Journal of Applied Business and Technology

Transfer Learning Model Evaluation on CNN Algorithm: Indonesian Sign Language System (SIBI)

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Article History
Received
21 April 2025
Received in revised form
28 April 2025
Accepted
28 April 2025
Published Online
31 May 2025

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Abstract
In Indonesia as much as elsewhere, the deaf can communicate using sign language. The Indonesian Sign Language System (SIBI) is one of the sign language systems used in Indonesia. A model produced by the Convolutional Neural Network (CNN) method can be used in computer science for the recognition of sign language. By using the Transfer Learning paradigm, CNN's performance may be enhanced. However, not many researches have been conducted to assess the effectiveness of transfer learning on sign language models, particularly those that use the TensorFlow library. In fact, the evaluation results can influence the selection of the transfer learning model together with CNN. This study aims to evaluate the efficacy of using the CNN model for SIBI sign language through Transfer Learning. The data used are images of 24 SIBI alphabets and are processed through the TensorFlow library. The images will be recognized through the transfer learning performance of 6 models, namely VGG16, VGG19, Resnet50, Desenet121, Inception-V3 and MobileNet-V2. The results of the study found that through the TensorFlow library, Mobilenetv2 had the highest accuracy of 78% after 20 epochs.

Keywords: Transfer Learning Models; Evaluation; SIBI; TensorFlow
DOI: https://doi.org/10.35145/jabt.v6i2.213
SDGs: Quality Education (4); Industry, Innovation and Infrastructure (9); Reduced Inequalities (10); Partnerships for the Goals (17)

1.0 INTRODUCTION

Currently, the use of sign language for deaf friends is increasingly prioritized. This is because it maintains equal rights and treatment with hearing friends or people who are not deaf. Technology is important to support the ease of acceptance of sign language by all parties (Maryamah et al., 2023). This was once conveyed by the World Health Organization (WHO) which was released on March 2, 2024 by United Nation News that sign language and other sensory substitutions are important options for many deaf friends to communicate, as are hearing aid technology and services, including closed captions and sign language interpretation. One of the sign languages that applies in Indonesia is the Indonesian Sign Language System (SIBI) and it is issued by the Ministry of Education and Culture (Angelyn & Putri, 2021). SIBI is used as a standard for communication for deaf friends in Indonesia (Syulistyo et al., 2020) and is implemented in Special Education (SLB). SIBI is not very widely mastered, especially by normal people, so it becomes one of the obstacles to communication with deaf friends.

Current technology in computer science also helps in the recognition of sign language. The use of transfer learning techniques in the Convolutional Neural Network (CNN) algorithm is one way to recognize SIBI in the form of alphabet images through a model generated by it (Suharjito et al., 2021). Transfer Learning is a new experimental research that aims to determine what defines a successful transfer and which network component is in charge of it by using a number of tests on visual domain and deep learning models. (Neyshabur et al., 2020). Therefore, the purpose of this research is to evaluate the efficacy of the CNN method for SIBI utilizing transfer learning models from the TensorFlow library. Transfer Learning Models are VGG16, VGG19, Resnet50, Desenet121, Inception-V3, and MobileNet-V2.

Several research have used CNN's transfer learning models with the TensorFlow framework. The VGG16, ResNet50, MobileNet-V2, and Inception-V3 transfer learning models on CNN are used to identify American sign language (Mohsin et al., 2024). An application developed from research has demonstrated transfer learning's ability to simultaneously detect multiple sign languages from various nations (Dinata & Marlim, 2020). The final model is able to identify the input sign images with high accuracy. ResNet50 is the transfer learning model that is being utilized (Patil et al., 2022). The use of the Tensorflow Library is also stated in research (Pathak et al., 2022) with the SSD Mobile net V2 transfer learning model. The VGG16 and Inception-V3 models have also been compared in studies of transfer learning (Abraham et al., 2022), while the ResNet-50 model has been studied (Saini et al., 2023), due to its ease of application to Indian sign languages. Previous studies demonstrate that CNN and Transfer Learning using the TanserFlow library may generate easily comprehensible classification models for sign languages.

