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Article

Sign Language Detection Based on EMG and IMU Sensors Using Neural Network

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Abstract: Sign language is a way of communication for people with hearing and speech impairments. Sign language is generally done using hand gestures to articulate sentences. Different countries use different sign languages, increasing the complexity of sign language recognition. Communication between non-disabled and disabled people is difficult because non-disabled people do not learn sign language. This research aims to develop a device that can translate sign language specific to telling body conditions so that people without disabilities can understand. The device uses sensors to determine hand movement patterns to recognize sign language. The sign language recognized in this study focuses on body conditions and diseases such as asthma, cough, dizziness, depression, and tonsils. The results of the test show that the Artificial Neural Network (ANN) model has good performance with 98% accuracy value, 98% precision value, 98% recall, and 98% F1-Score. The test was conducted after the model was implanted and used to perform sign language testing. The parameter value of the confusion matrix shows high results. It can be concluded that the model created can be used to translate sign language to express the condition of tonsils, cough, depression, dizziness, and asthma.

Keywords: Artificial Neural Network, Disabilities, Sign Language

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1. Introduction

Based on records released by the Badan Pusat Statistik (BPS) in 2020, there were 22.5 million people with disabilities in Indonesia. The largest group of people with functional disabilities in Indonesia, namely people with severe disabilities, with a total of 6.1 million people, which includes 1.2 million people with physical limitations, 3.07 million people with sensory limitations, 149,000 people with mental limitations, and 1.7 million people have intellectual disabilities [1].

Based on the survey results regarding the rights of persons with disabilities as stipulated in Law Number 8 of 2016 and Government Regulation Number 70 of 2019 concerning Planning, Implementation, and Evaluation of Respect, Protection and Realization of the Rights of Persons with Disabilities needs to be improved. The fulfilment of rights that are not maximized will cause various risks ranging from socioeconomic inequality and limitations on access to information, employment, health, education, and other issues compared to normal citizens [2]. Different types of people with disabilities have different needs. Based on data from BPS in 2020 states that the rate of speech disorders reached 0.35 per cent and hearing impairment reached 0.36 per cent [3]. People with speech and hearing impairments use the same method of communication, namely hand sign language.

Hand sign language is a language that is often used to help people with disabilities communicate. Sign languages that are often used are Bahasa Isyarat Indonesia (BISINDO) and Sistem Bahasa Isyarat Indonesia (SIBI). This sign language was developed directly by people with disabilities [4]. However, not everyone understands sign language, so there is often a communication gap that complicates between people with hearing and speech impairments and normal citizens. So that there is a misunderstanding or lack of information conveyed properly between sign language users and people who do not understand sign language [5]. This results in economic, social, and other access inequalities. Research about sign language recognition using a sensor is has high interest since so many disabled people. Research [6]–[8] discusses the use of EMG and IMU sensors to translate sign language into American and Persian. Sign language in unique and different countries has different gestures. This research aims to develop a sign language recognition device to translate Indonesian sign language. The device focuses on recognizing sign language to tell the body condition specific to hand gestures. The health conditions examined in this research include tonsillitis, cough, depression, dizziness, and asthma. These conditions are commonly encountered in everyday life and frequently arise in conversations. Understanding these health issues can help the general public recognize the challenges faced by individuals with disabilities in both school and workplace settings.

The large number of people who use sign language and have similar needs form the basis of the importance of developing a sign language translation device. In order to improve the accessibility of communication between individuals in normal conditions and people with disabilities, it is necessary to develop a device that is able to interpret sign language. With this sign language interpretation facility, it is expected that there will be a significant improvement in the ability to communicate effectively between people with disabilities and non-disabled people.

2. Methods

The research consisted of hardware and software system development. The hardware is used to measure the arm position and muscle signals when sign language is performed. The software is used to run the pre-trained model to recognize the sign language being performed. The final output of the developed device is a voice that provides information on the sign language performed. The study recognized 5 sign languages that indicate health, namely tonsils, asthma, cough, depression and headache.

