A SIGN LANGUAGE IDENTIFICATION SYSTEM TO SUPPORT DISABILITY LANGUAGE USING SUPPORT VECTOR MACHINE

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ABSTRACT

Communication between disability language individuals and non-disabled individuals often faces significant challenges. Currently, there are many people with disability language both worldwide and in Vietnam, and this calls for a useful solution to help individuals with speech impairments communicate more easily. This paper proposes a system to help disability language individuals communicate more easily with non-disabled people. The proposed system included a sensor glove to measure finger movement signals. The measured signals were preprocessed to remove noise and artifacts. The processed signals were then used to identify the letters corresponding to the gestures. Finally, the sounds corresponding to the identification letters were played through a speaker. The system achieves a 99.67% accuracy rate in sign language identification. These promising results suggest that the system could be applied in real-world scenarios to assist individuals with speech disabilities.

HỆ THỐNG NHẬN DẠNG NGÔN NGỮ KÝ HIỆU SỬ DỤNG PHƯƠNG PHÁP VECTOR MÁY HỖ TRỢ ĐỂ HỖ TRỢ NGƯỜI KHUYẾT TẬT NGÔN NGỮ

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TỪ KHÓA

Nhận dạng ngôn ngữ ký hiệu
Người khuyết tật ngôn ngữ
Máy vectơ hỗ trợ
Cảm biến gia tốc
Cảm biến uốn cong

TÓM TẮT

Giao tiếp giữa những người bị khuyết tật ngôn ngữ và những người không khuyết tật thường phải đối mặt với những thách thức đáng kể. Hiện nay, có rất nhiều người khuyết tật ngôn ngữ trên toàn thế giới và tại Việt Nam, do đó cần một giải pháp hữu ích để giúp cho người khuyết tật ngôn ngữ có thể giao tiếp dễ dàng hơn. Bài báo này đề xuất một hệ thống giúp những người khuyết tật ngôn ngữ giao tiếp dễ dàng hơn với những người không khuyết tật. Hệ thống được đề xuất bao gồm một găng tay cảm biến để đo tín hiệu chuyển động ngón tay. Các tín hiệu đo được sẽ được tiền xử lý để loại bỏ các nhiễu và artifacts. Sau đó, các tín hiệu đã xử lý được sử dụng để nhận dạng các chữ cái tương ứng với các cử chỉ. Cuối cùng, âm thanh tương ứng với các chữ cái nhận dạng được sẽ được phát qua loa. Hệ thống đạt được độ chính xác là 99,67% trong việc nhận dạng ngôn ngữ ký hiệu. Những kết quả đầy hứa hẹn này cho thấy hệ thống có thể được áp dụng trong các tình huống thực tế để hỗ trợ những người khuyết tật ngôn ngữ.

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1. Introduction

According to statistics from the World Health Organization in 2024, there are 1.5 billion people worldwide with hearing impairments, including 2.5 million individuals in Vietnam affected by this condition [1], [2]. Communication between disability language and non-disabled people faces many challenges due to language barriers. However, thanks to significant advancements in sensor technology and artificial intelligence, communication support systems have been developed, opening new opportunities for disability language to express their thoughts and emotions more easily [3] - [5]. These studies demonstrate that smart glove devices hold great potential for application, not only accurately recognizing gestures but also integrating various new features to adapt to different languages and communication contexts.

In 2014, a smart glove device was proposed to convert sign language into sound. The glove device was equipped with pairs of LED-LDR (Light Dependent Resistor) sensors on each finger to recognize sign gestures, transmitting data through an MSP430G2553 microcontroller and then sending data via ZigBee. The received sign data would be displayed on a computer and played as corresponding audio. However, the system could only recognize 10 characters from the English alphabet [6]. In 2015, another research project on language gloves was introduced under the name "SignSpeak." The SignSpeak sensor glove was designed to translate American Sign Language (ASL) into speech, enabling effective communication for disability language individuals. The glove integrated flex sensors, contact sensors, and accelerometers, which connected via Bluetooth to an Android application. The data was processed using Principal Component Analysis (PCA) to classify 26 letters with an accuracy of 92%. However, limitations included dependency on sensor accuracy and difficulties in distinguishing hand movements [7].

