Gmail

Bambang Krismono Triwijoyo <bkrismono@universitasbumigora.ac.id>

[JITEKI] Submission Acknowledgement

1 message

Alfian Ma'arif <alfianmaarif@ee.uad.ac.id> Sun, Oct 16, 2022 at 11:32 PM
To: "Mr. Bambang Krismono Triwijoyo" <bkrismono@universitasbumigora.ac.id>

Dear Mr. Bambang Krismono Triwijoyo,

Thank you for submitting the manuscript, "Deep Learning Approach For Sign Language Recognition" to Jurnal Ilmiah Teknik Elektro Komputer dan Informatika. With the online journal management system that we are using, you will be able to track its progress through the editorial process by logging in to the journal web site:

Manuscript URL:
http://journal.uad.ac.id/index.php/JITEKI/author/submission/25051
Username: bkrismono

If you have any questions, please contact me. Thank you for considering this journal as a venue for your work.

Alfian Ma'arif
Jurnal Ilmiah Teknik Elektro Komputer dan Informatika
Jurnal Ilmiah Teknik Elektro Komputer dan Informatika
email: alfianmaarif@ee.uad.ac.id
website: www.journal.uad.ac.id/index.php/JITEKI

Gmail **Bambang Krismono Triwijoyo <bkrismono@universitasbumigora.ac.id>**

[JITEKI] Editor Decision

4 messages

Alfian Ma'arif <alfianmaarif@ee.uad.ac.id> Tue, Dec 27, 2022 at 12:12 PM
To: "Mr. Bambang Krismono Triwijoyo" <bkrismono@universitasbumigora.ac.id>

Dear Bambang Krismono Triwijoyo,

We have reached a decision regarding your submission to Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI) with the title, "Deep Learning Approach For Sign Language Recognition"

Our decision is: Revision Required

The detail of the comment is at the bottom of the email. Please do the revision maximum of 20 days.

Also, please log in to the JITEKI website and find the PDF / Docx file from a reviewer in the review part.

The author needs to revise the manuscript based on the editor and reviewer's suggestions, advice, and comment. Then, send the revision manuscript using the JITEKI journal website system. Please highlight the change/revision using the yellow/green color in the revised manuscript.

Don't make a new submission, upload it on your previous submission. The maximal file is 2MB (Word or PDF, if PDF then send the word file to the editor email).

Thank you.

Best Regards,
Alfian Ma'arif
JITEKI Editor
alfianmaarif@ee.uad.ac.id
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Universitas Ahmad Dahlan, Yogyakarta, Indonesia

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Comment of Editor:

>> Please state the research contribution at the end of the introduction, and abstract for example "The research contribution is..." We need at least two research contributions.

The Method contains an explanation of the research method and the proposed method. This section can include research diagrams, system block diagrams, or flowcharts diagrams.

In the Results and Discussion section, Please provide a comparison to a similar method from previous works (including citation) to enhance the research contribution.

The minimal References are 40 from an English Journal that was published 5 years ago and used IEEE Style. See the guide to writing the references in IEEE Style Format https://youtu.be/ijmG7iZ0yz0

The reference must be from IEEE Xplore or Science Direct. All references must have Digital Object Identifier (DOI) or permanent link. See the guide to getting high-quality references from IEEE Xplore https://youtu.be/2dqiF6Xrs8c

Please use Mendeley to make the references.

The Figure must be in PNG format with 600-1200 dpi. Please don't crop, or use snipping and print-screens tools. Otherwise, the image resolution will be compromised. The images using vector format (EWM) are better.

The Tabel must be made using the Insert Table feature not from the cropping table as an image.

The Equation must be made using Insert Equation. We suggest using 3 columns of the table to help, and then to make the equation in the middle of the column and the number of the equation on the right-side column. The variable in the equation must be given information. Please see the guide in the link on how to make the equation in word and

give the equation number.
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All of the figures, tables, and equations must be cited in paragraphs and explained; please give some explanation, information, or analysis. All of the figures and tables must be given by some analysis in at least one paragraph.

>> Please use Grammarly to check your manuscript. The free Grammarly is enough for fixing some typos and grammar mistakes. Proofreading is recommended to increase the quality of the English language and writing.

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Comment of Reviewers
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- The abstract is not representative of the content and contributions of the paper. The abstract does not seem to convey the rigor of research properly.
- The abstract should contain Objectives, Methods/Analysis, Findings, and Novelty /Improvement. It must have 200-300 words that consist of 2-3 sentences about the Introduction, problem, and solution; 1-2 sentences about the research contribution (write the research contribution is…); 3-4 sentences about the method; 4-5 sentences about the result; and 1-2 sentences about conclusions.
- The research contributions of the paper should be articulated more clearly.
- Aside from the aim stated in the title, the research gap and goals are not specified, leading to the reader missing the significance of the research.
- The introduction section must contain the research problem, solution, state of the art, novelty, literature review from previous research, and research contribution (the most important). Please write the research contribution in the last part of the Introduction, such as "The research contribution is…." At least there are two research contributions.
- Commonly, there are research flow, research diagrams, system block diagrams, control system block diagrams, hardware wiring diagrams, pseudocode, or flowcharts in the method section. The figure must be clear, detailed, not blurry, easy to read and provide proper information.
- A flowchart should be added to the article to show the research methodology.
- Much more explanations and interpretations must be added to the method, which is not enough at all.
- In the results section, provide a comparison to a similar method from previous works (including citation) to enhance research contributions (compare the result with previous research). All figures and tables must be clear, detailed, not blurry, and easy to read. Each figure and table must be given a comprehensive explanation in at least one paragraph of analysis (crucial).
- The discussion section needs to be described scientifically. Kindly frame it along the following lines:
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ii. Comparison with other studies
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iv. Strengths and limitations
- It is suggested to compare the results of the present study with previous studies and analyze their results completely.
- Please add future work so that it can motivate other researchers to continue the research.
- The minimal number of references is 40 from Science Direct, IEEE Xplore, Springer Link, MDPI Scilit, or Scopus databases. Cited references must be taken from the journal. Each should have a Digital Object Identifier (DOI) or permanent link. The references were published in the last five years.
- However, in its present form, the manuscript contains several weaknesses. Appropriate revisions to all of the points should be undertaken to justify recommendations for publication.

Please add the DOI in the references. For example,

H. I. K. Fathurrahman, A. Ma'arif, and L.-Y. Chin, "The Development of Real-Time Mobile Garbage Detection Using Deep Learning," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, vol. 7, no. 3, p. 472, 2022, https://doi.org/10.26555/jiteki.v7i3.22295.

P. Purwono, A. Ma'arif, I. S. Mangku Negara, W. Rahmaniar, and J. Rahmawan, "Linkage Detection of Features that Cause Stroke using Feyn Qlattice Machine Learning Model," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, vol. 7, no. 3, p. 423, 2021, https://doi.org/10.26555/jiteki.v7i3.22237.

==

Alfian Ma'arif <alfianmaarif@ee.uad.ac.id> Tue, Dec 27, 2022 at 12:12 PM
Reply-To: "Assist. Prof. Alfian Ma'arif" <alfianmaarif@ee.uad.ac.id>

To: "Mr. Bambang Krismono Triwijoyo" <bkrismono@universitasbumigora.ac.id>

[Quoted text hidden]
email: alfianmaarif@ee.uad.ac.id
website: www.journal.uad.ac.id/index.php/JITEKI

Bambang Krismono Triwijoyo <bkrismono@universitasbumigora.ac.id> Tue, Dec 27, 2022 at 3:42 PM
To: Alfian Ma'arif <alfianmaarif@ee.uad.ac.id>

Dear Alfian Ma'arif
JITEKI Editor

Thank you for the information regarding submitting our paper to JITEKI with the title, "Deep Learning Approach For Sign Language Recognition" By decision: Revision Required. We will revise it according to the notes from the reviewers and editors within 20 days. Then send the revised manuscript using the JITEKI journal website system. Thank you.

Greetings,
Bambang Krismono Triwijoyo
[Quoted text hidden]

Bambang Krismono Triwijoyo <bkrismono@universitasbumigora.ac.id> Sun, Jan 15, 2023 at 2:04 AM
To: Alfian Ma'arif <alfianmaarif@ee.uad.ac.id>

Dear Alfian Ma'arif
JITEKI Editor

Here I attach our paper file with the title, "Deep Learning Approach For Sign Language Recognition" which has been revised according to the editor's and reviewer's notes. We also send notes on revisions containing comments from editors and reviewers, along with responses from authors. Thank you.

Best Regards,
Bambang Krismono Triwijoyo
Corresponding Author

On Tue, Dec 27, 2022 at 12:12 PM Alfian Ma'arif <alfianmaarif@ee.uad.ac.id> wrote:
[Quoted text hidden]

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3 attachments

BK Triwijoyo JITEKI 2022 (Revised).pdf
1015K

BK Triwijoyo JITEKI 2022 (Revised).docx
1346K

Revision Result.pdf
149K

Gmail **Bambang Krismono Triwijoyo <bkrismono@universitasbumigora.ac.id>**

[JITEKI] Editor Decision

2 messages

Alfian Ma'arif <alfianmaarif@ee.uad.ac.id> Sun, Jan 15, 2023 at 11:31 AM
To: "Mr. Bambang Krismono Triwijoyo" <bkrismono@universitasbumigora.ac.id>

Dear Mr. Bambang Krismono Triwijoyo,

We have reached a decision regarding your submission to Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, "Deep Learning Approach For Sign Language Recognition".

Our decision is to: Accept Submission.

The Article Publication Charge is IDR1,500,000. The Editing Charge is IDR500,000.
The Total Payment is IDR2,000,000.

Please send your payment promptly to one of the bank accounts listed below.

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Thank you.

Best regards,
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Bambang Krismono Triwijoyo <bkrismono@universitasbumigora.ac.id> Mon, Jan 16, 2023 at 8:46 AM
To: Alfian Ma'arif <alfianmaarif@ee.uad.ac.id>

Dear Assist. Prof. Alfian Ma'arif
JITEKI Editor

Thank you for the information that our paper entitled "Deep Learning Approach For Sign Language Recognition" has been accepted for publication on JITEKI. We have made the payment Publication Fee Amounting to IDR 2,000,000. (Copy of Transfer Proof file attached).
Thank you.

Best Regards,
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145K

Editor
2022-12-27 11:12 AM

Subject: [JITEKI] Editor Decision DELETE

Dear Bambang Krismono Triwijoyo,

We have reached a decision regarding your submission to Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI) with the title, "Deep Learning Approach For Sign Language Recognition"

Our decision is: Revision Required

The detail of the comment is at the bottom of the email. Please do the revision maximum of 20 days.

Also, please log in to the JITEKI website and find the PDF / Docx file from a reviewer in the review part.

The author needs to revise the manuscript based on the editor and reviewer's suggestions, advice, and comment. Then, send the revision manuscript using the JITEKI journal website system. Please highlight the change/revision using the yellow/green color in the revised manuscript.

Don't make a new submission, upload it on your previous submission. The maximal file is 2MB (Word or PDF, if PDF then send the word file to the editor email).

Thank you.

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P. Purwono, A. Ma'arif, I. S. Mangku Negara, W. Rahmaniar, and J. Rahmawan, "Linkage Detection of Features that Cause Stroke using Feyn Qlattice Machine Learning Model," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, vol. 7, no. 3, p. 423, 2021, https://doi.org/10.26555/jiteki.v7i3.22237.

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Author
2022-12-27 02:44 PM

Subject: Deep Learning Approach For Sign Language Recognition DELETE

Dear Assist. Prof. Alfian Ma'arif
JITEKI Editor

Thank you for the information regarding submitting our paper to JITEKI with the title, "Deep Learning Approach For Sign Language Recognition" By decision: Revision Required. We will revise it according to the notes from the reviewers and editors within 20 days. Then send the revised manuscript using the JITEKI journal website system. Thank you.

Greetings,
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Author
2023-01-15 06:52 AM

Subject: Revised Paper ID #25051 DELETE

Dear Assist. Prof. Alfian Ma'arif
JITEKI Editor

Here I attach our paper file (word format) with the title, "Deep Learning Approach For Sign Language Recognition" which has been revised according to the editor's and reviewer's notes. Thank you.

Best Regards,
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Editor
2023-01-15 10:29 AM

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Dear Mr. Bambang Krismono Triwijoyo,

We have reached a decision regarding your submission to Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, "Deep Learning Approach For Sign Language Recognition".

Our decision is to: Revision Required.

Thank you.

Best regards,
Assist. Prof. Alfian Ma'arif
Universitas Ahmad Dahlan
alfianmaarif@ee.uad.ac.id
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Editor
2023-01-15 10:31 AM

Subject: [JITEKI] Editor Decision DELETE

Dear Mr. Bambang Krismono Triwijoyo,

We have reached a decision regarding your submission to Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, "Deep Learning Approach For Sign Language Recognition".