According to the various studies that have been presented, the research on transfer learning is still possible. The objective of this research is to evaluate how well the CNN algorithm and transfer learning work for SIBI classification. The difference with previous studies lies in the number of transfer learning models used in the CNN algorithm, especially run through the TensorFlow library. The study's findings also show that there is Transfer Learning models are not as effective at identifying SIBI data as they may be. This study contributes to the expansion of knowledge of Transfer Learning through the TensorFlow library so that users can determine the best Transfer Learning model that works on the CNN algorithm for SIBI sign language.

2.0 LITERATURE REVIEW

Convulotional Neural Network (CNN)

CNN is a type of neural networks that focuses on image classification and recognition. To create the outcome, it takes inputs and runs them through a number of layers that extract various functionality (Purwono et al., 2022). The main advantage of CNN is its ability to automatically extract important features from image data without the need for time-consuming manual feature extraction. Compared to traditional manual feature extraction (Prihandoko et al., 2024). Ideally, the default input size of the image should be 224 × 224 × 3. The CNN architecture and the operation of its primary components are depicted in Figure 1.

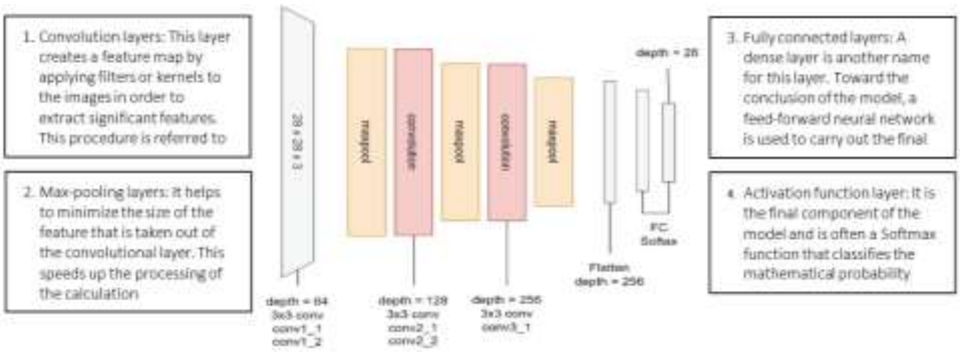


Figure 1. CNN Architectur and Its Fpur Main Components

Transfer Learning

Transfer learning involves adapting a model that was trained on one task to a comparable on. In conventional machine learning, models are trained separately for every job. In contrast, transfer learning enables models to enhance performance on a target task by reusing information from a source task (Noon, 2023).

Figure 2. Transfer Learning Concept

Transfer Learning enables models to leverage knowledge gained from one task or domain to improve performance on another. Figure 2 shows how Transfer Learning concept works. This approach has been particularly valuable in scenarios where large labeled datasets are scarce or computational resources are limited. Transfer Learning will make a model be taught and refined for one activity and then applied to a different one which is closely connected to it (Gupta et al., 2022). Transfer learning models that used in this research are six, namely VGG16, VGG19, Resnet50, Desenet121, Inception-V3 and MobileNet-V2.

In several studies, the performance of the six models in detecting objects produced high accuracy. MobileNet-V2 worked with an accuracy of 93.48% when detecting American Sign Language (Abu-Jamie et al., 2022) and 97% when detecting car images (Bouraya & Belangour, 2024). VGG16 and VGG19 produced accuracies of 97.5% and 96% when detecting American Sign Language (Dabwan et al., 2023). Resnet50 produced an accuracy of 0.53 in identifying 18 typologically different languages from speech recordings (Agangiba et al., 2023). Densenet121 works with an accuracy of 95.9% in recognizing weather images. For the Inception-V3 model, the accuracy is 85.40% when detecting SIBI which works embedded with the Random Forest algorithm (Sari & Jamzuri, 2025). The research references mentioned generally use the CNN algorithm. The implication of this study is that there is a possibility that these six Transfer Learning models can work with the same or lower accuracy than previous studies. Analysis of the evaluation results is expected to increase user knowledge of the appropriate model in reading SIBI sign language.