2.1 Hardware System

The hardware is developed using sensors, microcontrollers, and actuators. Sensors are used to record changes that occur in hand position and muscle signals when performing sign language. The microcontroller is used to process the data that has been recorded by the sensor and send control signals to the actuator. Actuators are used to provide sign language information that is being performed by people with disabilities.

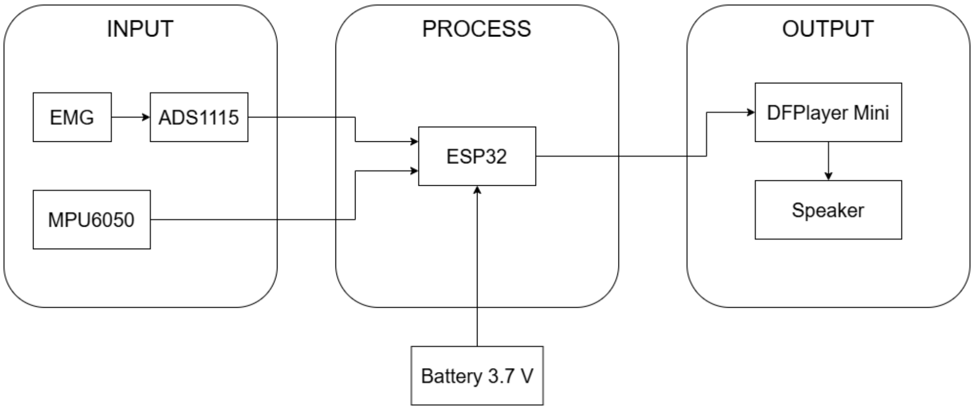


Figure 1. Hardware System Block Diagram

Figure 1 shows that the developed sign language translation device uses an esp32 microcontroller, EMG sensor, ADS1115 device, MPU6050 sensor, DFPlayer Mini, and speaker with a 3.7 volt battery power supply. The characterization pattern used to develop the translator device is the position characteristic recorded using the MPU6050 sensor. This sensor is able to provide position data in 3-dimensional space so that the position of the hand when translating sign language can be known [9]. This research also utilizes muscle signal features during sign language. The combination of hand location features and muscle strength used during sign language is a pattern that will be recognized using the neural network method. The ADS1115 device is used to convert analogue signals on EMG sensors into digital values. This tool is needed because the Analog Digital Converter (ADC) system on the ESP32 microcontroller has many quantization errors [10]. The digital data on the MPU6050 sensor and the muscle signal will be the input processed by the ESP32 microcontroller. The ESP32 microcontroller is used because it has a larger memory, which allows it to load the neural network model developed [11]. The result of the processing is a classification of the conditions of tonsils, asthma, cough, depression, and headache. The condition will be issued in the form of sound by the speaker so that the intentions of people with disabilities can be known by communication opponents who do not have disabilities.

2.2 Software System

The software system development in this research consists of the training process and the overall system performance software. Artificial Neural Network (ANN) is a type of machine learning used to model sign language translators. ANN is a data processing system inspired by the way the human brain works, consisting of interconnected processing units, such as neurons. Through the adjustment of weights and activation functions, ANN processes information to learn and adapt itself based on the given data [12].

Figure 2 is the architecture used to develop the sign language translator model in this study. The input used consists of 4 data, namely EMG, Pitch, Roll, and Yaw, which represent the movement and angle of the hand. There are 2 layers used in this research. The first layer consists of 50 neurons using the activation of each neuron in the form of relu, while the second layer consists of 25 neurons using the same activation in the form of relu. Relu activation is an activation function that will map the x value if x> 0. If the x value is a negative value, it will be converted to 0 [13]. The output part of the model consists of 5 classes (tonsils, asthma, cough, depression and headache) using softmax activation. Softmax activation is another form of Logistic Regression that can be used to classify more than two classes. This activation is used to transform the output of the last layer into its underlying probability distribution. Softmax activation calculates the probability for each class and then converts the vector of real values into a range between zero and one so that when summed up, they will all be worth one [14].