Our decision is to: Accept Submission.

Thank you.

Best regards,
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Deep Learning Approach For Sign Language Recognition

By Bambang Krismono Triwijoyo

Deep Learning Approach For Sign Language Recognition

Bambang Krismono Triwijoyo [1], L Yuda Rahmani Karnaen [2], Ahmat Adil [3]

[1,2,3] Universitas Bumigora, Jl. Ismail Marzuki No.22, Mataram 83127, Indonesia

ARTICLE INFO

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Received October 15, 2022
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Sign Language;
CNN;

ABSTRACT

Sign language is a method of communication that uses hand gestures between people with hearing loss. Each hand sign represents one meaning, but several terms don't have sign language, so they have to be spelled alphabetically. Problems occur when communicating between normal people with hearing loss, because not everyone understands sign language, so a model is needed to recognize sign language as well as a learning tool for beginners who want to learn sign language, especially alphabetic sign language. This study aims to create a hand sign language recognition model for alphabetic letters using a deep learning approach. The main contribution of this research is to produce a real-time hand sign language image acquisition, and hand sign language recognition model for Alphabet. The model used is a seven-layer Convolutional Neural Network (CNN). This model is trained using the ASL alphabet database which consists of 27 categories, where each category consists of 3000 images or a total of 87,000 hand gesture images measuring 200 x 200 pixels. First, the background correction process is carried out and the input image size is changed to 32 x 32 pixels using the bicubic interpolation method. Next, separate the dataset for training and validation respectively 75% and 25%. Finally the process of testing the model using data input of hand sign language images from a web camera. The test results show that the proposed model has good performance with an accuracy value of 99%. The experimental results show that image preprocessing using background correction can improve model performance.

Corresponding Author:

Bambang Krismono Triwijoyo, Universitas Bumigora, Jl. Ismail Marzuki No.22, Mataram 83127, Indonesia
Email: bkrismono@universitasbumigora.ac.id

1. INTRODUCTION

The research background is communication is very important in the process of social interaction. Communication leads to better understanding among the community, including the deaf [1]. Hand gesture recognition serves as the key to overcoming many difficulties and providing convenience for human life, especially for the deaf [3]. Sign language is a structured form of hand movement that involves visual movement and the use of various body parts namely fingers, hands, arms, head, body, and facial expressions to convey information in the communication process. For the deaf and speech-impaired community, sign language serves as a useful tool for everyday interactions.[4]. However, sign language is not common among normal people, and only a few people understand sign language. This creates a real problem in communication between the deaf community and other communities, which has not been fully resolved to this day [3]. Not all words have sign language, so special words that do not have sign language must be spelled using a letter sign one by one [5]. Based on the background, this study aims to develop a sign language recognition model for letters of the alphabet using a deep learning approach. The deep learning approach was chosen because deep learning methods are popular in the field of computer science and are proven to produce a good performance for image classification [6][7]. The novelty of this study is the

application of resizing and background correction of the input image for training and testing to improve model performance, where the results of testing the model we propose are better than previous similar studies.

The related work from past research is as follows. There have been many studies to recognize sign language, using various methods and varied datasets. Researchers [5] proposed a language recognition system using a 3D motion sensor by applying a k-nearest neighbor and support vector machine (SVM) to classify 26 letters in sign language. The average results of the highest classification levels of 72.78% and 79.83% were achieved by k-nearest neighbors and support vector machines, respectively. Based on previous studies that proposed hand sign language recognition models for alphabets, the results were not optimal, this is due to the complexity of lighting factors and other objects that appear in hand gesture images [5]. While there have been quite many studies on sign language recognition using a deep learning approach, here are several related studies including Study [8] has proposed a recognition system using a convolutional neural network (CNN) that can recognize 20 Italian gestures with high accuracy. Meanwhile, the following researchers introduced a sign language recognition (SLR) model using a deep learning approach. Study [9] implements transfer learning to improve accuracy. While study [10] has proposed the Restricted Boltzmann Machine (RBM) for automatic hand sign language recognition from visual data. The experimental results using four datasets show that the proposed multi-modal model achieves a fairly good accuracy. In the work [11], have proposed a deep learning-based framework for analyzing video features (images and optical flow) and skeletons (body, hands, and faces) using two sign language datasets. The results reveal the advantages of combining frame and video features optimally for SLR tasks.

A continuous deep learning-based sign language recognition model has also been introduced [12] which has proposed a 3D convolution residual network architecture and two-way LSTM, as a grammatical rule-based classification problem. The model has been evaluated on the benchmark of Chinese continuous sign language recognition with better performance. Other deep learning approach models have also been carried out for sign language recognition. A study [13] has proposed a ResNet50 Based Deep Neural Network architecture to classify finger-spelled words. The dataset used is the standard American Sign Language Hand gesture which produces an accuracy of 99.03%. While the study [14] Densely Connected Convolutional Neural Networks (DenseNet) to classify sign language in real-time using a web camera with an accuracy of 90.3%. The following studies [15][16][17][18][19] have implemented the CNN model for sign language recognition and tested using the American Sign Language (ASL) dataset, with an accuracy rate of 99.92%, 99.85%, 99.3%, 93%, and 99.91%.

Based on previous related studies, most of the sign language recognition methods use a deep learning approach. This study focuses on the introduction of hand sign language from the letters of the alphabet, which is used as a means of communication with the deaf. This study also uses the CNN model but with a different model architecture from previous studies. The CNN model was chosen because previous studies showed relatively better accuracy for image recognition [20][21][22]. The contributions of this research are: first, produce a real-time hand sign language image acquisition model by capturing each frame using a webcam video. Second, produce a hand sign language recognition model for the Alphabet, using a seven-layer CNN that has been trained using the ASL dataset and by applying resizing and background correction to the input image.

2. METHOD

This research is quantitative experimental research to measure the performance of hand sign language recognition models based on training datasets. Fig. 1 shows the proposed method for hand sign language recognition. In general, the proposed method consists of four stages, each of which is data acquisition, preprocessing, training and testing.

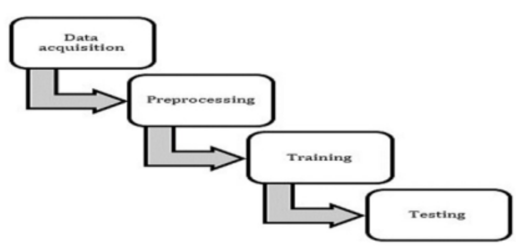

Fig. 1. Proposed Method

Based on the methodology applied in this study, as shown in Fig. 1, the first stage is data acquisition, where the data used in this study is the image. Image acquisition is the action of retrieving an image from an external source for further processing [23]. In this stage, the dataset used as model input is hand sign images, which are divided into 26 classes consisting of 26 sets of alphabets from A to Z. In this study, the dataset used as model input is hand sign images, which are divided into 26 classes consisting of 26 sets of alphabets from A to Z. The second stage is preprocessing. At this stage, the image size transformation is carried out to reduce the complexity of the model architecture. In this study, the transformation of the image size of the training data images from the initial size of 200x200 pixels was resized to 32x32 Pixels. In this study, we apply the bicubic interpolation method for resizing images as proposed by [24]. This resizing process is to reduce the computational time required for model training. To improve the segmentation accuracy of the hand sign language image below for complex lighting conditions, we apply a correction background method with luminance partition correction and adaptive threshold [25][26]. Furthermore, at the training stage, the CNN model architecture and its hyperparameters will be determined first. In this study, we use hyperparameter tuning to control the behavior of the machine learning model to produce optimal results. [27][28], then model training will be carried out using the dataset from the hand sign language image preprocessing. The last stage is model testing. At this stage, the model will be tested with hand sign language images in real-time using a webcam. The research proposed method flowchart is presented in Fig. 2.

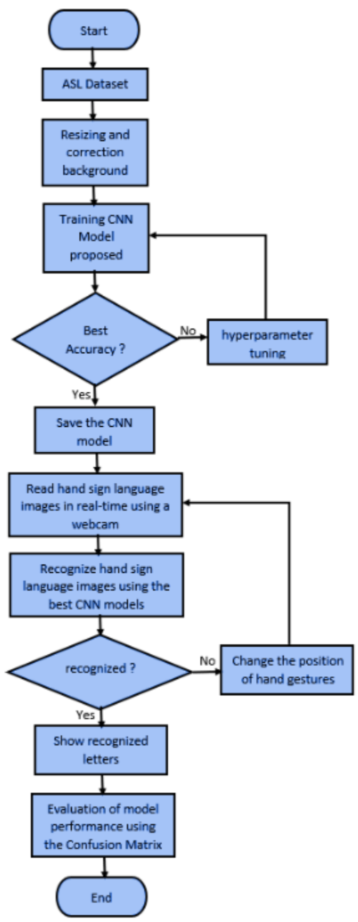

Fig 2. The Flowchart of Research Methodology

Furthermore, the results will be measured using a confusion matrix to determine the performance of the model [29]. Confusion matrices create result representations such as true positives (TP), true negatives (TN),

false positives (FP), and false negatives (FN). TP means a positive result that is predicted by machine learning correctly. TN means negative outcome predicted by machine learning Correct. While FP means positive results predicted by machine learning are wrong, and FN means negative outcomes predicted by machine learning are wrong. Confusion Matrix Performance evaluation with a confusion matrix results in accuracy, precision, and recall [30][31]. Accuracy is the number of data points that machine learning correctly predicts among all data. Can calculate as eq.1:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision is the percentage of relevant elements that can indicate the number of times the model can predict correctly and can be calculated as eq. 2.

$$Precission = \frac{TP}{TP + FP} \tag{2}$$

Meanwhile, recall is the percentage of relevant elements that are correctly classified by the model above all relevant elements. Recall calculation can be done using eq. 3.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

3. RESULTS AND DISCUSSION

3.1. Data Acquisition

The data is secondary data downloaded from kaggle.com in the ASL Alphabet repository which contains image datasets. in JPG format containing 29 folders with each containing 3,000 hand sign images. The total image data obtained amounted to 87,000 images [32]. Fig. 3 shows examples of hand sign language images sourced from the ASL Alphabet repository. The 87,000 images were distributed for the training process. The data is divided into two 75% for training and 25%. The train-test split is a technique for evaluating the performance of a machine-learning algorithm [33]. In the testing so for each class, there are 2,400 images for training and 600 images for testing, or a total of 69,600 images for training and 17,400 images for testing.

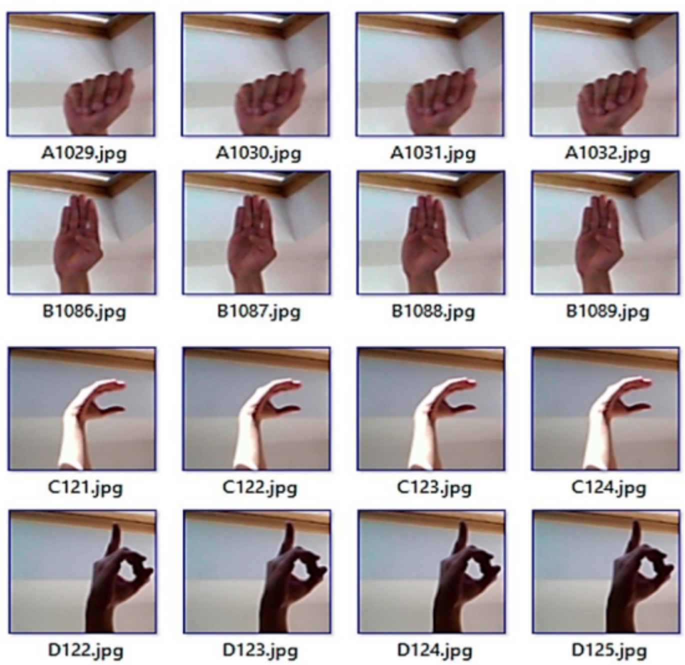

Fig. 3. Examples of hand sign language images from Kaggle

3.2. Preprocessing

At the preprocessing stage, the resizing process is carried out using the bicubic interpolation method [24], the results of this process produce an image size of 32x32 pixels, from the original image size of 200x200 pixels. This step is taken to reduce the time complexity during model training. the next preprocessing step is image background correction, to produce better accuracy using luminance partition correction and adaptive threshold [25]. Fig 4 shows examples of preprocessing results.