TensorFlow

TensorFlow is a symbolic math library that focuses on deep neural network training and inference by using dataflow and differentiable programming (Kennedy et al., 2022). TensorFlow is limited to working with numerical data (Joe & Joseph, 2021).

Figure 3. TensorFlow Architecture

Figure 3 illustrates TensorFlow's operation. Using the idea of a computational graph, the incoming data is processed and either transformed or displayed in mathematical (numerical) procedures. Additionally, constructing a model using the CNN Deep Learning algorithm for evaluation and training (Nasien et al., 2025). In certain experiments (Desnelita et al., 2025), the introduction of SIBI was also conducted using other libraries such as Mediapipe (Setiawan et al., 2024) (Wiraswendro & Soetanto, 2022). TensorFlow was chosen for this research because it becomes evident that the TensorFlow model performs better, particularly in reducing the number of false positives (Nesiga et al., 2024) so that it becomes a very potential library for testing. (Novac et al., 2022).

Evaluation Model

The resulting model is evaluated using a Confusion Matrix and visualized through a graph showing the number of epochs. A confusion matrix is a tabular format that aids in describing the model's ability to handle test data with known true values (Saini et al., 2023). All of the classes that exist are clearly distinguished in an ideal confusion matrix. As a result, it is evident that this was a poor assessment parameter because our model has much too many classes for a confusion matrix to be evaluated. Plotting the confusion matrix is useful because it makes important data and analytics, such as accuracy, precision, recall, and specificity, easier to see. In assessing and comprehending the findings of the suggested models, other assessment metrics such as accuracy, precision, recall, and F1-score produced superior results (Sathyanarayanan & Tantri, 2024). The following evaluation metrics were considered for all the models. The model with the best evaluation results is the recommended model.

$$Accuracy = \frac{True_{Positive} + True_{Negatif}}{True_{Positive} + False_{Positive} + True_{Negative} + False_{Negative}} \tag{1}$$

$$Precision = \frac{True_{Positive}}{True_{Positive} + False_{Positive}} \tag{2}$$

$$Recall = \frac{True_{Positive}}{True_{Positive} + False_{Negative}} \tag{3}$$

$$F1 - Score = 2 * \frac{Precision + Recall}{Precision + Recall} \tag{4}$$

3.0 METHODOLOGY

Numerous actions are taken to support this study in order to meet the objectives. The following stages are conducted to accomplish the research objectives, as seen in Figure 4.

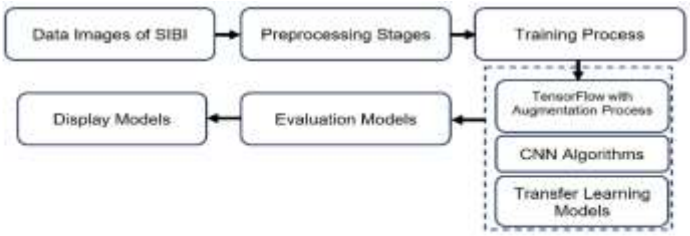


Figure 4. Research Stages

The study began with data preparation in the form of SIBI sign language images. Data were taken from the SIBI Dictionary of the Ministry of Education and Culture of the Republic of Indonesia. There are 24 alphabet sign images outside J and Z with a total of 600 data. The sign images processed with CNN and Transfer Learning is shown in Figure 5. Additionally, the picture data is examined to make sure it can be read through the augmentation process. The augmentation process is part of the success of the TensorFlow library in processing image data because TensorFlow can only work on numeric data. Data is transformed by inverting, rotating, and changing the lighting and color of the image. The image is also converted from RGB to grayscale and grayscale to binary, feature extraction with sobel edge detection and identification so that the image/picture is recognized. The source code of the augmentation process is in Figure 6.