In 2017, a group of students from California State University designed a language glove [8]. The project successfully developed a soft glove using piezoresistive carbon composite materials. The system included strain sensors made from conductive elastic materials, accelerometers, and pressure sensors, detecting finger movements and generating binary codes to identify each letter. The design cost of the glove was approximately $100, requiring neither specialized laboratories nor complex processes. The results showed that the system could accurately recognize all 26 letters, highlighting its potential for human-machine interaction in virtual reality environments and effective communication support for people with disabilities. In 2018, a research team from two universities in Malaysia and Iraq [9] conducted an analysis and evaluation of sensor glove technologies for sign language recognition from 2007 to 2017. These systems utilized flex sensors, accelerometers, and various other types of sensors to collect data on hand movements and shapes. The paper also discussed the advantages of each sensor type, proposing a classification and assessment of existing technologies. The results highlighted the limitations and provided a development roadmap for sign language recognition glove technology, offering researchers a comprehensive overview and guidance for future improvements.

In 2020, a smart glove system that employed multi-channel capacitive sensors for gesture recognition using on-device AI was developed [10]. That study focused on minimizing latency and data transmission demands by directly processing signals without requiring decoding. The system leveraged capacitive sensors and machine learning algorithms, implemented on a Raspberry Pi. The results demonstrated high accuracy, reaching 99.7%, while significantly reducing data transmission, making the system more flexible and energy-efficient [10]. In 2021, Ayodele et al. [11] conducted a study involving gloves. This research proposed using textile gloves embedded with force sensors to classify different grip patterns through convolutional neural networks (CNNs). The aim was to enhance the rehabilitation process by enabling doctors to monitor patients' movements more effectively and in greater detail. The method involved collecting data from five participants using 30 different objects, then applying CNNs and comparing the results with traditional algorithms like k-NN and the support vector machine

(SVM). The findings showed that a simple CNN model outperformed classical algorithms in accuracy, highlighting CNNs' ability to automatically extract features for gesture recognition from sensor-equipped gloves. In 2021, a system was developed to create an Android application supporting sign language for Indonesians [12]. The study introduced the BisAndro application, designed to facilitate communication for disability language individuals in Indonesia using BISINDO sign language. With the goal of enabling seamless two-way communication, the app utilized TensorFlow Lite and CNN to recognize gestures from video inputs. The methodology involved collecting gesture samples, building a dataset, and training a CNN model. Initial results highlighted BisAndro's potential in sign recognition and communication support, especially for those unfamiliar with sign language.

Recently, an Intelligent Glove (IG) system designed to enable two-way communication between disability language individuals and non-disabled people was developed [13]. The gloves utilized flex sensors to recognize hand movements and transmitted signals to an Arduino Nano, converting them into text and sound. Additionally, the gloves featured a screen and speaker to display and vocalize messages. The system also allowed disability language users to view text or 3D signs converted from audio input. Testing showed that the system performed as intended and was well-received by users based on the synthesis of notable studies, it is evident that the sensor glove for sign language identification has achieved significant milestones but still faces challenges in improving accuracy, reducing latency, and enhancing flexibility.

Based on the issues related to individuals with disability language mentioned above, this paper will focus on developing a smart glove system to support the recognition of sign language, excluding accented letters, to provide an effective communication tool tailored to the practical needs of disability language individuals in Vietnam. The remain of this paper is as follows: Section 2 outlines the implementation methodology and the theoretical foundations relevant to the study. Section 3 presents the experimental results along with a discussion of the findings. Finally, the conclusion is provided in Section 4, summarizing the key outcomes of the study.