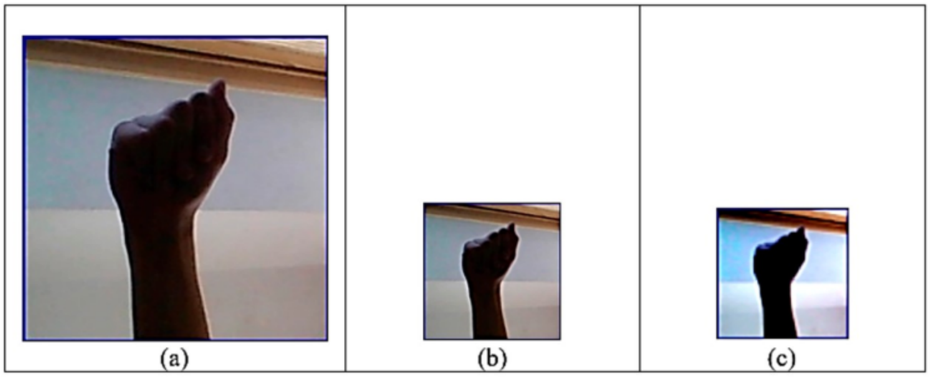

Fig. 4. (a). Original image size 200x200 pixels, (b). The result of resizing to a size of 32x32 pixels, (c). Background correction results.

In Fig.4 it can be seen that the dimensions of the hand sign language image size for the training dataset are reduced in size as well as the increase in color brightness and contrast resulting from the background correction process.

3.3. Training

At this stage, the CNN model design used in the training process is carried out to produce an appropriate model to classify hand sign language images. The CNN model applied uses hyperparameter values consisting of the learning rate, epoch, loss function, and optimizer. Table 1 below is the CNN architecture specification used in this study.

Table 1. CNN Model Architecture

Layer type	Description	Size
Input Layer	Input Image	32x32x3
Conv 1	Convolutional ReLU MaxPooling	8 kernel, 3x3 Window size 2x2
Conv 2	Convolutional ReLU MaxPooling	16 kernel, 3x3 Window size 2x2
Conv 3	Convolutional ReLU MaxPooling	32 kernel, 3x3 Window size 2x2
Flatten	Flatten	512
Fully Connected Layer	Dense ReLU	512
Output Layer	Dense Softmax	29

The CNN architectural design is as shown in table 1, there are input layers, 3 convolution layers, flatten, fully connected layers, and output layers. The Input Layer requires input with a size of 32x32x3 where 32x32 pixels 3 layers RGB, then in Conv 1 using 8 kernels measuring 3x3 after that using ReLU activation [34], and using Maxpool with a window size of 2x2, as well as Conv 2 and Conv 3, only on Conv 2 uses 16 kernels and Conv 3 uses 32 kernels. Next is the Flatten layer and Fully Connected Layer with 512 nodes, and

the last is the output layer containing Dense Softmax with 29 nodes [35], this is adjusted to the number of classes in the hand signal dataset of the alphabet.

The training process will be carried out through a series of iterations whose number of repetitions is determined by the maximum epoch value [36]. One epoch is a process when all training data has been used and passes through all network nodes once. While the hyperparameter used in this study is the Adam Optimizer [37], with The Batch Size is 32 and Epochs are 20. The model training process is carried out in a hardware and software environment with specifications for Dell Latitude E7440 Laptop, 12 GB DDR4 RAM, Processor Intel® Core™ i5-7200U CPU @ 2.50GHz, Nvidia GeForce 940MX GPU, 256 GB SSD. The operating system used is Windows 10 Professional and the training and testing model algorithms are implemented using python code by utilizing the Tensorflow library. The results of the training model as shown in Fig. 5.

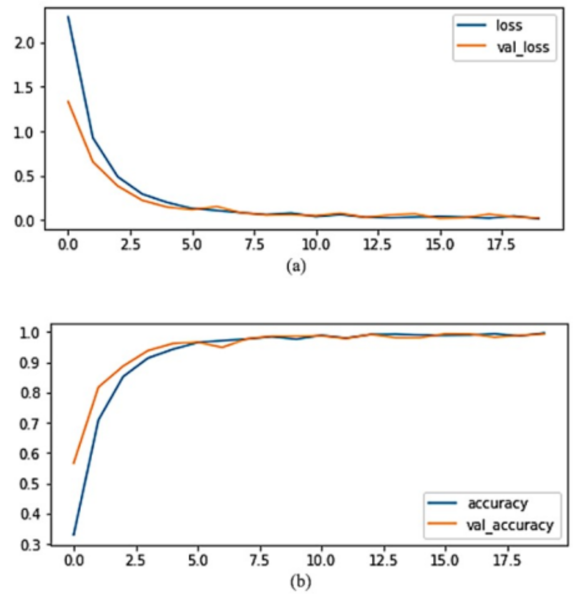

Fig. 5. Graphics of the Training Model Process: (a) Loss of Training and Validation, (b) Accuracy of Training and Validation

As seen in Fig. 5, The training process is carried out in 20 epochs, in the first epoch training accuracy is 33.04% and validation accuracy is 56.69%, while training loss is 28.26% and validation loss is 33.30%. in the tenth epoch, the training accuracy is 97.60% and validation accuracy is 98.57%, while the training loss is 8.11% and validation loss is 6.08%. Finally, in the last or twentieth epoch, the training accuracy is 99.60% and the validation accuracy is 99.68%, while the training loss is 1.64% and the validation loss is 2.55%. The main finding of this research is that the use of resizing and background correction methods, as well as setting hyperparameters can improve model accuracy.

3.4. Testing

After the model training process is complete, the next process is to test the model. The testing process is similar to the model training process, only the difference is that when the model testing process is not carried out backward pass or backpropagation iterations it does not change the weight or weight of the model as in the training process [38]. The Testing process is carried out using the data that is different from the training data set, to obtain valid testing results, this is following the recommendations of [39][40] regarding training and testing of the CNN model. Model testing is done by reading the hand signal image that is inputted by taking each frame from the webcam video, then the frame is identified based on the model that has been trained, then produces output in the form of identification results and accuracy values. Then the highest value from the identification results is directly written on the output board. Fig. 6 is a flowchart for the model testing process.

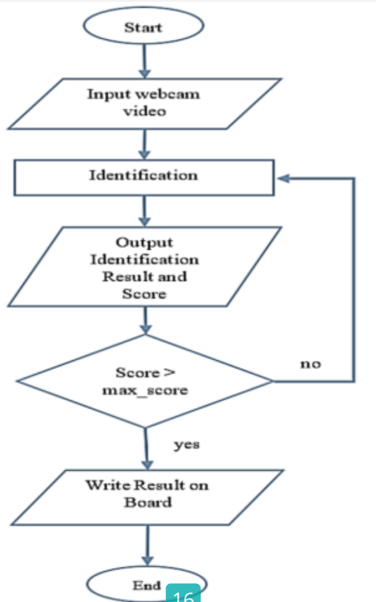

Fig. 6. Flowchart for the testing process

As shown in Fig. 6, the testing process is carried out by entering input in the form of hand signals via the Web camera on the Laptop Computer, where the hand makes a hand gesture in the Region of interest box on the Webcam display. Then the webcam display brings up the alphabetical prediction of the hand signal along with the score on the board display. Testing the model is carried out for each character letter 10 times, so a total of 290 times of testing. Fig. 7 and Fig. 8 Show the Confusion matrix value from the model testing results, for 29 types of hand sign language for each letter of the alphabet. Which consists of accuracy, precision, and recall.

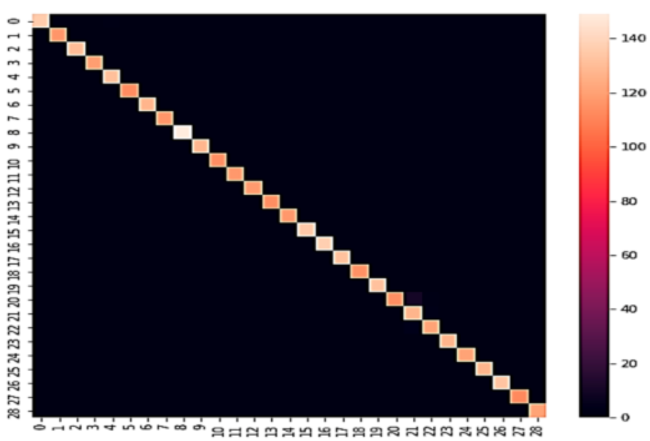

Fig. 7. Confusion Matrix of The Model Testing

A	1.00	0.99	0.99	138
B	1.00	1.00	1.00	116
C	1.00	1.00	1.00	130
D	1.00	1.00	1.00	119
E	0.98	1.00	0.99	131
F	1.00	1.00	1.00	113
G	1.00	1.00	1.00	127
H	1.00	0.99	1.00	117
I	1.00	1.00	1.00	149
J	0.99	1.00	1.00	128
K	1.00	1.00	1.00	114
L	1.00	1.00	1.00	117
M	1.00	1.00	1.00	118
N	1.00	1.00	1.00	114
O	1.00	1.00	1.00	117
P	1.00	0.99	1.00	136
Q	1.00	1.00	1.00	137
R	1.00	1.00	1.00	132
S	0.99	0.98	0.99	117
T	0.99	1.00	1.00	132
U	1.00	0.90	0.95	126
V	0.90	0.98	0.94	130
W	0.95	0.97	0.96	125
X	1.00	1.00	1.00	127
Y	0.99	0.99	0.99	122
Z	1.00	1.00	1.00	127
del	1.00	1.00	1.00	133
nothing	1.00	1.00	1.00	112
space	1.00	1.00	1.00	121
accuracy			0.99	3625
macro avg	0.99	0.99	0.99	3625
weighted avg	0.99	0.99	0.99	3625

Fig. 8. Performance of The Testing Model

Fig. 8 shows that the performance of the testing model achieves the best accuracy of 99%. and the Sensitivity, Recall, and f1-score levels are 99% respectively. This is because we apply resizing and background correction to the training and test images. These results are relatively better than previous similar studies as shown in Table 2.

Table 2. Comparison of Results with previous related studies

Study	Model	Dataset	Accuracy
Chong et al[5]	SVM, DNN	American Sign Language (ASL)	80.30% and 93.81%
Pigou et al[8]	CNN	Italian gestures	91.7%
Rastgoo et al[10]	RBM	Massey University Gesture Dataset 2012	99.31%
Rathi et al[13]	ResNet50 based	American Sign Language Hand gesture	99.03%
Daroya et al[14]	CNN	American Finger Spelling format	90.03%
Abdulhussein et al[17]	CNN	American Sign Language (ASL)	99.3%
Sabeenian et al[18]	CNN	MNIST ASL dataset	93 %
Al-Hammadi et al[20]	CNN	King Saud University Saudi Sign Language (KSU-SSL) dataset	87.69%
Our Methode	CNN	ASL Alphabet repository	99%

The findings of this study imply that this hand sign language recognition model can be a hand sign language independent learning tool with a relatively better level of recognition accuracy than previous similar studies. The strength of this study is that the proposed hand sign language recognition model can perform hand sign language recognition from the alphabet in real-time. While the limitation of this model is that the performance of model is strongly influenced by the specifications of the web camera and lighting system.

4. CONCLUSION

In this study, a hand signal recognition model from letters of the alphabet using the CNN model has been successfully created, with significant results compared to previous related studies. Our contribution is

the addition of preprocessing to the background correction which results in good accuracy in the proposed model. Our future work is to add to the sign language dataset basic words in addition to the letters of the alphabet, and also to increase the accuracy of the model by adding other hyperparameters.

Deep Learning Approach For Sign Language Recognition

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Deep Learning Approach For Sign Language Recognition

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ABSTRACT

Sign language is a method of communication that uses hand gestures between people with hearing loss. Each hand sign represents one meaning, but several terms don't have sign language, so they have to be spelled alphabetically. Problems occur when communicating between normal people with hearing loss, because not everyone understands sign language, so a model is needed to recognize sign language as well as a learning tool for beginners who want to learn sign language, especially alphabetic sign language. This study aims to create a hand sign language recognition model for alphabetic letters using a deep learning approach. The main contribution of this research is to produce a real-time hand sign language image acquisition, and hand sign language recognition model for Alphabet. The model used is a seven-layer Convolutional Neural Network (CNN). This model is trained using the ASL alphabet database which consists of 27 categories, where each category consists of 3000 images or a total of 87,000 hand gesture images measuring 200 x 200 pixels. First, the background correction process is carried out and the input image size is changed to 32 x 32 pixels using the bicubic interpolation method. Next, separate the dataset for training and validation respectively 75% and 25%. Finally the process of testing the model using data input of hand sign language images from a web camera. The test results show that the proposed model has good performance with an accuracy value of 99%. The experimental results show that image preprocessing using background correction can improve model performance.