Figure 5. SIBI Image Data

```
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.1,
    zoom_range=0.1,
    brightness_range=[0.9, 1.1],
    horizontal_flip=True,
    vertical_flip=False,
    fill_mode='nearest',
    validation_split=0.2
)

print
```

Figure 6. Augmentation Process for MobileNet-V2 Model

Data splitting is the following stage once augmentation is finished. A composition of 80:20 separates the data into training and test data. The TensorFlow library, Transfer Learning, and the CNN algorithm are used to process the data. Six models are generated from the training data. We use the Confusion Matrix to analyze the six models. The model with the highest accuracy becomes the recommended model and is displayed through the application created by the user. The program is run with the Python programming language. Deployment used flask from Anaconda.

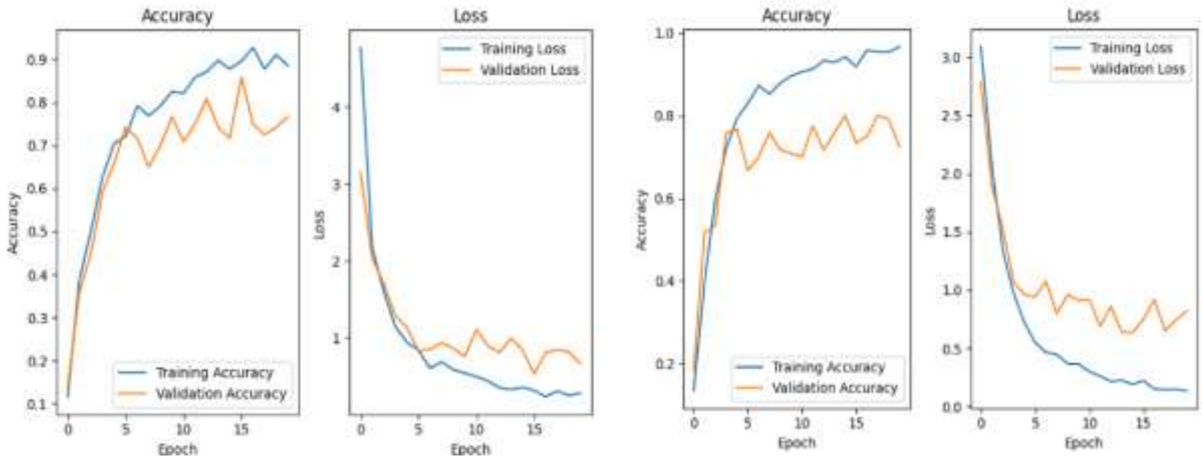
4.0 RESULTS AND DISCUSSION

After completing the preprocessing step, Python is used to process SIBI gesture image data. The split that has been established indicates that 80% of the data is trained. According on the training findings, every Transfer Learning model was able to correctly collect 24 classes of 480 image data. 120 image data were successfully validated after going through 20 epochs where each epoch processed 30 image data randomly.

CNN and Transfer Learning Models Result

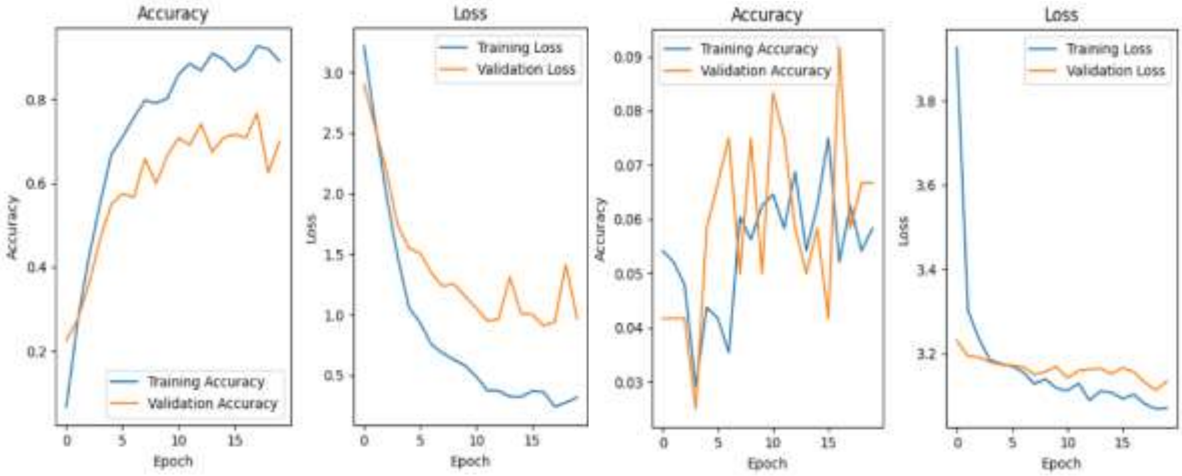
TensorFlow is used in this work to interpret images following the augmentation procedure before training them on all models. Each transfer learning model detects image data from library with different results even from the same 480 image data. Figure 7 shows examples of images validated using the MobileNet-V2 model. Visualization of the results of successful and unsuccessful image data validation for each model depending on epochs, displays in Figure 8-10.