2. Materials and Methods

2.1. Proposed a sign language identification system to support disability language individuals

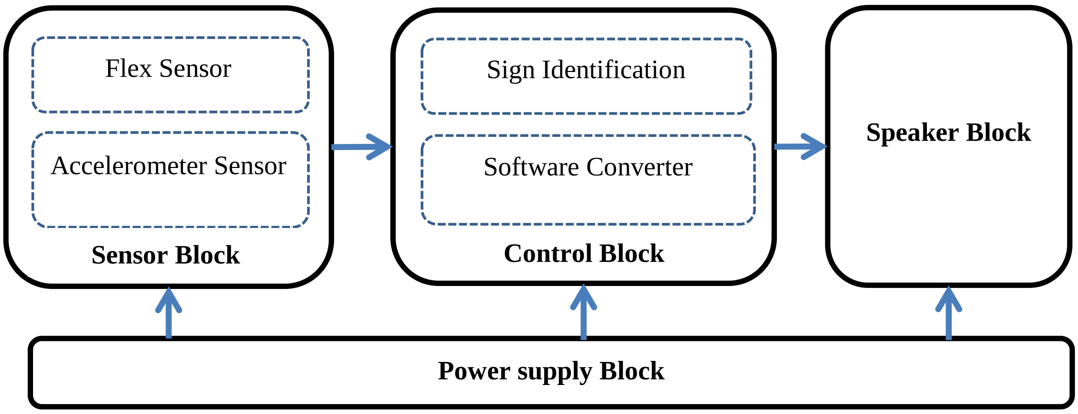


Figure 1. *Block diagram of the proposed method for a sign language identification system to support disability language individuals*

In this paper, a sign language identification (SLI) system is proposed to assist disability language individuals as shown in Figure 1. The system consists of a sensor glove designed to measure the gestures of sign language. In particular, the glove is designed using flexion sensors and accelerometers. The flexion sensor is used to measure the flexion of the fingers and the accelerometer is used to measure the movement of the hand. The measured signals are preprocessed using the Kalman filter to remove noise and artifacts. The processed signals are then used to identify the corresponding letters using SVM method. The letters after recognition will be played with corresponding sounds through the speakers on the computer.

2.2. Table of Vietnamese Alphabet Symbol

Sign language, also known as manual language, is a form of communication that uses gestures, movements, and hand expressions instead of spoken words. It was created to help the disability language individuals communicate with one another and interact with non-disabled individuals. In Figure 2, a list of sign language alphabets for disability language individuals as specified in Circular 17/2020/TT-BGDĐT is presented, which regulates sign language for disability language under the Law on Persons with Disabilities in Vietnam [14]. This paper will identify the signs as shown in Figure 2 using the proposed systeman. Moreover, in this study we did not fully recognize all Vietnamese accented letters as in Circular 17/2020/TT-BGDĐT. The recognition results of the characters will generate corresponding sounds to support individuals with speech disabilities. Furthermore, we only recognize individual characters and do not process entire sentences.

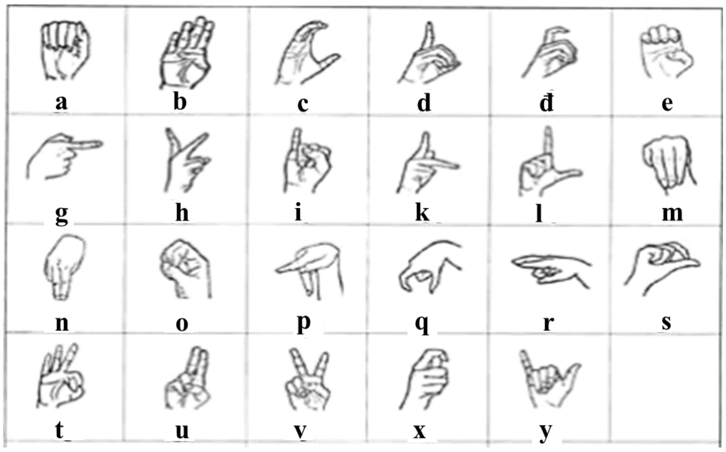


Figure 2. *The Vietnamese alphabet symbol for disability language individuals*

2.3. Signal preprocessing using Kalman filter

The filter configuration is set as follows: initial default value (x_0 = 0.01), system noise variance (Q = 2), and measurement noise variance (R = 2). Each sensor signal is filtered independently through two main stages: prediction and update. Prediction: Estimate the next state based on the current state and the system model. State prediction is:

$$\hat{x}_k^- = \hat{x}_{k-1} \tag{1}$$

The predicted of the error covariance is:

$$P_k^- = P_{k-1} + Q \tag{2}$$

State Update: Adjust the estimate based on the new measurement signal, balancing between the predicted value and the measurement signal using the Kalman Gain. Kalman Gain is:

$$K_k = \frac{P_k^-}{P_k^- + R} \tag{3}$$

Status update is:

$$\hat{x}_k = \hat{x}_k^- + K_k \cdot (z_k - \hat{x}_k^-) \tag{4}$$

In which, $z_k - \hat{x}_k^-$ is the error between the measured value and the predicted value. The updated error covariance is:

$$P_k = (1 - K_k) \cdot P_k^- \tag{5}$$

2.4. SVM for identify of sign language

SVM, which is a supervised machine learning, is used to determine the optimal hyperplanes between data points of different sign gestures from sensor data [15]. Given a pair of sensor data, the optimization equation of the SVM is defined as follows:

$$\min_{w,\zeta,b} J((w,\zeta) = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \zeta_i \tag{6}$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i,\ i = 1,\ldots,N \tag{7}$$

$$\zeta_i \geq 0,\ i = 1,\ldots,N \tag{8}$$

In this case, w is the weight vector parameters in the training term, C is a constant value, and φ is the mapping function. The mapping function is utilized to map input data point x_i into a higher-dimensional space. In addition, ζ_i is a slack variable. This value determines the distance of x_i with respect to the decision boundary. The Lagrange multipliers on the SVM term are applied to rewrite this expression as follows:

$$L(x) = \sum_{x_i \in SV} \alpha_i\, y_i K(x, x_i) + b \tag{9}$$

In which, $\alpha_i \geq 0$ denotes the Lagrange elements. $K(x, x_i)$ describes the kernel function of the SVM, and it is defined as follows:

$$K(x_i, x_j) = \alpha_i(x_i)^T \alpha_i(x_j) \tag{10}$$

In this paper, a one-against-one multi-class classifier is utilized to identify the sign gestures. Moreover, the kernel function $K(x, x_i)$ with the Gaussian radial basis function is in this paper, and it is defined as follow:

$$K(x_i, x_j) = e^{-\sigma \|x_i - x_j\|^2} \tag{11}$$

3. Results and Discussion

3.1. Glove sensor device

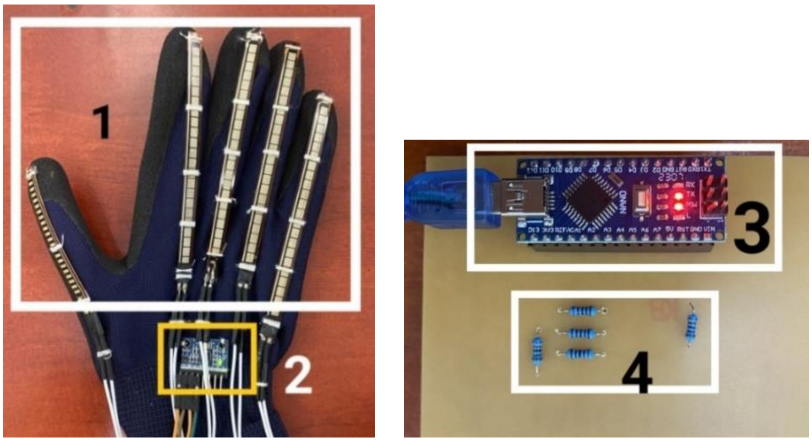


Figure 3. *Glove sensor device and PCB for control*

The accelerometer sensor is mounted on the glove corresponding to the position of the back of the hand, while five flex sensors are attached sequentially, each corresponding to one of the five fingers as shown in Figure 3. In addition, 10 KΩ resistors and the Arduino are mounted on a PCB circuit. The system is designed to include the following blocks: 1) Flex sensors attached to the fingers, 2) Accelerometer sensor, 3) Arduino Nano, 4) 10 KΩ resistor.

3.2. Data acquisition

The signals from the flex sensor before and after using Kalman filtering are shown in Figure 4. The unfiltered signal (blue line) shows many irregular fluctuations and noise, especially at sharp peaks and large fluctuations, making it difficult to analyze and identify. After applying Kalman filtering (red line), the signal becomes smoother, removing most of the noise and artifacts. In the early stages (0-100 samples), the signal is relatively stable, but the unfiltered data still has slight fluctuations. From 100-200 samples, the signal drops sharply, and the Kalman filter has smoothed the signal, avoiding unusual fluctuations. After 300 samples, the filtered signal remains much more stable than the original signal. The effect of the Kalman filter helps reduce noise and improve signal quality, ensuring higher accuracy.