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1. INTRODUCTION

The research background is communication is very important in the process of social interaction. Communication leads to better understanding among the community, including the deaf [1]. Hand gesture recognition serves as the key to overcoming many difficulties and providing convenience for human life, especially for the deaf [2][3]. Sign language is a structured form of hand movement that involves visual movement and the use of various body parts namely fingers, hands, arms, head, body, and facial expressions to convey information in the communication process. For the deaf and speech-impaired community, sign language serves as a useful tool for everyday interactions.[4]. However, sign language is not common among normal people, and only a few people understand sign language. This creates a real problem in communication between the deaf community and other communities, which has not been fully resolved to this day [3]. Not all words have sign language, so special words that do not have sign language must be spelled using a letter sign one by one [5]. Based on the background, this study aims to develop a sign language recognition model for letters of the alphabet using a deep learning approach. The deep learning approach was chosen because deep learning methods are popular in the field of computer science and are proven to produce a good performance for image classification [6][7]. The novelty of this study is the

application of resizing and background correction of the input image for training and testing to improve model performance, where the results of testing the model we propose are better than previous similar studies.

The related work from past research is as follows. There have been many studies to recognize sign language, using various methods and varied datasets. Researchers [5] proposed a language recognition system using a 3D motion sensor by applying a k-nearest neighbor and support vector machine (SVM) to classify 26 letters in sign language. The average results of the highest classification levels of 72.78% and 79.83% were achieved by k-nearest neighbors and support vector machines, respectively. Based on previous studies that proposed hand sign language recognition models for alphabets, the results were not optimal, this is due to the complexity of lighting factors and other objects that appear in hand gesture images [5]. While there have been quite many studies on sign language recognition using a deep learning approach, here are several related studies including Study [8] has proposed a recognition system using a convolutional neural network (CNN) that can recognize 20 Italian gestures with high accuracy. Meanwhile, the following researchers introduced a sign language recognition (SLR) model using a deep learning approach. Study [9] implements transfer learning to improve accuracy. While study [10] has proposed the Restricted Boltzmann Machine (RBM) for automatic hand sign language recognition from visual data. The experimental results using four datasets show that the proposed multi-modal model achieves a fairly good accuracy. In the work [11], have proposed a deep learning-based framework for analyzing video features (images and optical flow) and skeletons (body, hands, and faces) using two sign language datasets. The results reveal the advantages of combining frame and video features optimally for SLR tasks.

A continuous deep learning-based sign language recognition model has also been introduced [12] which has proposed a 3D convolution residual network architecture and two-way LSTM, as a grammatical rule-based classification problem. The model has been evaluated on the benchmark of Chinese continuous sign language recognition with better performance. Other deep learning approach models have also been carried out for sign language recognition. A study [13] has proposed a ResNet50 Based Deep Neural Network architecture to classify finger-spelled words. The dataset used is the standard American Sign Language Hand gesture which produces an accuracy of 99.03%. While the study [14] Densely Connected Convolutional Neural Networks (DenseNet) to classify sign language in real-time using a web camera with an accuracy of 90.3%. The following studies [15][16][17][18][19] have implemented the CNN model for sign language recognition and tested using the American Sign Language (ASL) dataset, with an accuracy rate of 99.92%, 99.85%, 99.3%, 93%, and 99.91%.

Based on previous related studies, most of the sign language recognition methods use a deep learning approach. This study focuses on the introduction of hand sign language from the letters of the alphabet, which is used as a means of communication with the deaf. This study also uses the CNN model but with a different model architecture from previous studies. The CNN model was chosen because previous studies showed relatively better accuracy for image recognition [20][21][22]. The contributions of this research are: first, produce a real-time hand sign language image acquisition model by capturing each frame using a webcam video. Second, produce a hand sign language recognition model for the Alphabet, using a seven-layer CNN that has been trained using the ASL dataset and by applying resizing and background correction to the input image.

2. METHOD

This research is quantitative experimental research to measure the performance of hand sign language recognition models based on training datasets. Fig. 1 shows the proposed method for hand sign language recognition. In general, the proposed method consists of four stages, each of which is data acquisition, preprocessing, training and testing.

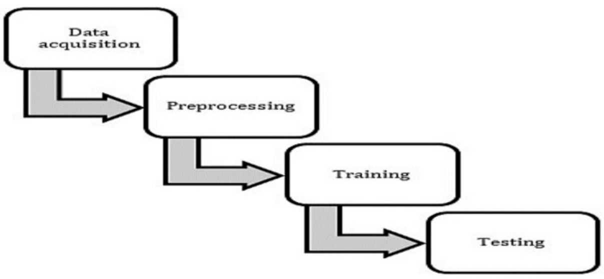

Fig. 1. Proposed Method

Based on the methodology applied in this study, as shown in Fig. 1, the first stage is data acquisition, where the data used in this study is the image. Image acquisition is the action of retrieving an image from an external source for further processing [23]. In this stage, the dataset used as model input is hand sign images, which are divided into 26 classes consisting of 26 sets of alphabets from A to Z. In this study, the dataset used as model input is hand sign images, which are divided into 26 classes consisting of 26 sets of alphabets from A to Z. The second stage is preprocessing. At this stage, the image size transformation is carried out to reduce the complexity of the model architecture. In this study, the transformation of the image size of the training data images from the initial size of 200x200 pixels was resized to 32x32 Pixels. In this study, we apply the bicubic interpolation method for resizing images as proposed by [24]. This resizing process is to reduce the computational time required for model training. To improve the segmentation accuracy of the hand sign language image below for complex lighting conditions, we apply a correction background method with luminance partition correction and adaptive threshold [25][26]. Furthermore, at the training stage, the CNN model architecture and its hyperparameters will be determined first. In this study, we use hyperparameter tuning to control the behavior of the machine learning model to produce optimal results. [27][28], then model training will be carried out using the dataset from the hand sign language image preprocessing. The last stage is model testing. At this stage, the model will be tested with hand sign language images in real-time using a webcam. The research proposed method flowchart is presented in Fig. 2.

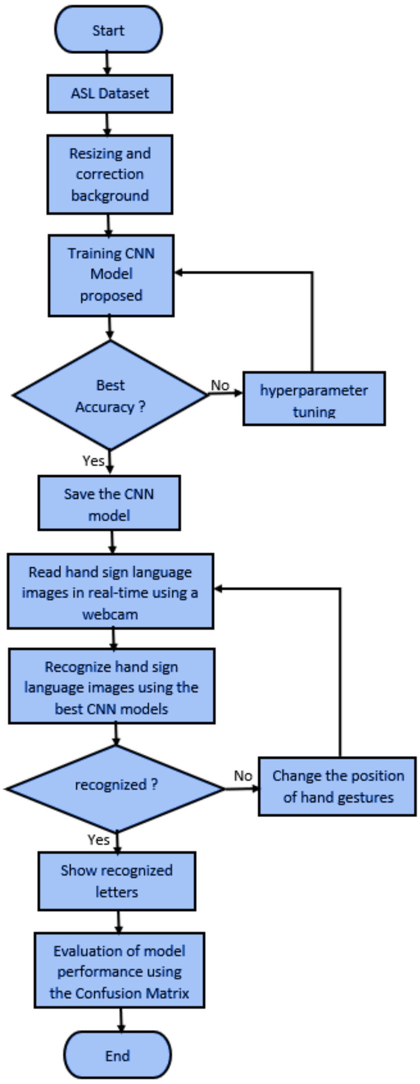

Fig 2. The Flowchart of Research Methodology

Furthermore, the results will be measured using a confusion matrix to determine the performance of the model [29]. Confusion matrices create result representations such as true positives (TP), true negatives (TN),

false positives (FP), and false negatives (FN). TP means a positive result that is predicted by machine learning correctly. TN means negative outcome predicted by machine learning Correct. While FP means positive results predicted by machine learning are wrong, and FN means negative outcomes predicted by machine learning are wrong. Confusion Matrix Performance evaluation with a confusion matrix results in accuracy, precision, and recall [30][31]. Accuracy is the number of data points that machine learning correctly predicts among all data. Can calculate as eq.1:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision is the percentage of relevant elements that can indicate the number of times the model can predict correctly and can be calculated as eq. 2.

$$Precission = \frac{TP}{TP + FP} \tag{2}$$

Meanwhile, recall is the percentage of relevant elements that are correctly classified by the model above all relevant elements. Recall calculation can be done using eq. 3.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

3. RESULTS AND DISCUSSION

3.1. Data Acquisition

The data is secondary data downloaded from kaggle.com in the ASL Alphabet repository which contains image datasets. in JPG format containing 29 folders with each containing 3,000 hand sign images. The total image data obtained amounted to 87,000 images [32]. Fig. 3 shows examples of hand sign language images sourced from the ASL Alphabet repository. The 87,000 images were distributed for the training process. The data is divided into two 75% for training and 25%. The train-test split is a technique for evaluating the performance of a machine-learning algorithm [33]. In the testing so for each class, there are 2,400 images for training and 600 images for testing, or a total of 69,600 images for training and 17,400 images for testing.

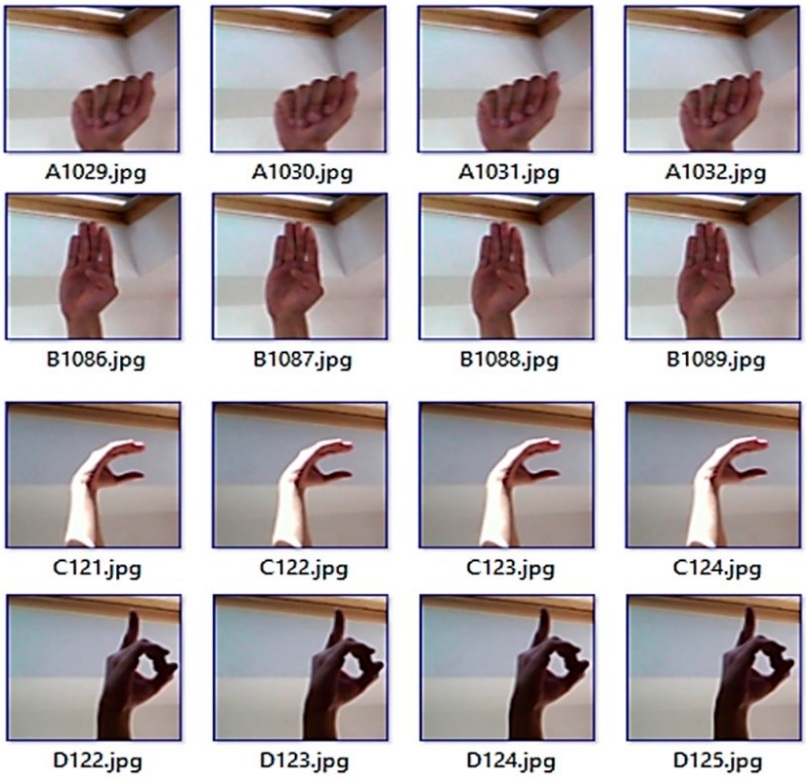

Fig. 3. Examples of hand sign language images from Kaggle

3.2. Preprocessing

At the preprocessing stage, the resizing process is carried out using the bicubic interpolation method [24], the results of this process produce an image size of 32x32 pixels, from the original image size of 200x200 pixels. This step is taken to reduce the time complexity during model training. the next preprocessing step is image background correction, to produce better accuracy using luminance partition correction and adaptive threshold [25]. Fig 4 shows examples of preprocessing results.

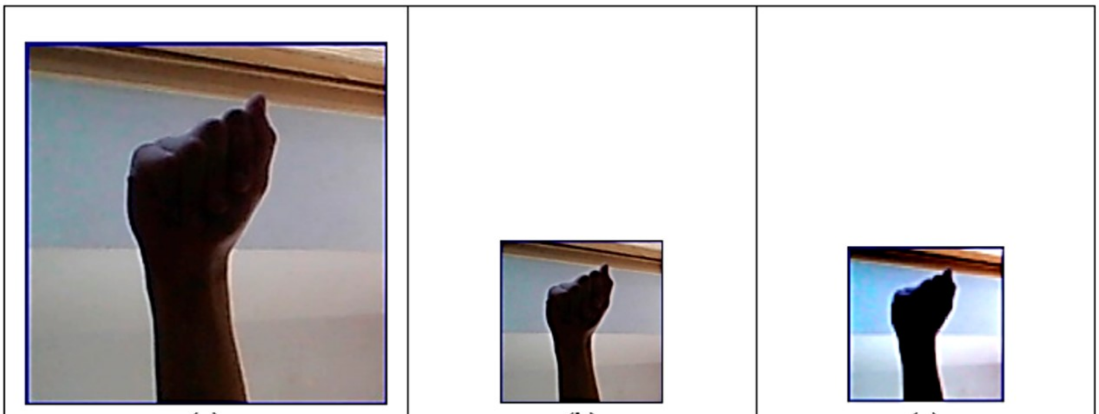

Fig. 4. (a). Original image size 200x200 pixels, (b). The result of resizing to a size of 32x32 pixels, (c). Background correction results.