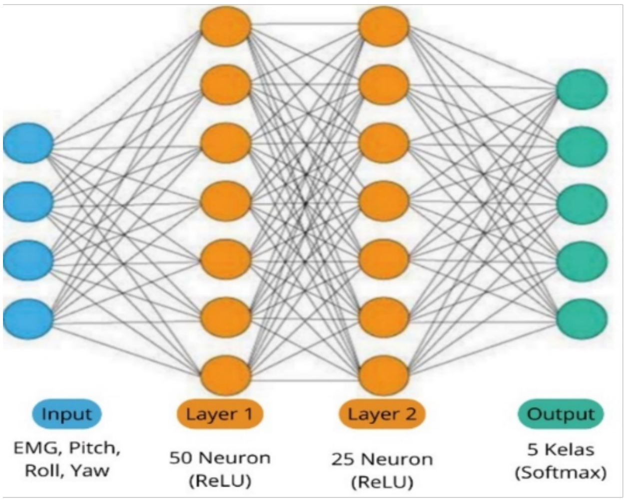


Figure 2. Artificial Neural Network (ANN) Architecture

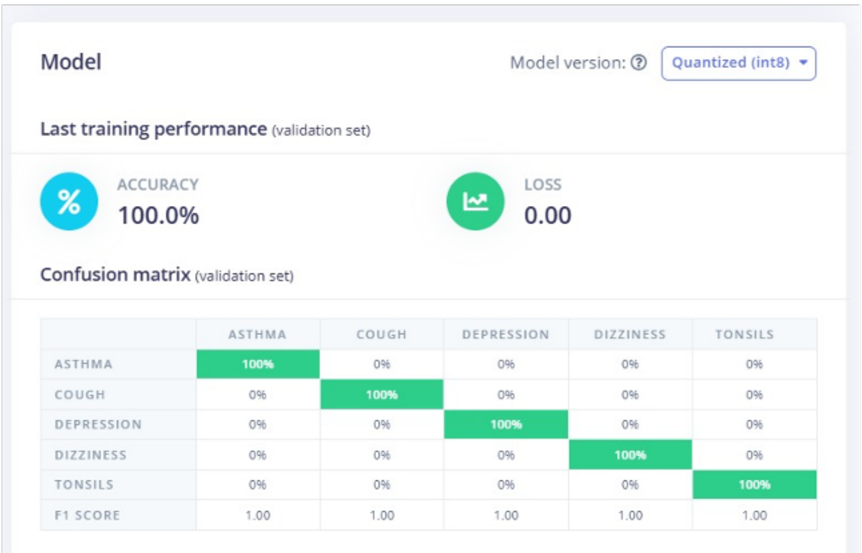
2.2.1 Dataset Collection

Datasets are structured and organized collections of data used to train and test machine learning models in pattern recognition or classification. In this research, the dataset contains gesture data representing various disease classes, which are used to train a machine learning-based sign language interpreter model [15]. The dataset used in this research acts as the main component in the development of the machine learning-based sign language interpreter system. Dataset collection is done with the aim of obtaining representative data from various gestures that represent certain disease classes. The collected dataset has a unique characteristic, where each gesture is recorded with a special device designed to capture hand gestures with high precision. The collected data consists of 300 time points with 9 features at each point, resulting in 2700 data points per gesture. Data capture was done at a frequency of 76.92 Hz, where each gesture was recorded with a timestamp every 13 milliseconds, ensuring that each gesture could be analyzed in detail. Each gesture was then saved in a CSV file for easy data management and processing. For each disease class, 20 data were collected, resulting in 100 CSV files covering 5 disease classes: Tonsils, Asthma, Cough, Depression, and Headache. This dataset is expected to provide a strong representation for training machine learning models to recognize gestures accurately so that the developed sign language translator system can work well in various conditions.