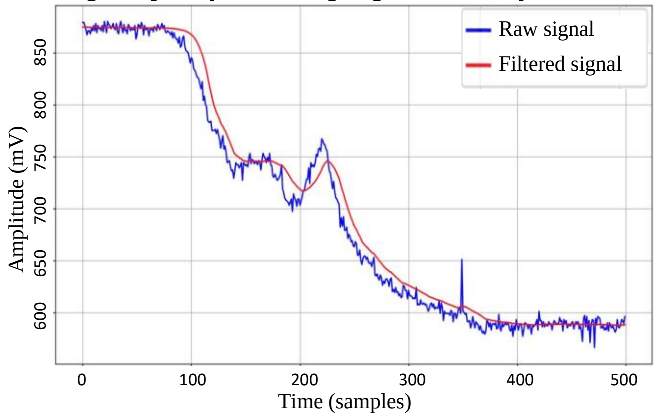
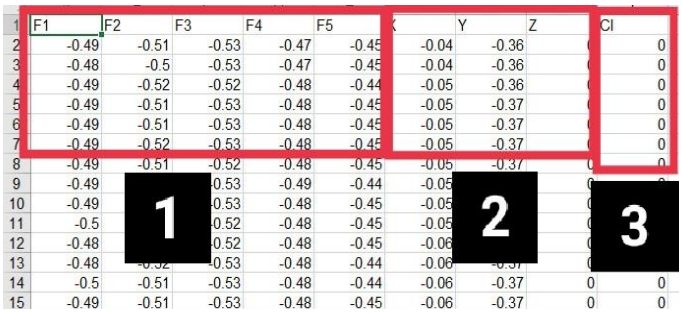


Figure 4. *Comparison of raw and filtered signals of flex sensor using Kalman filter*

When collecting sensor data, the recorded values are displayed on the Terminal and automatically saved to a CSV file. The collected data consists of 8 values: the first 5 values are obtained from the flex sensors corresponding to the movements of the 5 fingers, and the last 3 values are from the MPU 6050 accelerometer as shown in Figure 5. The recorded values change based on the hand and finger movements. The 5 values from the flex sensors are labeled as F1 to F5, while the 3 values from the MPU 6050 accelerometer are labeled as X, Y, and Z. A label Cl is assigned to classify different characters for identification purposes. In this paper, each sign language identification is collected with 1,600 data samples. The data was collected from six participants (all participants were students, 3 males and 3 females, aged between 20 and 24). They were also informed about the purpose of participating in the data collection experiments. With 22 sign language identification and one case with no motion (none), the total amount of data collected is 36,800 samples. This data will be split into 80% for training and 20% for testing.



1	F1	F2	F3	F4	F5	X	Y	Z	Cl
2	-0.49	-0.51	-0.53	-0.47	-0.45	-0.04	-0.36	[illegible]	0
3	-0.48	-0.5	-0.53	-0.47	-0.45	-0.04	-0.36	[illegible]	0
4	-0.49	-0.52	-0.52	-0.48	-0.44	-0.05	-0.36	[illegible]	0
5	-0.49	-0.51	-0.53	-0.48	-0.45	-0.05	-0.37	[illegible]	0
6	-0.49	-0.51	-0.53	-0.48	-0.45	-0.05	-0.37	[illegible]	0
7	-0.49	-0.52	-0.53	-0.48	-0.45	-0.05	-0.37	[illegible]	0
8	-0.49	-0.51	-0.52	-0.48	-0.45	-0.05	-0.37	[illegible]	0
9	-0.49	[illegible]	-0.53	-0.49	-0.44	-0.05	[illegible]	[illegible]	[illegible]
10	-0.49	[illegible]	-0.53	-0.48	-0.45	-0.05	[illegible]	[illegible]	[illegible]
11	-0.5	[illegible]	-0.52	-0.48	-0.45	-0.05	[illegible]	[illegible]	[illegible]
12	-0.48	[illegible]	-0.52	-0.48	-0.45	-0.06	[illegible]	[illegible]	[illegible]
13	-0.48	[illegible]	-0.53	-0.48	-0.44	-0.06	[illegible]	[illegible]	[illegible]
14	-0.5	-0.51	-0.53	-0.48	-0.44	-0.06	-0.37	0	0
15	-0.49	-0.51	-0.53	-0.48	-0.45	-0.06	-0.37	0	0