In Fig.4 it can be seen that the dimensions of the hand sign language image size for the training dataset are reduced in size as well as the increase in color brightness and contrast resulting from the background correction process.

3.3. Training

At this stage, the CNN model design used in the training process is carried out to produce an appropriate model to classify hand sign language images. The CNN model applied uses hyperparameter values consisting of the learning rate, epoch, loss function, and optimizer. Table 1 below is the CNN architecture specification used in this study.

Table 1. CNN Model Architecture

Layer type	Description	Size
Input Layer	Input Image	32x32x3
Conv 1	Convolutional ReLU MaxPooling	8 kernel, 3x3 Window size 2x2
Conv 2	Convolutional ReLU MaxPooling	16 kernel, 3x3 Window size 2x2
Conv 3	Convolutional ReLU MaxPooling	32 kernel, 3x3 Window size 2x2
Flatten	Flatten	512
Fully Connected Layer	Dense ReLU	512
Output Layer	Dense Softmax	29

The CNN architectural design is as shown in table 1, there are input layers, 3 convolution layers, flatten, fully connected layers, and output layers. The Input Layer requires input with a size of 32x32x3 where 32x32 pixels 3 layers RGB, then in Conv 1 using 8 kernels measuring 3x3 after that using ReLU activation [34], and using Maxpool with a window size of 2x2, as well as Conv 2 and Conv 3, only on Conv 2 uses 16 kernels and Conv 3 uses 32 kernels. Next is the Flatten layer and Fully Connected Layer with 512 nodes, and

the last is the output layer containing Dense Softmax with 29 nodes [35], this is adjusted to the number of classes in the hand signal dataset of the alphabet.

The training process will be carried out through a series of iterations whose number of repetitions is determined by the maximum epoch value [36]. One epoch is a process when all training data has been used and passes through all network nodes once. While the hyperparameter used in this study is the Adam Optimizer [37], with The Batch Size is 32 and Epochs are 20. The model training process is carried out in a hardware and software environment with specifications for Dell Latitude E7440 Laptop, 12 GB DDR4 RAM, Processor Intel® Core™ i5-7200U CPU @ 2.50GHz, Nvidia GeForce 940MX GPU, 256 GB SSD. The operating system used is Windows 10 Professional and the training and testing model algorithms are implemented using python code by utilizing the Tensorflow library. The results of the training model as shown in Fig. 5.

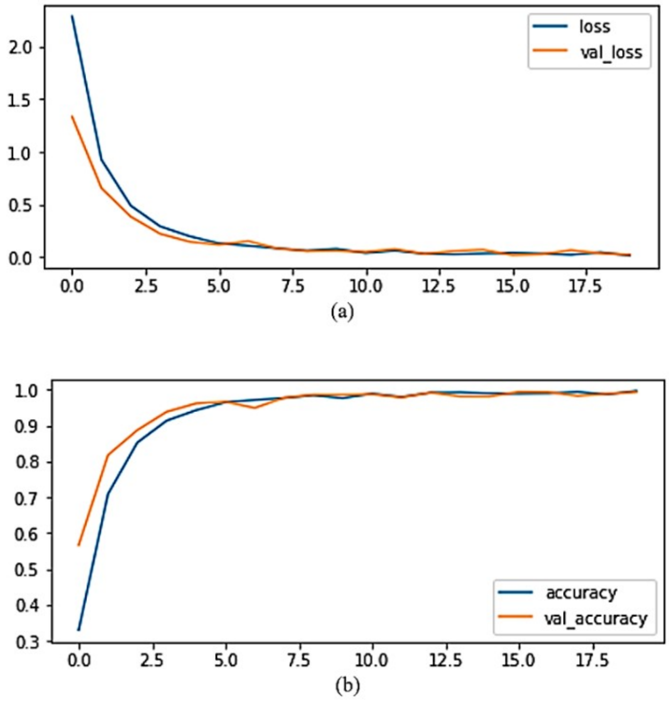

Fig. 5. Graphics of the Training Model Process: (a) Loss of Training and Validation, (b) Accuracy of Training and Validation

As seen in Fig. 5, The training process is carried out in 20 epochs, in the first epoch training accuracy is 33.04% and validation accuracy is 56.69%, while training loss is 28.26% and validation loss is 33.30%. in the tenth epoch, the training accuracy is 97.60% and validation accuracy is 98.57%, while the training loss is 8.11% and validation loss is 6.08%. Finally, in the last or twentieth epoch, the training accuracy is 99.60% and the validation accuracy is 99.68%, while the training loss is 1.64% and the validation loss is 2.55%. The main finding of this research is that the use of resizing and background correction methods, as well as setting hyperparameters can improve model accuracy.

3.4. Testing

After the model training process is complete, the next process is to test the model. The testing process is similar to the model training process, only the difference is that when the model testing process is not carried out backward pass or backpropagation iterations it does not change the weight or weight of the model as in the training process [38]. The Testing process is carried out using test data that is different from the training data set, to obtain valid testing results, this is following the recommendations of [39][40] regarding training and testing of the CNN model. Model testing is done by reading the hand signal image that is inputted by taking each frame from the webcam video, then the frame is identified based on the model that has been trained, then produces output in the form of identification results and accuracy values. Then the highest value from the identification results is directly written on the output board. Fig. 6 is a flowchart for the model testing process.

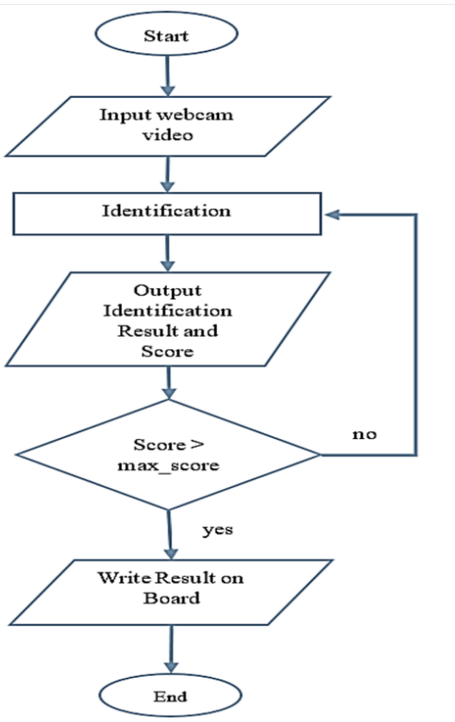

Fig. 6. Flowchart for the testing process

As shown in Fig. 6, the testing process is carried out by entering input in the form of hand signals via the Web camera on the Laptop Computer, where the hand makes a hand gesture in the Region of interest box on the Webcam display. Then the webcam display brings up the alphabetical prediction of the hand signal along with the score on the board display. Testing the model is carried out for each character letter 10 times, so a total of 290 times of testing. Fig. 7 and Fig. 8 Show the Confusion matrix value from the model testing results, for 29 types of hand sign language for each letter of the alphabet. Which consists of accuracy, precision, and recall.

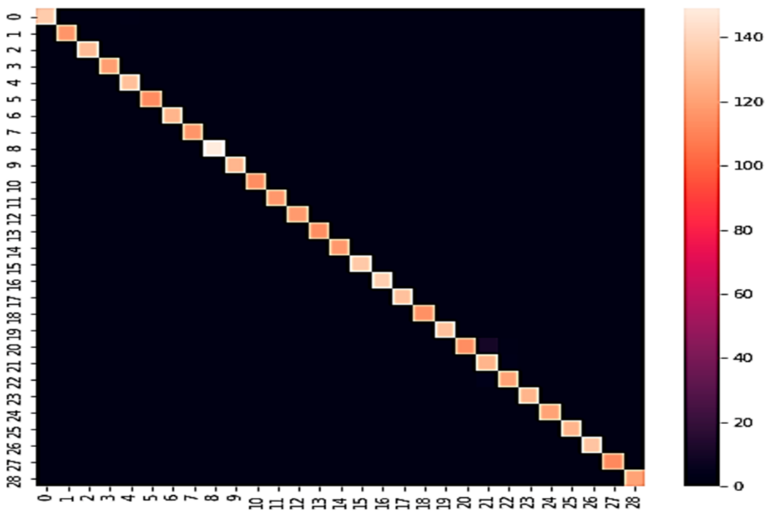

Fig. 7. Confusion Matrix of The Model Testing

A	1.00	0.99	0.99	138
B	1.00	1.00	1.00	116
C	1.00	1.00	1.00	130
D	1.00	1.00	1.00	119
E	0.98	1.00	0.99	131
F	1.00	1.00	1.00	113
G	1.00	1.00	1.00	127
H	1.00	0.99	1.00	117
I	1.00	1.00	1.00	149
J	0.99	1.00	1.00	128
K	1.00	1.00	1.00	114
L	1.00	1.00	1.00	117
M	1.00	1.00	1.00	118
N	1.00	1.00	1.00	114
O	1.00	1.00	1.00	117
P	1.00	0.99	1.00	136
Q	1.00	1.00	1.00	137
R	1.00	1.00	1.00	132
S	0.99	0.98	0.99	117
T	0.99	1.00	1.00	132
U	1.00	0.90	0.95	126
V	0.90	0.98	0.94	130
W	0.95	0.97	0.96	125
X	1.00	1.00	1.00	127
Y	0.99	0.99	0.99	122
Z	1.00	1.00	1.00	127
del	1.00	1.00	1.00	133
nothing	1.00	1.00	1.00	112
space	1.00	1.00	1.00	121
accuracy			0.99	3625
macro avg	0.99	0.99	0.99	3625
weighted avg	0.99	0.99	0.99	3625

Fig. 8. Performance of The Testing Model

Fig. 8 shows that the performance of the testing model achieves the best accuracy of 99%. and the Sensitivity, Recall, and f1-score levels are 99% respectively. This is because we apply resizing and background correction to the training and test images. These results are relatively better than previous similar studies as shown in Table 2.

Table 2. Comparison of Results with previous related studies

Study	Model	Dataset	Accuracy
Chong et al[5]	SVM, DNN	American Sign Language (ASL)	80.30% and 93.81%
Pigou et al[6]	CNN	Italian gestures	91.7%
Rastgoo et al[8]	RBM	Massey University Gesture Dataset 2012	99.31%
Rathi et al[11]	ResNet50 based	American Sign Language Hand gesture	99.03%
Daroya et al[12]	CNN	American Finger Spelling format	90.03%
Abdulhussein et al[15]	CNN	American Sign Language (ASL)	99.3%
Sabeenian et al[16]	CNN	MNIST ASL dataset	93 %
Al-Hammadi et al[17]	CNN	King Saud University Saudi Sign Language (KSU-SSL) dataset	87.69%
Our Methode	CNN	ASL Alphabet repository	99%

The findings of this study imply that this hand sign language recognition model can be a hand sign language independent learning tool with a relatively better level of recognition accuracy than previous similar studies. The strength of this study is that the proposed hand sign language recognition model can perform hand sign language recognition from the alphabet in real-time. While the limitation of this model is that the performance of model is strongly influenced by the specifications of the web camera and lighting system.

4. CONCLUSION

In this study, a hand signal recognition model from letters of the alphabet using the CNN model has been successfully created, with significant results compared to previous related studies. Our contribution is

the addition of preprocessing to the background correction which results in good accuracy in the proposed model. Our future work is to add to the sign language dataset basic words in addition to the letters of the alphabet, and also to increase the accuracy of the model by adding other hyperparameters.

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Revision results.

Comment of Editor:

Please state the research contribution at the end of the introduction, and the abstract for example "The research contribution is..." We need at least two research contributions.

Authors' responses >> Thanks for the correction, we have stated the research contribution at the end of the introduction, and the abstract. In the abstract: “The main contribution of the study is to produce a real-time hand sign language image acquisition, and a hand sign language recognition model for Alphabet, using CNN”. In the introduction: “The contributions of this research are: first, produce a real-time hand sign language image acquisition model by capturing each frame using a webcam video. Second, produce a hand sign language recognition model for the Alphabet, using a seven-layer CNN that has been trained using the ASL dataset and by applying resizing and background correction to the input image”.

The Method contains an explanation of the research method and the proposed method. This section can include research diagrams, system block diagrams, or flowchart diagrams.

Authors' responses >> Thanks for the correction. We have included Figure 1, a diagram of the proposed method along with a detailed explanation of each stage of the hand sign language recognition method.