2.2.2 Dataset Training Process

The dataset training process is an important stage in building a model using ANN architecture. At this stage, the model is trained using data that has been prepared in order to recognize the patterns and characteristics contained in the dataset. The main objective of this stage is to produce a model that has high generalization ability so that the model can work well on data that has never been seen before.

In testing, the dataset is divided into two parts, namely training data (train) and test data (test), with a ratio of 75:25, where 75% of the data is used to train the model, and the remaining 25% is used to test the performance of the model after training. This division aims to ensure that the model can generalize well and does not experience overfitting of the training data. Testing involves setting several parameters, such as the number of epochs, learning rate, and optimization algorithm, to achieve optimal results. Figure 3 shows the results of the model training process, with an accuracy rate of 100%, indicating that the model could classify each class very well without any identification errors. This accuracy result demonstrates the model's ability to recognize and distinguish gestures in each tested disease class, even on data that has never been processed before. In addition, other evaluation parameters such as F1-score, precision, and recall also reached 100%, which illustrates that the model not only classifies the data correctly (precision) but also has a very high sensitivity in detecting each relevant class (recall). The F1-score reaching 100% indicates a very good balance between precision and recall, which is important to minimize misclassification. These results show that the model has optimal performance in terms of precision and sensitivity to each class-tested. With these excellent results, it can be concluded that the developed model has a very stable and reliable performance in recognizing sign language gestures and is ready to be used in real applications. The model demonstrates outstanding capabilities in gesture recognition and can be relied upon for various applications that require an accurate gesture recognition system.



Model

Model version: Quantized (int8)

Last training performance (validation set)

ACCURACY 100.0%

LOSS 0.00

Confusion matrix (validation set)

	ASTHMA	COUGH	DEPRESSION	DIZZINESS	TONSILS
ASTHMA	100%	0%	0%	0%	0%
COUGH	0%	100%	0%	0%	0%
DEPRESSION	0%	0%	100%	0%	0%
DIZZINESS	0%	0%	0%	100%	0%
TONSILS	0%	0%	0%	0%	100%
F1 SCORE	1.00	1.00	1.00	1.00	1.00

Figure 3. AI Model Training Result

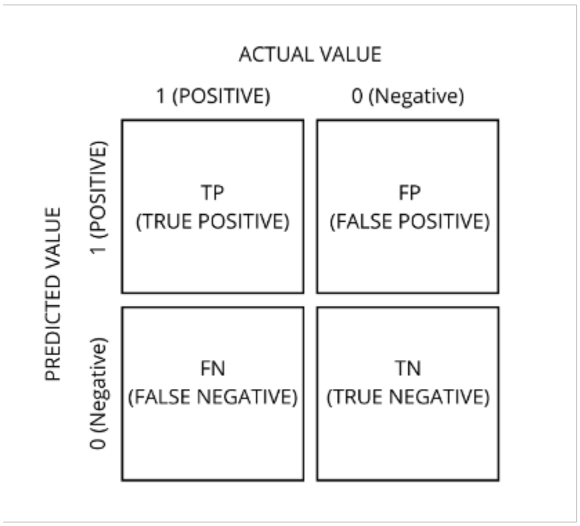


Figure 4. Confusion Matrix Model

2.2.3 Model Performance Measurement

Confusion Matrix is an evaluation method used to measure the accuracy of machine learning model classification results based on the algorithm used. This matrix provides an overview of the model's performance by presenting the number of correct and incorrect predictions. The predicted data is then classified into four main categories, namely positive and negative classes, which include correct predictions for the positive class (true positive), correct predictions for the negative class (true negative), and incorrect predictions for both classes (false positive and false negative).