Figure 5. *Definition of collected data frames for sign language identification*

3.3. Sign language identification

The signals from the sensors after processing will be classified by character using the SVM method. The confusion matrix is applied to evaluate the performance of hand gesture classification. From the confusion matrix as shown in Figure 6, it can be seen that the classification performance is very good. The identification result achieves an accuracy of 99.67% on the test set. With 12 tests conducted, the system's ability to identify sign language identification is shown in Table 1. In this table, pre denotes predicted results, while T and F describe truth and fault, respectively. Furthermore, ACC and Ave represent the accuracy and average accuracy, respectively. In practice, the average accuracy (Ave) of 12 recognition tests for all symbols is 96.74%. Statistical results after 12 tests indicate that the system performs very well in identifying sign language. However, there is some confusion between the letters "u" and "v". This confusion arises because the sensors only detect the bending of the fingers based on the voltage readings from the Arduino, while the hand signs for "u" and "v" differ only in the contact between the index and middle fingers. Moreover, the current system only identifies individual sign language and does not generate sound for a complete sentence and it is designed to not recognize all accented characters in Vietnamese letters. In the future, the system will be further developed to identify both individual sign language and complete sentences for more effective communication.

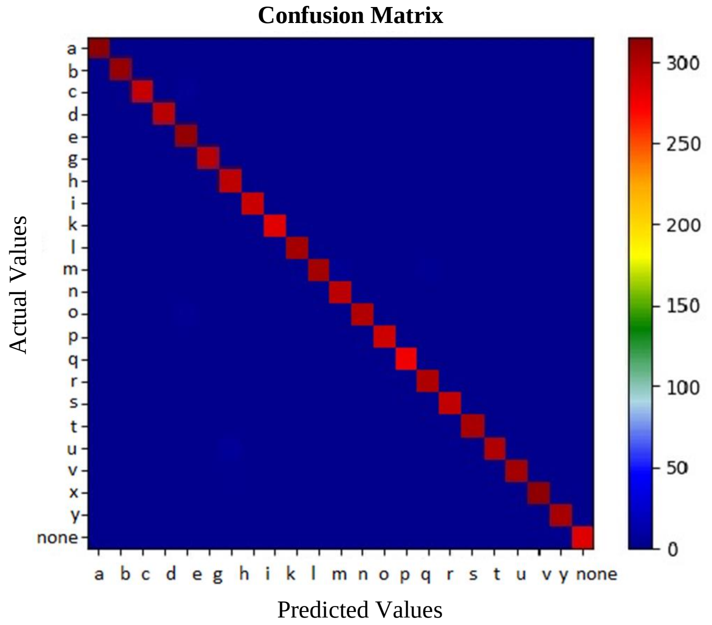


Figure 6. *Representation of confusion matrix for sign language identification*

Table 1. *Statistics of 12 times of sign language identification*

Pre	a	b	c	d	e	g	h	i	k	l	m	n	o	p	q	r	s	t	u	v	x	y	none
T	12	12	12	11	12	12	11	12	12	12	11	12	11	12	12	12	12	12	11	9	12	11	12
F	0	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	3	0	1	0
ACC	100	100	100	91.7	100	100	91.7	100	100	100	91.7	100	91.7	100	100	100	100	100	91.7	75.0	100	91.7	100
Ave	**96.74%**																						

4. Conclusion

The sign language identification is an essential research task aimed at assisting individuals with disability language. This paper has developed a sign language identification system that integrates sensor gloves and the SVM method. The experimental results highlight the advantages of the proposed system. Specifically, the identification accuracy with the training dataset reached 99.67%. In addition, an experiment with 12 times of sign language identification trials was conducted, achieving an average accuracy of 96.7%. With these results, the proposed method demonstrates the potential for practical application in supporting disability language individuals.

In future work, the system will be enhanced to identify both individual characters and complete sentences, with the capability to generate audio output of the sentences to better support disability language individuals. In addition, deep learning network structures will be studied and applied to improve recognition accuracy for all Vietnamese characters.

Acknowledgments

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