In the Results and Discussion section, Please provide a comparison to a similar method from previous works (including citation) to enhance the research contribution.

Authors' responses >> Thanks for the correction. In the results and discussion section, we have included Table 2, which contains a comparison of the results of hand sign language recognition from previous research.

The minimal References are 40 from an English Journal that was published 5 years ago and used IEEE Style. See the guide to writing the references in IEEE Style Format https://youtu.be/ijmG7iZ0yz0.

Authors' responses >> Thanks for the correction. We have added references, to 40 English Journal references published 5 years ago and use the IEEE Style

The reference must be from IEEE Xplore or Science Direct. All references must have Digital Object Identifier (DOI) or permanent link. See the guide to getting high-quality references from IEEE Xplore https://youtu.be/2dqiF6Xrs8c

Authors' responses >> Thanks for the correction. We have used references from IEEE Xplore or Science Direct sources. All references have Digital Object Identifier (DOI) or permanent links.

Please use Mendeley to make the references.

Authors' responses >> Thanks for the hint. We have used Mendeley to make the references.

The Figure must be in PNG format with 600-1200 dpi. Please don't crop, or use snipping and print-screens tools. Otherwise, the image resolution will be compromised. The images using vector format (EWM) are better.

Authors' responses >> Thanks for the correction. We have converted all figures into PNG format with 1200 dpi.

The Tabel must be made using the Insert Table feature not from the cropping table as an image.

Authors' responses >> Thanks for the hint. We've created a table using the Insert Table feature.

The Equation must be made using Insert Equation. We suggest using 3 columns of the table to help and then making the equation in the middle of the column and the number of the equation on the right-side column. The variable in the equation must be given information. Please see the guide in the link on how to make the equation in word and give the equation number. https://youtu.be/O57_TLI5vGA

Authors' responses >> Thanks for the hint. We have written Equation using Insert Equation. We've also used the 3-column table to create the equations, and listed the equation in the middle column and the equation number in the right-hand column. All variables in the equation have also been informed.

All of the figures, tables, and equations must be cited in paragraphs and explained; please give some explanation, information, or analysis. All of the figures and tables must be given by some analysis in at least one paragraph.

Authors' responses >> Thanks for the hint. All figures, tables, and equations have been cited in paragraphs and explained. We've also added explanations, information, and analysis. We have provided all the figures and tables with an analysis in at least one paragraph.

Please use Grammarly to check your manuscript. The free Grammarly is enough for fixing some typos and grammar mistakes. Proofreading is recommended to increase the quality of the English language and writing.

Authors' responses >> Thanks for the hint. We have used Grammarly to check the manuscript.

Please use the template journal and make sure the percentage of plagiarism is under 25% or the manuscript will be rejected.

Authors' responses >> Thanks for the hint. We have used a template journal and ensured that the plagiarism percentage is below 25%.

The minimal pages are 8 included references.

>> Thanks for the hint. We have confirmed that the minimum number of pages is 8 including references.

Comment of Reviewers

- The abstract is not representative of the content and contributions of the paper. The abstract does not seem to convey the rigor of research properly.

Authors' responses >> Thanks for the correction. We've revised the abstract so that it represents the content and contributions of the paper.

- The abstract should contain Objectives, Methods/Analysis, Findings, and Novelty /Improvement. It must have 200-300 words that consist of 2-3 sentences about the Introduction, problem, and solution; 1-2 sentences about the research contribution (write the research contribution is…); 3-4 sentences about the method; 4-5 sentences about the result; and 1-2 sentences about conclusions.

Authors' responses >> Thanks for the correction. We have revised the contents of the abstract according to the reviewer's notes

- The research contributions of the paper should be articulated more clearly.

Authors' responses >> Thanks for the correction. we have added explicitly an explanation of the research contribution.

"The main contribution of this research is to produce a real-time hand sign language image acquisition, and hand sign language recognition model for Alphabet".

- Aside from the aim stated in the title, the research gap and goals are not specified, leading to the reader missing the significance of the research.

Authors' responses >> Thanks for the correction. we have written more specific descriptions of research gaps and research objectives.

The research gap: "Not all words have sign language, so special words that do not have sign language must be spelled using a letter sign one by one"

The goal: "this study aims to develop a sign language recognition model for letters of the alphabet using a deep learning approach"

- The introduction section must contain the research problem, solution, state of the art, novelty, literature review from previous research, and research contribution (the most important). Please write the research contribution in the last part of the Introduction, such as "The research contribution is…." At least there are two research contributions.

Authors' responses >> Thanks for the correction. We have revised it according to the reviewer's notes, including:

research problem: "sign language is not common among normal people, and only a few people understand sign language. This creates a real problem in communication between the deaf community and other communities, which has not been fully resolved to this day [3]. Not all words have sign language, so special words that do not have sign language must be spelled using a letter sign one by one [5]"

solution: "this study aims to develop a sign language recognition model for letters of the alphabet using a deep learning approach" state of the art: “Based on previous studies that proposed hand sign language recognition models for alphabets, the results were not optimal, this is due to the complexity of lighting factors and other objects that appear in hand gesture images [5]”

novelty: “The novelty of this study is the application of resizing and background correction of the input image for training and testing to improve model performance, where the results of testing the model we propose are better than previous similar studies”

literature review of previous studies: “A continuous deep learning-based sign language recognition model has also been introduced [12] which has proposed a 3D convolution residual network architecture and two-way LSTM, as a grammatical rule-based classification problem. The model has been evaluated on the benchmark of Chinese continuous sign language recognition with better performance. Other deep learning approach models have also been carried out for sign language recognition. A study [13] has proposed a ResNet50 Based Deep Neural Network architecture to classify finger-spelled words. The dataset used is the standard American Sign Language Hand gesture which produces an accuracy of 99.03%. While the study [14] Densely Connected Convolutional Neural Networks (DenseNet) to classify sign language in real-time using a web camera with an accuracy of 90.3%. The following studies [15][16][17][18][19] have implemented the CNN model for sign language recognition and tested using the American Sign Language (ASL) dataset, with an accuracy rate of 99.92%, 99.85%, 99.3%, 93%, and 99.91%.”

contribution:” The contributions of this research are: first, produce a real-time hand sign language image acquisition model by capturing each frame using a webcam video. Second, produce a hand sign language recognition model for the Alphabet, using a seven-layer CNN that has been trained using the ASL dataset and by applying resizing and background correction to the input image.”

- Commonly, there are research flow, research diagrams, system block diagrams, control system block diagrams, hardware wiring diagrams, pseudocode, or flowcharts in the method section. The figure must be clear, detailed, not blurry, easy to read, and provide proper information.

Authors' responses >> “Thanks for the correction. We have included a block diagram of the research flow in figure 1. Apart from that, we have also improved the quality of all images so that they are easy to read and provide the right information.”

- A flowchart should be added to the article to show the research methodology.

Authors' responses >> Thanks for the correction. we have added the flowchart of the research methodology in Figure 2.

- Much more explanations and interpretations must be added to the method, which is not enough at all.

Authors' responses >> Thanks for the correction. we have added explanations and interpretations to the method.

- In the results section, provide a comparison to a similar method from previous works (including citation) to enhance research contributions (compare the result with previous research). All figures and tables must be clear, detailed, not blurry, and easy to read. Each figure and table must be given a comprehensive explanation in at least one paragraph of analysis (crucial).

Authors' responses >> Thanks for the correction. We have added in the results section, a comparison with similar methods from previous work to enhance research contribution and we have added at least one paragraph explanation for each figure and table.

- The discussion section needs to be described scientifically. Kindly frame it along the following lines:

i. Main findings of the present study

ii. Comparison with other studies

iii. Implication and explanation of findings

iv. Strengths and limitations

Authors' responses >>

- It is suggested to compare the results of the present study with previous studies and analyze their results completely.

Authors' responses >> Thank you for the advice. We have compared the results of this study with previous studies and analyzed the results.

"Fig. 7 shows that the performance of the testing model achieves the best accuracy of 99%. and the Sensitivity, Recall, and f1-score levels are 99% respectively. This is because we apply resizing and background correction to the training and test images. These results are relatively better than previous similar studies as shown in Table 2"

- Please add future work so that it can motivate other researchers to continue the research.

Authors' responses >> Thanks for the correction. We have added future work in the conclusion section as follows: "Our future work is to add to the sign language dataset basic words in addition to the letters of the alphabet, and also to increase the accuracy of the model by adding other hyperparameters"

- The minimal number of references is 40 from Science Direct, IEEE Xplore, Springer Link, MDPI Scilit, or Scopus databases. Cited references must be taken from the journal. Each should have a Digital Object Identifier (DOI) or permanent link. The references were published in the last five years.

Authors' responses >> Thanks for the correction. We have added references, to 40 English Journal references published 5 years ago and use the IEEE Style and we have confirmed that all references have Digital Object Identifier (DOI) or permanent links

- However, in its present form, the manuscript contains several weaknesses. Appropriate revisions to all of the points should be undertaken to justify recommendations for publication.

Authors' responses >> Thanks for the correction. We have revised and corrected the weaknesses in the contents of the manuscript according to the input notes from the editors and reviewers.

Please add the DOI in the references. For example,

H. I. K. Fathurrahman, A. Ma'arif, and L.-Y. Chin, "The Development of Real-Time Mobile Garbage Detection Using Deep Learning," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, vol. 7, no. 3, p. 472, 2022, https://doi.org/10.26555/jiteki.v7i3.22295 .

P. Purwono, A. Ma'arif, I. S. Mangku Negara, W. Rahmaniar, and J. Rahmawan, "Linkage Detection of Features that Cause Stroke using Feyn Qlattice Machine Learning Model," Jurnal Ilmiah Teknik Elektro Komputer dan Informatika, vol. 7, no. 3, p. 423, 2021, https://doi.org/10.26555/jiteki.v7i3.22237.

Authors' responses >> Thanks for the correction. We have confirmed that all references have Digital Object Identifier (DOI) or permanent links.

Deep Learning Approach For Sign Language Recognition

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ABSTRACT

Sign language is a method of communication that uses hand gestures between people with hearing loss. Each hand sign represents one meaning, but several terms don't have sign language, so they have to be spelled alphabetically. Problems occur when communicating between normal people with hearing loss, because not everyone understands sign language, so a model is needed to recognize sign language as well as a learning tool for beginners who want to learn sign language, especially alphabetic sign language. This study aims to create a hand sign language recognition model for alphabetic letters using a deep learning approach. The main contribution of this research is to produce a real-time hand sign language image acquisition, and hand sign language recognition model for Alphabet. The model used is a seven-layer Convolutional Neural Network (CNN). This model is trained using the ASL alphabet database which consists of 27 categories, where each category consists of 3000 images or a total of 87,000 hand gesture images measuring 200 x 200 pixels. First, the background correction process is carried out and the input image size is changed to 32 x 32 pixels using the bicubic interpolation method. Next, separate the dataset for training and validation respectively 75% and 25%. Finally the process of testing the model using data input of hand sign language images from a web camera. The test results show that the proposed model has good performance with an accuracy value of 99%. The experimental results show that image preprocessing using background correction can improve model performance.

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1. INTRODUCTION

The research background is communication is very important in the process of social interaction. Communication leads to better understanding among the community, including the deaf [1]. Hand gesture recognition serves as the key to overcoming many difficulties and providing convenience for human life, especially for the deaf [2][3]. Sign language is a structured form of hand movement that involves visual movement and the use of various body parts namely fingers, hands, arms, head, body, and facial expressions to convey information in the communication process. For the deaf and speech-impaired community, sign language serves as a useful tool for everyday interactions.[4]. However, sign language is not common among normal people, and only a few people understand sign language. This creates a real problem in communication between the deaf community and other communities, which has not been fully resolved to this day [3]. Not all words have sign language, so special words that do not have sign language must be spelled using a letter sign one by one [5]. Based on the background, this study aims to develop a sign language recognition model for letters of the alphabet using a deep learning approach. The deep learning approach was chosen because deep learning methods are popular in the field of computer science and are proven to produce a good performance for image classification [6][7]. The novelty of this study is the

application of resizing and background correction of the input image for training and testing to improve model performance, where the results of testing the model we propose are better than previous similar studies.