Figure 7. SIBI Images Detected by MobileNet-V2 Model



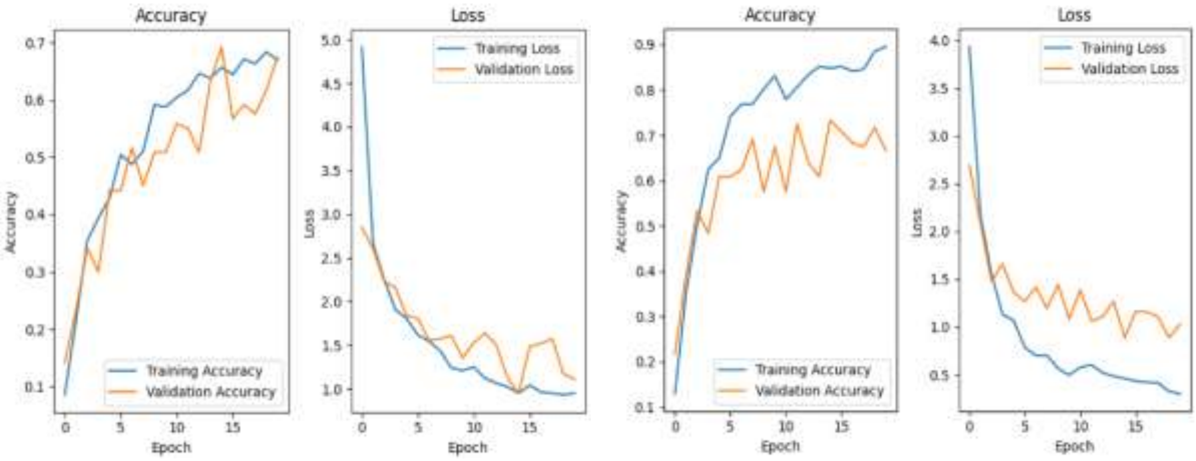
(a) b)

Figure 8. (a) MobileNet-V2 Visualization. (b) VGG16 Visualization



(a) (b)

Figure 9. (a) VGG19 Visualization. (b) Resnet50 Visualization



(a) (b)

Figure 10. (a) Inception-V3 Visualization. (b) Densenet121 Visualization

Figure 8-10 demonstrates that the epoch results vary per model. The number of times the deep learning algorithm—in this example, CNN—runs over the full dataset both forward and backward is determined by the hyperparameter-epoch (Susanto et al., 2024). All batches must successfully go through the neural network once to reach one epoch. In the aforementioned example, 30 batches of training data samples are processed to reach 1 epoch. MobileNet-V2, VGG16, VGG19, and Densenet121 exhibit validation assessment and training accuracy that are near or over 90% and generally constant across epochs. Inception-V3 is not the same as this. As in the four transfer learning models previously described, there is less consistency between the training and validation assessment outcomes. Resnet50 has the lowest accuracy of all the models, with inconsistent training and validation outcomes from the start (Purnama et al., 2025).

All SIBI signal images can be identified with high accuracy, according to the training results. The fact that not all models have constant accuracy and validation demonstrates how effectively TensorFlow, CNN, and Transfer Learning can identify images using models. This can be found in the results of the model evaluation through the confusion matrix.