Figure 4 shows the model prediction results displayed in the form of a Confusion Matrix, which consists of four main categories. First, True Positive (TP) describes the condition where test data that is positive is correctly predicted as positive. Next, False Positive (FP), or Type I error, occurs when data that should be positive is mistakenly predicted as negative. Also, True Negative (TN) is a condition where test data that is actually negative is correctly predicted as negative. Finally, a False Negative (FN), or Type II error, indicates a situation where data that should be negative is wrongly predicted as positive. These four categories help evaluate the accuracy and precision of the predictions produced by the classification model. From the above, several evaluation metrics can be formulated to measure model performance, such as accuracy, precision, and recall [16].

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \, x \, 100\% \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \, x \, 100\% \tag{2}$$

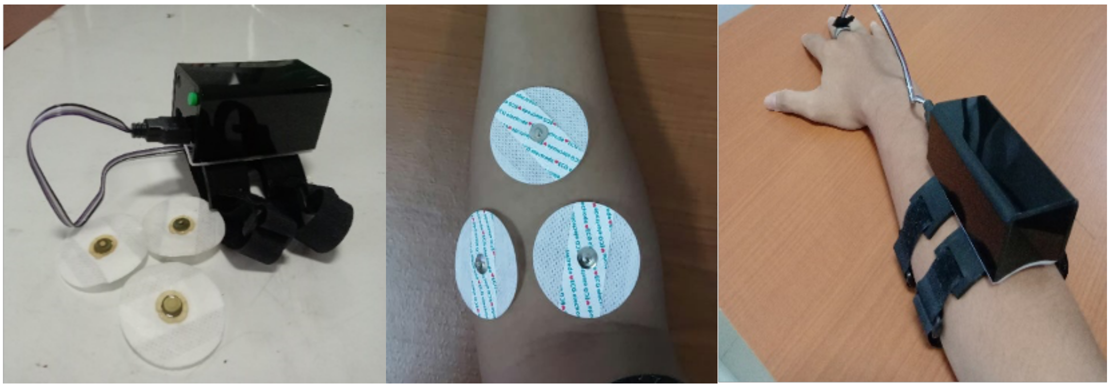
$$Recall = \frac{TP}{TP+FN} \, x \, 100\% \tag{3}$$

$$F1 - Score = 2 \, x \, \frac{Precision \, x \, Recall}{Precision + Recall} \, x \, 100\% \tag{4}$$

Confusion matrix is an evaluation tool used to measure the performance of classification models in machine learning by comparing the model's predicted results against the actual labels [17]. The matrix consists of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) elements that facilitate the calculation of various metrics, including accuracy, precision, recall, and F1-score. Accuracy indicates the overall proportion of correct predictions, precision indicates the model'smodel's accuracy in positive predictions, recall measures the model'smodel's ability to recognize positive data, and F1-score balances precision and recall for cases of unbalanced data. The confusion matrix enables comprehensive analysis of model performance, making it an effective tool for assessing the strengths and weaknesses of classification models in each class. The total data used in this research is 100 data for training, 25 data for validation, and 50 data for testing. Sign language recognition in testing is obtained by performing new sign language by disabilities person. The range of accuracy, precision, recall and F1 – Score from 0 -100%. The minimum range of TP, TN, FP, and FN is 0, and the maximum value is 100 in training, 25 data for validation, and 50 for testing.

Results

Figure 5 shows the sign language translation device that has been successfully developed in this research. The device is designed to detect and interpret hand and finger movements that represent sign language and translate them into sounds that can be understood by the user. The device consists of several main components, including an EMG sensor to capture hand movements and an MPU6050 sensor to read the angle of hand movements. Further development can be done to improve the translation capabilities, as well as enrich the vocabulary of the signs that can be recognized. The EMG lead in Figure 5 (C) is placed in Flexor Carpi Radialis, Extensor Carpi Radialis, and Brachioradialis muscles.