The related work from past research is as follows. There have been many studies to recognize sign language, using various methods and varied datasets. Researchers [5] proposed a language recognition system using a 3D motion sensor by applying a k-nearest neighbor and support vector machine (SVM) to classify 26 letters in sign language. The average results of the highest classification levels of 72.78% and 79.83% were achieved by k-nearest neighbors and support vector machines, respectively. Based on previous studies that proposed hand sign language recognition models for alphabets, the results were not optimal, this is due to the complexity of lighting factors and other objects that appear in hand gesture images [5]. While there have been quite many studies on sign language recognition using a deep learning approach, here are several related studies including Study [8] has proposed a recognition system using a convolutional neural network (CNN) that can recognize 20 Italian gestures with high accuracy. Meanwhile, the following researchers introduced a sign language recognition (SLR) model using a deep learning approach. Study [9] implements transfer learning to improve accuracy. While study [10] has proposed the Restricted Boltzmann Machine (RBM) for automatic hand sign language recognition from visual data. The experimental results using four datasets show that the proposed multi-modal model achieves a fairly good accuracy. In the work [11], have proposed a deep learning-based framework for analyzing video features (images and optical flow) and skeletons (body, hands, and faces) using two sign language datasets. The results reveal the advantages of combining frame and video features optimally for SLR tasks.

A continuous deep learning-based sign language recognition model has also been introduced [12] which has proposed a 3D convolution residual network architecture and two-way LSTM, as a grammatical rule-based classification problem. The model has been evaluated on the benchmark of Chinese continuous sign language recognition with better performance. Other deep learning approach models have also been carried out for sign language recognition. A study [13] has proposed a ResNet50 Based Deep Neural Network architecture to classify finger-spelled words. The dataset used is the standard American Sign Language Hand gesture which produces an accuracy of 99.03%. While the study [14] Densely Connected Convolutional Neural Networks (DenseNet) to classify sign language in real-time using a web camera with an accuracy of 90.3%. The following studies [15][16][17][18][19] have implemented the CNN model for sign language recognition and tested using the American Sign Language (ASL) dataset, with an accuracy rate of 99.92%, 99.85%, 99.3%, 93%, and 99.91%.

Based on previous related studies, most of the sign language recognition methods use a deep learning approach. This study focuses on the introduction of hand sign language from the letters of the alphabet, which is used as a means of communication with the deaf. This study also uses the CNN model but with a different model architecture from previous studies. The CNN model was chosen because previous studies showed relatively better accuracy for image recognition [20][21][22]. The contributions of this research are: first, produce a real-time hand sign language image acquisition model by capturing each frame using a webcam video. Second, produce a hand sign language recognition model for the Alphabet, using a seven-layer CNN that has been trained using the ASL dataset and by applying resizing and background correction to the input image.

2. METHOD

This research is quantitative experimental research to measure the performance of hand sign language recognition models based on training datasets. Fig. 1 shows the proposed method for hand sign language recognition. In general, the proposed method consists of four stages, each of which is data acquisition, preprocessing, training and testing.

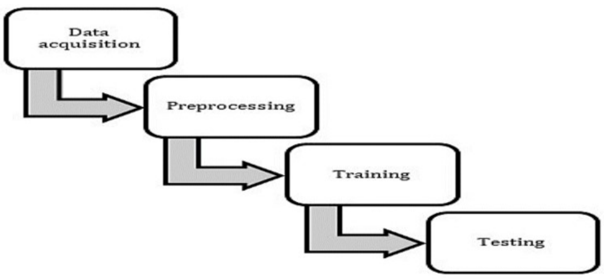

Fig. 1. Proposed Method

Based on the methodology applied in this study, as shown in Fig. 1, the first stage is data acquisition, where the data used in this study is the image. Image acquisition is the action of retrieving an image from an external source for further processing [23]. In this stage, the dataset used as model input is hand sign images, which are divided into 26 classes consisting of 26 sets of alphabets from A to Z. In this study, the dataset used as model input is hand sign images, which are divided into 26 classes consisting of 26 sets of alphabets from A to Z. The second stage is preprocessing. At this stage, the image size transformation is carried out to reduce the complexity of the model architecture. In this study, the transformation of the image size of the training data images from the initial size of 200x200 pixels was resized to 32x32 Pixels. In this study, we apply the bicubic interpolation method for resizing images as proposed by [24]. This resizing process is to reduce the computational time required for model training. To improve the segmentation accuracy of the hand sign language image below for complex lighting conditions, we apply a correction background method with luminance partition correction and adaptive threshold [25][26]. Furthermore, at the training stage, the CNN model architecture and its hyperparameters will be determined first. In this study, we use hyperparameter tuning to control the behavior of the machine learning model to produce optimal results. [27][28], then model training will be carried out using the dataset from the hand sign language image preprocessing. The last stage is model testing. At this stage, the model will be tested with hand sign language images in real-time using a webcam. The research proposed method flowchart is presented in Fig. 2.

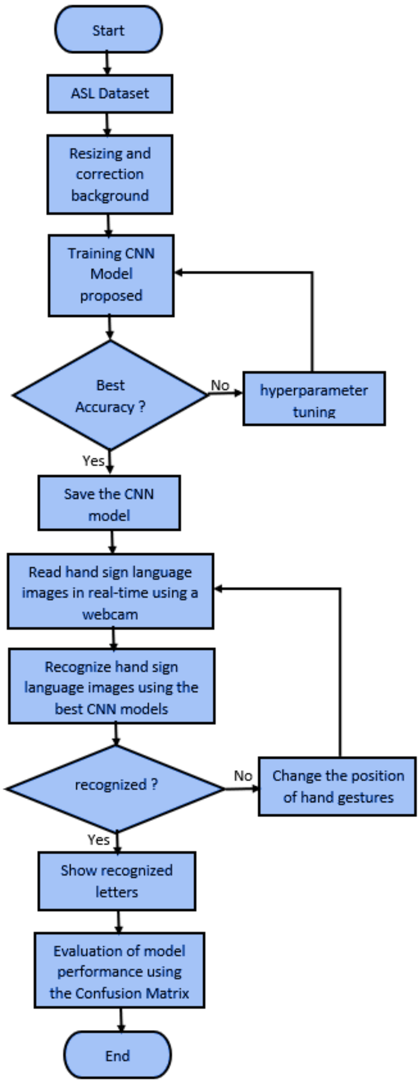

Fig 2. The Flowchart of Research Methodology

Furthermore, the results will be measured using a confusion matrix to determine the performance of the model [29]. Confusion matrices create result representations such as true positives (TP), true negatives (TN),

false positives (FP), and false negatives (FN). TP means a positive result that is predicted by machine learning correctly. TN means negative outcome predicted by machine learning Correct. While FP means positive results predicted by machine learning are wrong, and FN means negative outcomes predicted by machine learning are wrong. Confusion Matrix Performance evaluation with a confusion matrix results in accuracy, precision, and recall [30][31]. Accuracy is the number of data points that machine learning correctly predicts among all data. Can calculate as eq.1:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision is the percentage of relevant elements that can indicate the number of times the model can predict correctly and can be calculated as eq. 2.

$$Precission = \frac{TP}{TP + FP} \tag{2}$$

Meanwhile, recall is the percentage of relevant elements that are correctly classified by the model above all relevant elements. Recall calculation can be done using eq. 3.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

3. RESULTS AND DISCUSSION

3.1. Data Acquisition

The data is secondary data downloaded from kaggle.com in the ASL Alphabet repository which contains image datasets. in JPG format containing 29 folders with each containing 3,000 hand sign images. The total image data obtained amounted to 87,000 images [32]. Fig. 3 shows examples of hand sign language images sourced from the ASL Alphabet repository. The 87,000 images were distributed for the training process. The data is divided into two 75% for training and 25%. The train-test split is a technique for evaluating the performance of a machine-learning algorithm [33]. In the testing so for each class, there are 2,400 images for training and 600 images for testing, or a total of 69,600 images for training and 17,400 images for testing.

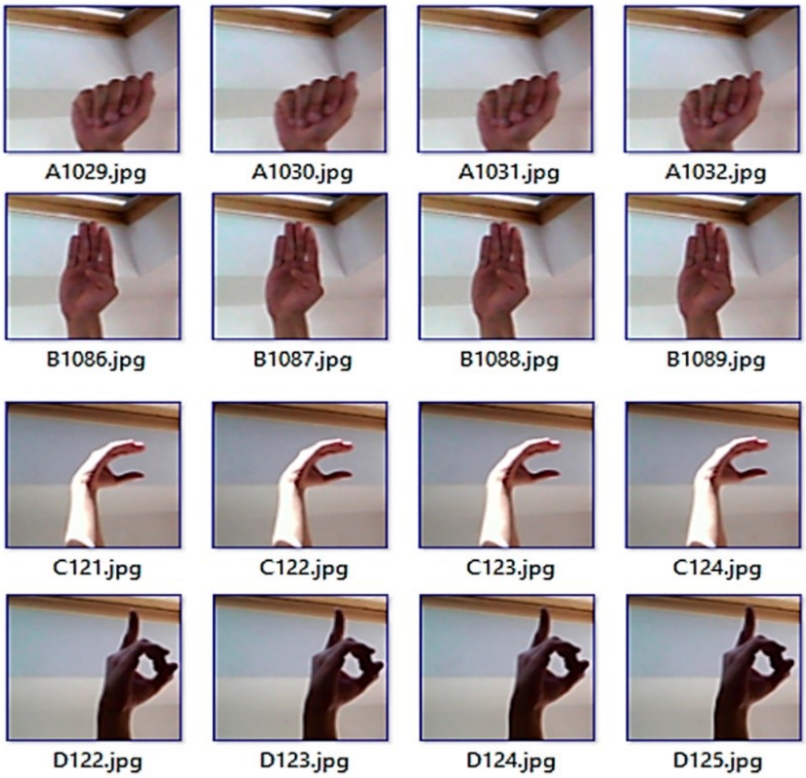

Fig. 3. Examples of hand sign language images from Kaggle

3.2. Preprocessing

At the preprocessing stage, the resizing process is carried out using the bicubic interpolation method [24], the results of this process produce an image size of 32x32 pixels, from the original image size of 200x200 pixels. This step is taken to reduce the time complexity during model training. the next preprocessing step is image background correction, to produce better accuracy using luminance partition correction and adaptive threshold [25]. Fig 4 shows examples of preprocessing results.

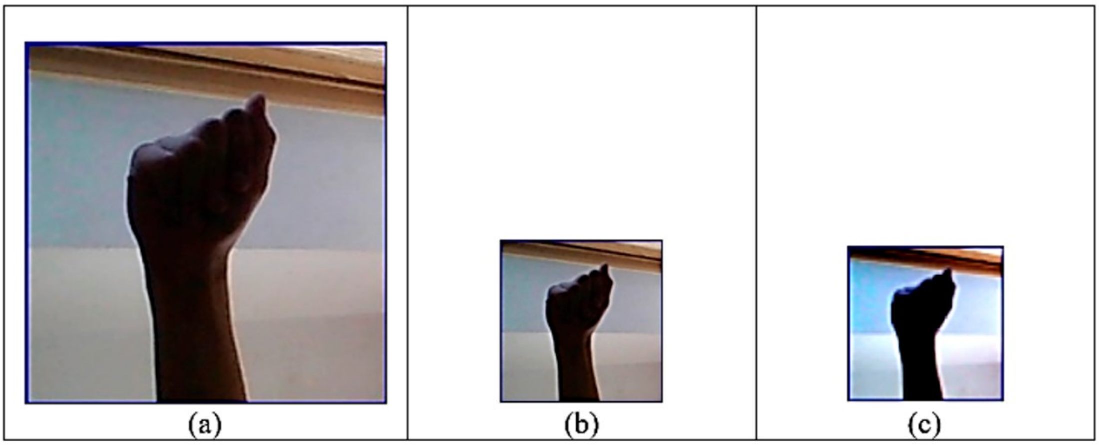

Fig. 4. (a). Original image size 200x200 pixels, (b). The result of resizing to a size of 32x32 pixels, (c). Background correction results.

In Fig.4 it can be seen that the dimensions of the hand sign language image size for the training dataset are reduced in size as well as the increase in color brightness and contrast resulting from the background correction process.

3.3. Training

At this stage, the CNN model design used in the training process is carried out to produce an appropriate model to classify hand sign language images. The CNN model applied uses hyperparameter values consisting of the learning rate, epoch, loss function, and optimizer. Table 1 below is the CNN architecture specification used in this study.

Table 1. CNN Model Architecture

Layer type	Description	Size
Input Layer	Input Image	32x32x3
Conv 1	Convolutional ReLU MaxPooling	8 kernel, 3x3 Window size 2x2
Conv 2	Convolutional ReLU MaxPooling	16 kernel, 3x3 Window size 2x2
Conv 3	Convolutional ReLU MaxPooling	32 kernel, 3x3 Window size 2x2
Flatten	Flatten	512
Fully Connected Layer	Dense ReLU	512
Output Layer	Dense Softmax	29

The CNN architectural design is as shown in table 1, there are input layers, 3 convolution layers, flatten, fully connected layers, and output layers. The Input Layer requires input with a size of 32x32x3 where 32x32 pixels 3 layers RGB, then in Conv 1 using 8 kernels measuring 3x3 after that using ReLU activation [34], and using Maxpool with a window size of 2x2, as well as Conv 2 and Conv 3, only on Conv 2 uses 16 kernels and Conv 3 uses 32 kernels. Next is the Flatten layer and Fully Connected Layer with 512 nodes, and

the last is the output layer containing Dense Softmax with 29 nodes [35], this is adjusted to the number of classes in the hand signal dataset of the alphabet.

