing the OK button. Figure 7(c). displays the result or output after detecting the gesture or hand movement photo according to SIBI. The image above indicates that the gesture was detected as the letter C, with a high detection accuracy rate for the letter C at 71.4%.

3.3 Letter-by-Letter Test Results in the Application

To evaluate the functionality of the proposed Android application, a letter-by-letter recognition test was conducted using all static SIBI alphabet gestures. The visual recognition results generated by the application are presented in Table 3, which illustrates several examples of the detected hand gestures and their corresponding classification outputs.

Table 3. Application Result Display

Letter	Figure Result	Letter	Figure Result
A		**B**	



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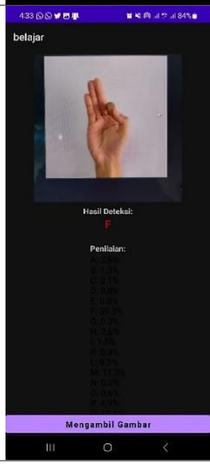
Letter	Figure Result	Letter	Figure Result
C		**D**	
E		**F**	

Table 3 presents examples of recognition results obtained from the developed Android application. The application successfully identifies input hand gestures and displays the corresponding SIBI alphabet as the predicted result. The examples shown for letters A-Z except for letters J and Z demonstrate that the proposed Transfer Learning model is capable of correctly recognizing various static hand gesture patterns. These results indicate that the trained model can be effectively integrated into an Android application for real-time alphabet recognition.
The overall results of the letter-by-letter recognition test are summarized in Table 4. The table presents the recognition status for each static SIBI alphabet letter used during the application testing process.

Table 4. Application test results per letter in the application.

Num.	Letter	Result
1	A	Success
2	B	Success
3	C	Success
4	D	Success
5	E	Success
6	F	Success
7	G	Success
8	H	Success
9	I	Success
10	K	Success
11	L	Success
12	M	Success
13	N	Success
14	O	Success
15	P	Success
16	Q	Success
17	R	Success
18	S	Success
19	T	Success
20	U	Success

Num.	Letter	Result
21	V	Success
22	W	Success
23	X	Success
24	Y	Success

Based on the testing results presented in Table 4, the Belajar SIBI application successfully detected all tested alphabet letters, namely A to Y (excluding J and Z, which are dynamic gestures). All testing results were categorized as "Success," indicating that the transfer learning model developed using Google Teachable Machine was able to accurately recognize each SIBI hand gesture pattern that had been trained previously.

The successful recognition of all alphabet classes demonstrates that the dataset collection process, consisting of 200 images for each letter class, provided sufficient representation for the model to learn the unique characteristics of every gesture. Furthermore, the implementation of the optimal training parameters, namely Epoch 50, Batch Size 16, and Learning Rate 0.001, significantly contributed to the model's classification performance. These parameter settings enabled the model to achieve high accuracy while maintaining a very low error rate during the training process.

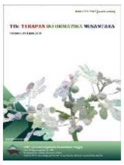
The testing results also confirm that the integration of the TensorFlow Lite model into the Android application was successfully implemented. When users capture hand gesture images through the smartphone camera, the application can process the image and classify the corresponding alphabet letter in real time. This capability indicates that the developed model performs well not only during the training stage but also in practical implementation on mobile devices.

3.4 Discussion

The experimental results demonstrate that the proposed Transfer Learning model effectively recognizes static SIBI alphabet gestures with high accuracy and stable performance. The optimal configuration, using Epoch 50, Batch Size 16, and Learning Rate 0.001, achieved the best training results, indicating that appropriate hyperparameter selection significantly influences model convergence and recognition accuracy. These findings are consistent with previous studies by Prasad et al. (2022) and Kamruzzaman (2020), which reported that Transfer Learning can provide high recognition accuracy while maintaining computational efficiency. However, unlike previous studies that focused mainly on recognition performance or employed more complex deep learning architectures, this research systematically evaluates the impact of training hyperparameters before deploying the model into an Android application. The successful implementation of the optimized TensorFlow Lite model demonstrates that a lightweight Transfer Learning approach can provide reliable real-time SIBI hand gesture recognition. Therefore, the proposed system offers a practical solution for supporting SIBI learning and improving communication accessibility for deaf and speech-impaired individuals.