Evaluation Models

A confusion matrix is used to evaluate the models with measures accuracy, precision, recall and F1-score. The calculation of the confusion matrix refers to equations (1)-(4). Figures 11-13 show the accuracy of each model. Based on the training results with 80:20 data splitting, the lowest accuracy is found in Resnet50 at 0.09. The model failed to read 21 letters out of 24 letters. The only letter detected was the letter G with precision = 0.06, recall = 1.00 F1-score = 0.11. The next letter is Q, which has precision = 0.75, recall = 0.60, and F1-score = 0.67. MobileNet-V2, the Transfer Learning model with the highest accuracy, has a value of 0.78. Six SIBI images—the letters A, L, Q, R, T, and U—are perfectly detected for all matrix measurements with a value of 1.00. It makes MobileNet-V2 the best model in this study for SIBI detection of sign language.

	precision	recall	f1-score	support
A	1.00	1.00	1.00	5
B	0.56	1.00	0.71	5
C	0.38	1.00	0.56	5
D	0.83	1.00	0.91	5
E	1.00	0.80	0.89	5
F	1.00	0.60	0.75	5
G	0.67	0.40	0.50	5
H	1.00	0.80	0.89	5
I	0.45	1.00	0.62	5
K	1.00	0.40	0.57	5
L	1.00	1.00	1.00	5
M	1.00	0.40	0.57	5
N	0.50	0.40	0.44	5
O	1.00	0.20	0.33	5
P	1.00	0.80	0.89	5
Q	1.00	1.00	1.00	5
R	1.00	1.00	1.00	5
S	1.00	0.80	0.89	5
T	1.00	1.00	1.00	5
U	1.00	1.00	1.00	5
V	0.67	0.40	0.50	5
W	0.57	0.80	0.67	5
X	0.83	1.00	0.91	5
Y	1.00	0.80	0.89	5
accuracy			0.78	120
macro avg	0.85	0.78	0.77	120
weighted avg	0.85	0.78	0.77	120

(a)

	precision	recall	f1-score	support
A	0.71	1.00	0.83	5
B	0.62	1.00	0.77	5
C	0.56	1.00	0.71	5
D	0.80	0.80	0.80	5
E	1.00	0.40	0.57	5
F	1.00	0.60	0.75	5
G	0.00	0.00	0.00	5
H	1.00	1.00	1.00	5
I	0.62	1.00	0.77	5
K	0.71	1.00	0.83	5
L	0.71	1.00	0.83	5
M	0.33	0.60	0.43	5
N	0.00	0.00	0.00	5
O	1.00	0.60	0.75	5
P	1.00	0.80	0.89	5
Q	1.00	1.00	1.00	5
R	0.00	0.00	0.00	5
S	1.00	0.40	0.57	5
T	0.45	1.00	0.62	5
U	1.00	1.00	1.00	5
V	1.00	0.60	0.75	5
W	0.71	1.00	0.83	5
X	1.00	0.80	0.89	5
Y	1.00	1.00	1.00	5
accuracy			0.73	120
macro avg	0.72	0.73	0.69	120
weighted avg	0.72	0.73	0.69	120

(b)

Figure 11. (a) MobileNet-V2 Accuracy. (b) VGG16 Accuracy

	precision	recall	f1-score	support
A	0.83	1.00	0.91	5
B	0.71	1.00	0.83	5
C	0.56	1.00	0.71	5
D	0.83	1.00	0.91	5
E	0.80	0.80	0.80	5
F	1.00	0.40	0.57	5
G	0.71	1.00	0.83	5
H	1.00	0.80	0.89	5
I	1.00	0.40	0.57	5
K	0.62	1.00	0.77	5
L	0.71	1.00	0.83	5
M	0.67	0.40	0.50	5
N	0.75	0.60	0.67	5
O	1.00	0.40	0.57	5
P	1.00	0.20	0.33	5
Q	1.00	0.80	0.89	5
R	1.00	1.00	1.00	5
S	0.75	0.60	0.67	5
T	0.62	1.00	0.77	5
U	0.50	1.00	0.67	5
V	0.75	0.60	0.67	5
W	0.67	0.40	0.50	5
X	1.00	0.40	0.57	5
Y	0.71	1.00	0.83	5
accuracy			0.74	120
macro avg	0.80	0.74	0.72	120
weighted avg	0.80	0.74	0.72	120