(a) (b) (c)

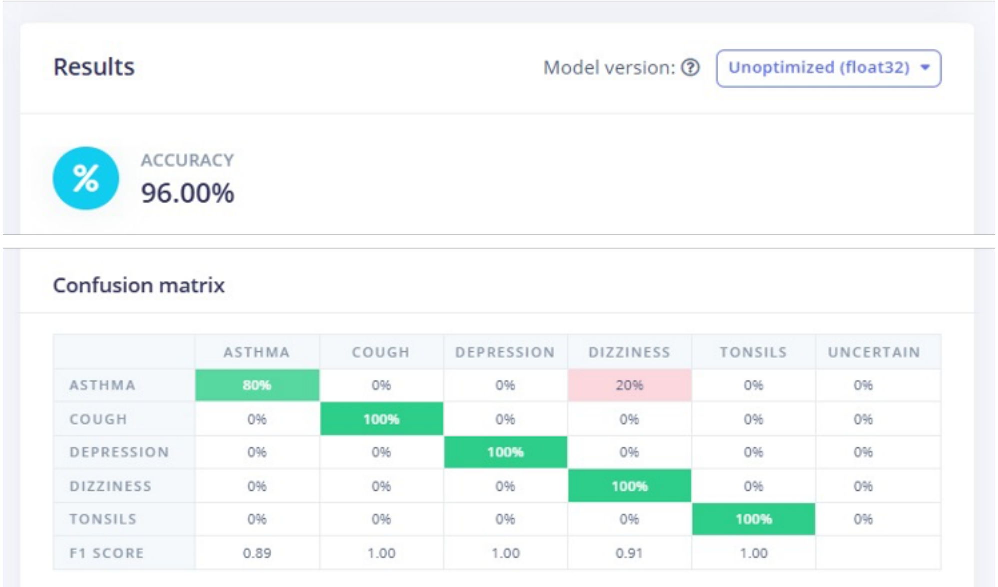
Figure 5. Sign Language Interpreting Tool (a) Device Wear by User (b) Whole Device (c) Lead Position in Arm

3.1. Machine Learning Model Accuracy Evaluation

This machine learning model is developed using the ANN algorithm for hand sign language classification. The testing process is conducted through the cross-validation method, which aims to obtain accuracy, precision, recall, and F1-score values that reflect the comprehensive performance of the model. Based on the training results, the model achieved a high accuracy rate of 100% with a low loss value of 0.00%. From the results of the training model obtained, a testing process is carried out using the dataset that was previously taken. The results of testing show that the accuracy value obtained is 96% with a precision value obtained of 97%, which indicates that the model has high accuracy in classifying positive data, while the recall value is 96%, which confirms its ability to detect all positive data. With an F1-score of 96%, the model shows a balance between precision and recall, indicating that the model is consistent and reliable in recognizing hand signals. With this performance, the developed ANN model has a high potential to be used effectively in hand sign language classification applications. The following figure is the result of the model testing that has been done.

The test results in Figure 6 show that the developed artificial intelligence model performed very satisfactorily with a global accuracy rate of 96.00%. Evaluation using confusion matrix revealed that the model was able to classify six categories of health conditions with a high level of precision. From the test results, it was seen that the model achieved 100% perfect accuracy for the categories of tonsils, asthma, depression, and headache, indicating good discrimination ability for these conditions. These results show that the model has great potential in assisting medical diagnosis with a high degree of accuracy.

Further analysis of the F1-Score metric confirmed the consistency of the model's performance, with very high values across all categories tonsils 100%, asthma 89%, cough 100%, depression 100%, and headache 91%. These high F1-Score values indicate an optimal balance between precision and recall, suggesting that the model is not only accurate in its predictions but also consistent in its performance across categories. The only area that requires special attention is the classification of Cough conditions, where the model shows 80% accuracy, with 20% of cases misclassified as tonsillitis. This phenomenon is likely due to the overlap or similarity in symptom manifestation between the two conditions. Nonetheless, an 80% accuracy rate for the Cough category is still a fairly good result in the context of medical classification.