The training process will be carried out through a series of iterations whose number of repetitions is determined by the maximum epoch value [36]. One epoch is a process when all training data has been used and passes through all network nodes once. While the hyperparameter used in this study is the Adam Optimizer [37], with The Batch Size is 32 and Epochs are 20. The model training process is carried out in a hardware and software environment with specifications for Dell Latitude E7440 Laptop, 12 GB DDR4 RAM, Processor Intel® Core™ i5-7200U CPU @ 2.50GHz, Nvidia GeForce 940MX GPU, 256 GB SSD. The operating system used is Windows 10 Professional and the training and testing model algorithms are implemented using python code by utilizing the Tensorflow library. The results of the training model as shown in Fig. 5.

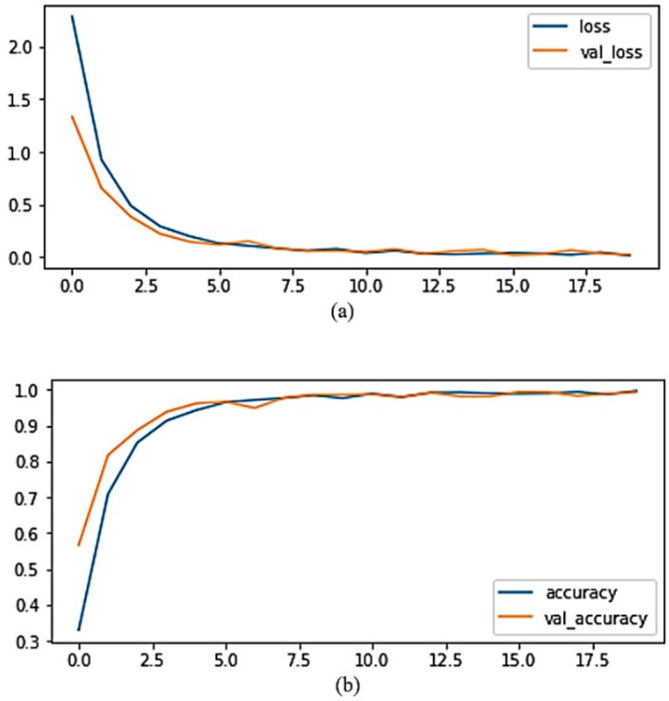

Fig. 5. Graphics of the Training Model Process: (a) Loss of Training and Validation, (b) Accuracy of Training and Validation

As seen in Fig. 5, The training process is carried out in 20 epochs, in the first epoch training accuracy is 33.04% and validation accuracy is 56.69%, while training loss is 28.26% and validation loss is 33.30%. in the tenth epoch, the training accuracy is 97.60% and validation accuracy is 98.57%, while the training loss is 8.11% and validation loss is 6.08%. Finally, in the last or twentieth epoch, the training accuracy is 99.60% and the validation accuracy is 99.68%, while the training loss is 1.64% and the validation loss is 2.55%. The main finding of this research is that the use of resizing and background correction methods, as well as setting hyperparameters can improve model accuracy.

3.4. Testing

After the model training process is complete, the next process is to test the model. The testing process is similar to the model training process, only the difference is that when the model testing process is not carried out backward pass or backpropagation iterations it does not change the weight or weight of the model as in the training process [38]. The Testing process is carried out using test data that is different from the training data set, to obtain valid testing results, this is following the recommendations of [39][40] regarding training and testing of the CNN model. Model testing is done by reading the hand signal image that is inputted by taking each frame from the webcam video, then the frame is identified based on the model that has been trained, then produces output in the form of identification results and accuracy values. Then the highest value from the identification results is directly written on the output board. Fig. 6 is a flowchart for the model testing process.

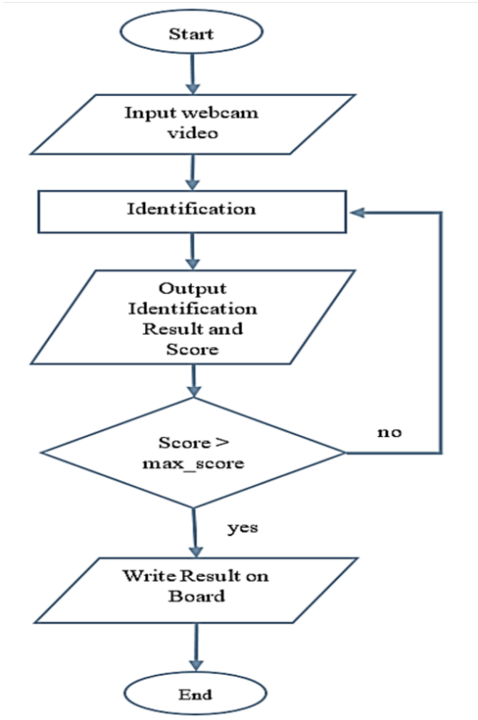

Fig. 6. Flowchart for the testing process

As shown in Fig. 6, the testing process is carried out by entering input in the form of hand signals via the Web camera on the Laptop Computer, where the hand makes a hand gesture in the Region of interest box on the Webcam display. Then the webcam display brings up the alphabetical prediction of the hand signal along with the score on the board display. Testing the model is carried out for each character letter 10 times, so a total of 290 times of testing. Fig. 7 and Fig. 8 Show the Confusion matrix value from the model testing results, for 29 types of hand sign language for each letter of the alphabet. Which consists of accuracy, precision, and recall.

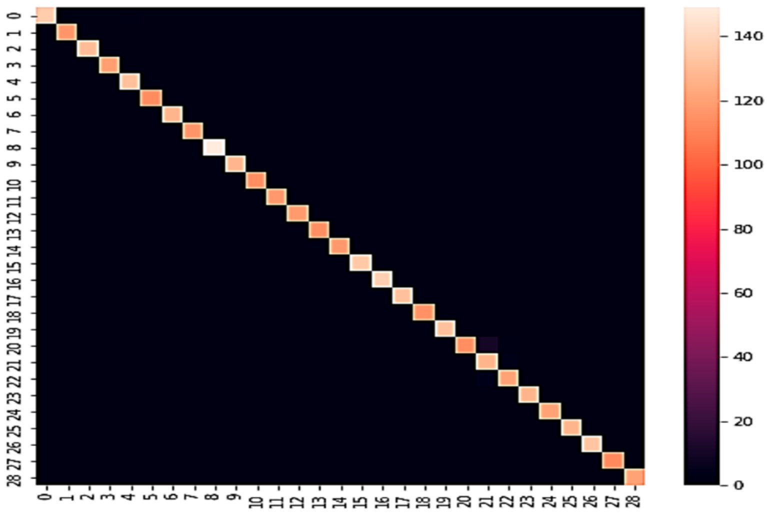

Fig. 7. Confusion Matrix of The Model Testing

A	1.00	0.99	0.99	138
B	1.00	1.00	1.00	116
C	1.00	1.00	1.00	130
D	1.00	1.00	1.00	119
E	0.98	1.00	0.99	131
F	1.00	1.00	1.00	113
G	1.00	1.00	1.00	127
H	1.00	0.99	1.00	117
I	1.00	1.00	1.00	149
J	0.99	1.00	1.00	128
K	1.00	1.00	1.00	114
L	1.00	1.00	1.00	117
M	1.00	1.00	1.00	118
N	1.00	1.00	1.00	114
O	1.00	1.00	1.00	117
P	1.00	0.99	1.00	136
Q	1.00	1.00	1.00	137
R	1.00	1.00	1.00	132
S	0.99	0.98	0.99	117
T	0.99	1.00	1.00	132
U	1.00	0.90	0.95	126
V	0.90	0.98	0.94	130
W	0.95	0.97	0.96	125
X	1.00	1.00	1.00	127
Y	0.99	0.99	0.99	122
Z	1.00	1.00	1.00	127
del	1.00	1.00	1.00	133
nothing	1.00	1.00	1.00	112
space	1.00	1.00	1.00	121
accuracy			0.99	3625
macro avg	0.99	0.99	0.99	3625
weighted avg	0.99	0.99	0.99	3625

Fig. 8. Performance of The Testing Model

Fig. 8 shows that the performance of the testing model achieves the best accuracy of 99%. and the Sensitivity, Recall, and f1-score levels are 99% respectively. This is because we apply resizing and background correction to the training and test images. These results are relatively better than previous similar studies as shown in Table 2.

Table 2. Comparison of Results with previous related studies

Study	Model	Dataset	Accuracy
Chong et al[5]	SVM, DNN	American Sign Language (ASL)	80.30% and 93.81%
Pigou et al[8]	CNN	Italian gestures	91.7%
Rastgoo et al[10]	RBM	Massey University Gesture Dataset 2012	99.31%
Rathi et al[13]	ResNet50 based	American Sign Language Hand gesture	99.03%
Daroya et al[14]	CNN	American Finger Spelling format	90.03%
Abdulhussein et al[17]	CNN	American Sign Language (ASL)	99.3%
Sabeenian et al[18]	CNN	MNIST ASL dataset	93 %
Al-Hammadi et al[20]	CNN	King Saud University Saudi Sign Language (KSU-SSL) dataset	87.69%
Our Methode	CNN	ASL Alphabet repository	99%

The findings of this study imply that this hand sign language recognition model can be a hand sign language independent learning tool with a relatively better level of recognition accuracy than previous similar studies. The strength of this study is that the proposed hand sign language recognition model can perform hand sign language recognition from the alphabet in real-time. While the limitation of this model is that the performance of model is strongly influenced by the specifications of the web camera and lighting system.

4. CONCLUSION

In this study, a hand signal recognition model from letters of the alphabet using the CNN model has been successfully created, with significant results compared to previous related studies. Our contribution is

the addition of preprocessing to the background correction which results in good accuracy in the proposed model. Our future work is to add to the sign language dataset basic words in addition to the letters of the alphabet, and also to increase the accuracy of the model by adding other hyperparameters.

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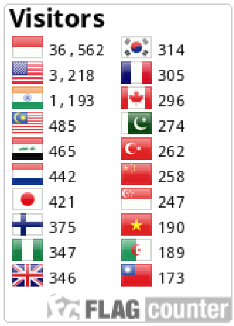
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#25051 Summary

SUMMARY REVIEW EDITING

Submission

Authors	Bambang Krismono Triwijoyo
Title	Deep Learning Approach For Sign Language Recognition
Original file	25051-65980-1-SM.PDF 2022-10-16
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Authors

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Country	Indonesia
Bio Statement	Assistant Professor at Computer Science Departement, Bumigora University

Principal contact for editorial correspondence.

Title and Abstract

Title Deep Learning Approach For Sign Language Recognition

Abstract

Sign language is a method of communication that uses hand movements between fellow people with hearing loss. Problems occur when communication between normal people with hearing disorders, because not everyone understands sign language, so the model is needed for sign language recognition. This study aims to make the model of the introduction of hand sign language using a deep learning approach. The model used is Convolutional Neural Network (CNN). This model is tested using the ASL alphabet database consisting of 27 categories, where each category consists of 3000 images or a total of 87,000 images of 200 x 200 pixels of hand signals. First is the process of resizing the image input to 32 x 32 pixels. Furthermore, separating the dataset for training and validation respectively 75% and 25%. The test results indicate that the proposed model has good performance with a value of 99% accuracy. Experiment results show that preprocessing images using background correction can improve model performance.

Indexing

Keywords	Deep Learning; Sign Language; CNN
Language	en

Supporting Agencies

Agencies	Universitas Bumigora

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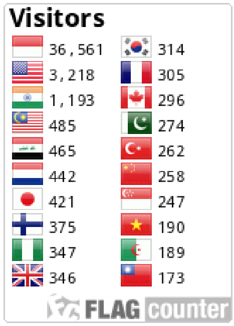

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#25051 Review

SUMMARY **REVIEW** EDITING

Submission

Authors	Bambang Krismono Triwijoyo
Title	Deep Learning Approach For Sign Language Recognition
Section	Articles
Editor	Alfian Ma'arif

Peer Review

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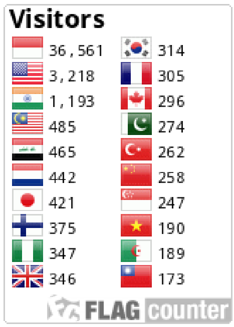
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Submission

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