(a)

	precision	recall	f1-score	support
A	0.00	0.00	0.00	5
B	0.00	0.00	0.00	5
C	0.00	0.00	0.00	5
D	0.00	0.00	0.00	5
E	0.00	0.00	0.00	5
F	0.00	0.00	0.00	5
G	0.06	1.00	0.11	5
H	0.00	0.00	0.00	5
I	0.00	0.00	0.00	5
K	0.00	0.00	0.00	5
L	0.00	0.00	0.00	5
M	0.00	0.00	0.00	5
N	0.00	0.00	0.00	5
O	0.00	0.00	0.00	5
P	0.00	0.00	0.00	5
Q	0.75	0.60	0.67	5
R	0.00	0.00	0.00	5
S	0.00	0.00	0.00	5
T	0.00	0.00	0.00	5
U	0.00	0.00	0.00	5
V	0.00	0.00	0.00	5
W	0.60	0.60	0.60	5
X	0.00	0.00	0.00	5
Y	0.00	0.00	0.00	5
accuracy			0.09	120
macro avg	0.06	0.09	0.06	120
weighted avg	0.06	0.09	0.06	120

(b)

Figure 12. (a) VGG19 Accuracy. (b) Resnet50 Accuracy

	precision	recall	f1-score	support
A	0.80	0.80	0.80	5
B	0.57	0.80	0.67	5
C	0.75	0.60	0.67	5
D	0.67	0.80	0.73	5
E	0.50	1.00	0.67	5
F	1.00	0.80	0.89	5
G	0.83	1.00	0.91	5
H	1.00	0.80	0.89	5
I	0.20	0.20	0.20	5
K	0.31	0.80	0.44	5
L	1.00	0.40	0.57	5
M	1.00	0.20	0.33	5
N	0.33	0.20	0.25	5
O	1.00	1.00	1.00	5
P	1.00	0.80	0.89	5
Q	0.80	0.80	0.80	5
R	0.25	0.20	0.22	5
S	1.00	0.40	0.57	5
T	1.00	0.80	0.89	5
U	0.75	0.60	0.67	5
V	0.43	0.60	0.50	5
W	0.67	0.40	0.50	5
X	0.33	0.20	0.25	5
Y	0.33	0.60	0.43	5
accuracy			0.62	120
macro avg	0.69	0.62	0.61	120
weighted avg	0.69	0.62	0.61	120

(a)

	precision	recall	f1-score	support
A	1.00	0.40	0.57	5
B	0.50	0.80	0.62	5
C	0.38	1.00	0.56	5
D	1.00	1.00	1.00	5
E	0.71	1.00	0.83	5
F	1.00	0.40	0.57	5
G	0.57	0.80	0.67	5
H	1.00	0.80	0.89	5
I	1.00	1.00	1.00	5
K	0.57	0.80	0.67	5
L	1.00	1.00	1.00	5
M	1.00	0.20	0.33	5
N	0.50	0.40	0.44	5
O	0.75	0.60	0.67	5
P	1.00	0.80	0.89	5
Q	0.83	1.00	0.91	5
R	0.50	0.20	0.29	5
S	0.22	0.40	0.29	5
T	0.57	0.80	0.67	5
U	1.00	0.60	0.75	5
V	0.50	0.20	0.29	5
W	0.50	0.60	0.55	5
X	1.00	0.60	0.75	5
Y	1.00	0.80	0.89	5
accuracy			0.68	120
macro avg	0.75	0.67	0.67	120
weighted avg	0.75	0.68	0.67	120

(b)

Figure 13. (a) Inception-V3 Accuracy. (b) Dansenet121 Accuracy

Deployment Model

This research developed an application to demonstrate the model's precision for detecting SIBI letters. The model tested was the Transfer Learning model with the highest accuracy, namely MobileNet-V2. The MobileNetV2 model was deployed using Flask to develop a web application capable of receiving SIBI, processing them with the SIBI detection model, and displaying the analysis results. Flask handles HTTP requests, loads the trained model, and presents the predicted SIBI type to the user. Figure 14 and 15 is the result of the deployment of the MobileNet-V2 model.