Results

Model version: ⓘ Unoptimized (float32) ▾

ACCURACY

96.00%

Confusion matrix

	ASTHMA	COUGH	DEPRESSION	DIZZINESS	TONSILS	UNCERTAIN
ASTHMA	80%	0%	0%	20%	0%	0%
COUGH	0%	100%	0%	0%	0%	0%
DEPRESSION	0%	0%	100%	0%	0%	0%
DIZZINESS	0%	0%	0%	100%	0%	0%
TONSILS	0%	0%	0%	0%	100%	0%
F1 SCORE	0.89	1.00	1.00	0.91	1.00	

Figure 6. Model Testing Results

Based on these test results, it can be concluded that the developed model has significant potential to be implemented in clinical decision support systems. The consistently high performance of the model in almost all categories, as evidenced by the 96.00% global accuracy and excellent F1-Score, indicates the reliability of the model in classifying various health conditions. However, it should be noted that for cases indicated as Cough or Tonsil, additional verification may be required to ensure the accuracy of the diagnosis. This finding also opens up opportunities for further development, particularly in improving the model's ability to distinguish between Cough and Tonsil conditions with more precision.

3.2 Implementation and Test Results of Sign Language Translator System Implementation

The implementation and testing phase of the system was conducted to evaluate the performance of the machine learning-based sign language translator system in identifying hand gestures that represent various types of diseases. The system is focused on five predetermined disease classes, namely tonsils, asthma, cough, depression, and headache. Each disease class is tested ten times to obtain more representative data so that a more accurate picture of the system's performance can be obtained. This test aims to assess the level of accuracy and consistency of the system in recognizing and translating sign language gestures associated with each disease tested. To ensure the objectivity of the results, each experiment was conducted with a wide variety of hand gestures in accordance with sign language standards and was conducted with sufficient repetition to obtain reliable results. The test data obtained is then analyzed to measure how effective this system is in recognizing and classifying hand gestures that represent these diseases. The test results can be seen in more detail in Table 1.

Tests were conducted on five classes of health conditions where Asthma represents Tonsil condition, Cough for Asthma condition, Depression for Cough condition, Dizziness for Depression condition, and Tonsils for Headache condition. Each class underwent ten trials to ensure the consistency and reliability of the model in classifying each of these health conditions. Based on the test results, four out of the five tested classes performed very well, with an accuracy rate of 100%. This perfect accuracy indicates that the system successfully recognized all samples tested in these classes without any errors in the classification process. The success with 100% accuracy in most of these classes confirms that the sign language interpreter system has an excellent ability to distinguish hand gestures representing various diseases and shows high stability and reliability in the classification process despite being tested under uniform and standardized testing conditions.

Table 1. Testing Results of Sign Language Translator System Implementation

	Asthma	Cough	Depression	Dizziness	Tonsils
Asthma	10	0	0	0	0
Cough	0	9	0	0	1
Depression	0	0	10	0	0
Dizziness	0	0	0	10	0
Tonsils	0	0	0	0	10

However, in one of the test classes, the Cough class, there was one misclassification out of five samples tested. This resulted in an accuracy rate for that class of 90%, with an error rate of 10%. This misclassification could be caused by several factors, including the similarity between the gestures in the class and the gestures from other classes or small variations in the execution of the hand gestures performed by the user during the test. However, even though there was one error in the Asthma class, it did not have a significant impact on the overall performance of the system, as most of the other classes continued to show very high accuracy. Overall, the average accuracy of the system across all classes reached 98%, indicating that the performance of the system in classifying sign language gestures is very good and acceptable.

5. Conclusions

This research successfully developed a machine learning-based sign language translation system using a combination of EMG sensors and MPU6050 on an ESP32 microcontroller. The system can classify five types of gestures representing common diseases with an average accuracy of 98%. The evaluation shows that the system has a high level of precision and recall, which proves the effectiveness of the model in classifying hand gestures with good consistency. The implementation of this system is expected to facilitate communication between people with disabilities and the general public and improve their social inclusion. Further research is recommended to explore the development of the model with a larger number of classes and test the implementation in a real environment to improve the robustness of the system to individual user variations.

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