4. KESIMPULAN

This study demonstrates that the proposed Android-based application using the Transfer Learning approach implemented through Google Teachable Machine provides an effective solution for recognizing static hand gestures of the Indonesian Sign Language System (SIBI). The experimental evaluation confirms that the developed model is capable of achieving reliable recognition performance, with the optimal training configuration producing high classification accuracy and a low error rate, indicating that the model can effectively learn and generalize the characteristics of SIBI hand gesture images. Furthermore, the implementation results show that the developed application successfully recognizes all tested static alphabet gestures and provides recognition outputs in real time, demonstrating its practical applicability on mobile devices. The use of Google Teachable Machine combined with TensorFlow Lite also proves that an accurate hand gesture recognition system can be developed without requiring complex model architectures or high computational resources, making the proposed approach suitable for lightweight Android applications. Beyond its technical performance, the developed application has the potential to serve as an educational medium for learning SIBI and as a supporting tool to facilitate communication between deaf or speech-impaired individuals and the general public. The primary contribution of this research lies in the development of a lightweight and practical SIBI hand gesture recognition framework that integrates Google Teachable Machine, Transfer Learning, and TensorFlow Lite for Android implementation. In addition, this study provides experimental evidence regarding the influence of training hyperparameters, namely Epoch, Batch Size, and Learning Rate, on the performance of SIBI hand gesture recognition models. These findings can serve as a valuable reference for future research on mobile-based sign language recognition systems while promoting the adoption of artificial intelligence technologies to support inclusive communication and accessibility. The findings also indicate that Transfer Learning is an efficient approach for developing image-based recognition systems with limited datasets while maintaining stable performance. Therefore, this research contributes to the advancement of artificial intelligence applications in the field of accessibility by providing a practical, accurate, and efficient SIBI hand gesture recognition system that can support inclusive communication and may serve as a foundation for future studies involving dynamic gestures, larger datasets, and more advanced real-time recognition techniques.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REFERENCES

Anggraeni, M. E., Sarinastiti, W., & Wati, S. (2019). Indonesian Sign Language (SIBI) Vocabulary Learning Media Design Based on Augmented Reality for Hearing-Impaired Children. *Jurnal EECCIS*, *13*(3), 139–144.

Anwar, A., Basuki, A., & Sigit, R. (2020). Hand Gesture Recognition For Indonesian Sign Language Interpreter System With Myo Armband Using Support Vector Machine. *Klik - Kumpulan Jurnal Ilmu Komputer*, *7*(2), 164. https://doi.org/10.20527/klik.v7i2.320

Camgoz, N. C., Hadfield, S., Koller, O., & Bowden, R. (2017). SubUNets: End-to-End Hand Shape and Continuous Sign Language Recognition. *2017 IEEE International Conference on Computer Vision (ICCV)*, 3075–3084. https://doi.org/10.1109/ICCV.2017.332

Den Hoed, J., & Fisher, S. E. (2020). Genetic pathways involved in human speech disorders. *Current Opinion in Genetics & Development*, *65*, 103–111. https://doi.org/10.1016/j.gde.2020.05.012

DiMarzio, J. F. (2016). *Beginning Android® Programming with Android Studio* (1 ed.). Wiley. https://doi.org/10.1002/9781119419334

Eldeen, R. K., & H.G.Yousif, E. (2021). *A Hand Gesture Recognition System for Deaf-Mute Individuals*. *21*(3).

Forchhammer, S., Abu-Ghazaleh, A., Metzler, G., Garbe, C., & Eigentler, T. (2022). Development of an Image Analysis-Based Prognosis Score Using Google's Teachable Machine in Melanoma. *Cancers*, *14*(9), 2243. https://doi.org/10.3390/cancers14092243

Gresse Von Wangenheim, C., Marques, L. S., & Hauck, J. C. R. (2020). *Machine Learning for All – Introducing Machine Learning in K-12*. https://doi.org/10.31235/osf.io/wj5ne

Harditya, A. (2020). Indonesian Sign Language (BISINDO) As Means to Visualize Basic Graphic Shapes Using Teachable Machine: *Proceedings of the International Conference of Innovation in Media and Visual Design (IMDES 2020)*. International Conference of Innovation in Media and Visual Design (IMDES 2020), Tangerang, Indonesia. https://doi.org/10.2991/assehr.k.201202.045

Huang, Z., Siniscalchi, S. M., & Lee, C.-H. (2016). A unified approach to transfer learning of deep neural networks with applications to speaker adaptation in automatic speech recognition. *Neurocomputing*, *218*, 448–459. https://doi.org/10.1016/j.neucom.2016.09.018