Figure 14. Flask Based SIBI Detection - Input Page

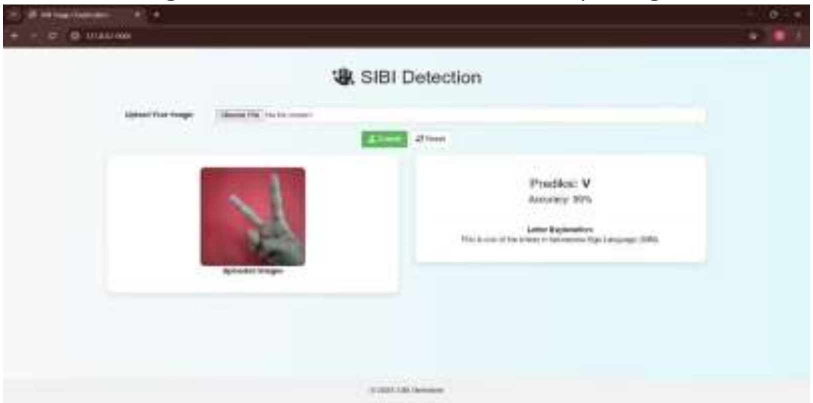


Figure 15. Flask Based SIBI Detection Page – Results Page

The SIBI letter detection MobileNet-V2 model testing application is displayed in Figures 14 and 15. For instance, the letter L. The program has a 97% accuracy level in detecting SIBI signals for the letter L. The letter Y has an 89% accuracy level, whereas the letter K has a 100% accuracy level, among other SIBI signals. On the other hand, several letters have accuracy under 78%. This means that the model will work to detect letters with a probability of accuracy above or below 78%. This is understandable, because the MobileNet-V2 model only has an accuracy of 78% for all SIBI signal images.

5.0 CONCLUSION

Evaluation of Transfer Learning in CNN algorithms using TensorFlow library shows the efficacy of the six models used in this study and opens up opportunities for increasing understanding of model performance. The efficacy of using Transfer Learning on CNN is obtained from the data training process that is tested into a number of epochs. This study found the consistency of the best model accuracy at epoch 20, although the Resnet model failed to find consistent accuracy and validation. This is likely due to image data that is not read properly or the augmentation process that is less suitable for Resnet.

This study differs significantly from earlier research that was similar in terms of model accuracy. In earlier research, accuracy was higher even if the same or different objects were detected. Nevertheless, this can be explained by various caused such as image sources, data preprocessing procedures like augmentation that the algorithm reads less when building models, and figuring out the number of epochs, which can have an indirect impact on the validation of SIBI images when Transfer Learning models are used.

MobileNet is the study's most accurate model, and the application allows it to demonstrate its accuracy in identifying SIBI sign images. The average accuracy of all image detection was higher than the model accuracy. Merely 4 images, or around 16%, fell short of the model's accuracy. To assist deaf friends and others in need comprehend and identify SIBI sign language, MobileNet might be a suggested model. Evaluation of the efficacy of Transfer Learning has been proven to contribute to achieving research objectives and expanding knowledge of the best CNN model for SIBI gesture recognition. This research can be developed by testing other Transfer Learning models such as EfficientNet and Xception or using Deep Learning algorithms other than CNN such as Deep Neural Network (DNN) and Artificial Neural Network (ANN).

Acknowledgement

Thank you to Institut Bisnis dan Teknologi Pelita Indonesia which has become a place for researchers to develop this journal research. Hopefully, this research can make a major contribution to the advancement of technology in Indonesia.

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