Kamruzzaman, M. M. (2020). Arabic Sign Language Recognition and Generating Arabic Speech Using Convolutional Neural Network. *Wireless Communications and Mobile Computing*, *2020*, 1–9. https://doi.org/10.1155/2020/3685614

Kumar, L. A., Renuka, D. K., Rose, S. L., Shunmuga Priya, M. C., & Wartana, I. M. (2022). Deep learning based assistive technology on audio visual speech recognition for hearing impaired. *International Journal of Cognitive Computing in Engineering*, *3*, 24–30. https://doi.org/10.1016/j.ijcce.2022.01.003

Kumar, M., Singh, S., Singh, D. P., & Rai, A. K. (2025). Hybrid CNN–LSTM Transfer Learning for Real-Time Hand Gesture Recognition. *2025 3rd International Conference on IoT, Communication and Automation Technology (ICICAT)*, 1–6. https://doi.org/10.1109/ICICAT68430.2025.11414484

Kurhekar, P., Phadtare, J., Sinha, S., & Shirsat, K. P. (2019). Real Time Sign Language Estimation System. *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, 654–658. https://doi.org/10.1109/ICOEI.2019.8862701

Li, J., Jiang, X., Fan, J., Geng, Y., Jia, F., & Dai, C. (2025). Deep end-to-end transfer learning for robust inter-subject and inter-day hand gesture recognition using surface EMG. *Biomedical Signal Processing and Control*, *100*, 106892. https://doi.org/10.1016/j.bspc.2024.106892

Lian, Y., Lu, Z., Huang, X., Shangguan, Q., Yao, L., Huang, J., & Liu, Z. (2024). A Transfer Learning Strategy for Cross-Subject and Cross-Time Hand Gesture Recognition Based on A-Mode Ultrasound. *IEEE Sensors Journal*, *24*(10), 17183–17192. https://doi.org/10.1109/JSEN.2024.3382040

Malahina, E. A. U., Hadjon, R. P., & Bisilisin, F. Y. (2022). Teachable Machine: Real-Time Attendance of Students Based on Open Source System. *The IJICS (International Journal of Informatics and Computer Science)*, *6*(3), 140. https://doi.org/10.30865/ijics.v6i3.4928

Prasad, P. Y., Prasad, D. D., & Malleswari, D. D. N. (2022). Implementation of Machine Learning Based Google Teachable Machine in Early Childhood Education. *International Journal of Early Childhood Special Education*, *14*(03).

Rakun, E., Arymurthy, A. M., Stefanus, L. Y., Wicaksono, A. F., & Wisesa, I. W. W. (2018). Recognition of Sign Language System for Indonesian Language Using Long Short-Term Memory Neural Networks. *Advanced Science Letters*, *24*(2), 999–1004. https://doi.org/10.1166/asl.2018.10675

Ribeiro, A., Ferreira, J. F., & Mendes, A. (2021). EcoAndroid: An Android Studio Plugin for Developing Energy-Efficient Java Mobile Applications. *2021 IEEE 21st International Conference on Software Quality, Reliability and Security (QRS)*, 62–69. https://doi.org/10.1109/QRS54544.2021.00017

Vaidya, O., Gandhe, S., Sharma, A., Bhate, A., Bhosale, V., & Mahale, R. (2020). Design and Development of Hand Gesture based Communication Device for Deaf and Mute People. *2020 IEEE Bombay Section Signature Conference (IBSSC)*, 102–106. https://doi.org/10.1109/IBSSC51096.2020.9332208

Weiss, K., Khoshgoftaar, T. M., & Wang, D. (2016). A survey of transfer learning. *Journal of Big Data*, *3*(1), 9. https://doi.org/10.1186/s40537-016-0043-6

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Zhang, Z., Liu, S., Wang, Y., Song, W., & Zhang, Y. (2024). Online cross session electromyographic hand gesture recognition using deep learning and transfer learning. *Engineering Applications of Artificial Intelligence*, *127*, 107251. https://doi.org/10.1016/j.engappai.2023.107251

Zhang, Z., Ming, Y., & Wang, Y. (2024). A federated transfer learning approach for surface electromyographic hand gesture recognition with emphasis on privacy preservation. *Engineering Applications of Artificial Intelligence*, *136*, 108952. https://doi.org/10.1016/j.engappai.2024.108952