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Implementation of the Template Matching Algorithm for Smart Light Control through Speech Recognition for People with Disabilities

SHOLIHAH AYU WULANDARI[1], ADISTY PRAMUDITA PUTRI RUDI[2], ADI SUCIPTO[3], BEKTI MARYUNI SUSANTO[4], DHONY MANGGALA PUTRA[5]

[1,2,3,4,5]Politeknik Negeri Jember, Jember, Indonesia

CORESPONDING AUTHOR: SHOLIHAH AYU WULANDARI (email:sholihah.ayuwulan@polije.ac.id)

ABSTRACT Voice control systems in smart homes provide significant convenience for people with disabilities, especially in operating household devices such as lights without physical interaction. This study develops a voice-based light control system that runs locally on IoT devices using the template matching method. This system utilizes Mel-Frequency Cepstral Coefficients (MFCC) for voice feature extraction and Dynamic Time Warping (DTW) to match test voices with pre-recorded templates. Out of 66 voice samples tested, the system successfully recognized 13 out of 22 voices belonging to the primary user and rejected 43 out of 44 voices from other users, with an accuracy rate of 84.85%. Thus, this system shows potential as an inclusive, efficient, and disability-friendly voice control solution for smart home environments.

KEYWORDS: Disability, DTW, MFCC, Template Matching, Voice Control

I.INTRODUCTION

Smart homes continue to develop as a solution to improve comfort, efficiency, and accessibility in everyday life [1]. One of the most widely used features is smart lighting, which allows users to control lights through various interfaces, such as mobile applications, sensors, and voice commands. Among all these methods, voice control is very important because it allows natural and hands-free interaction, which is very beneficial for individuals with physical disabilities, such as amputations, paralysis, motor disorders, and visual impairments [2], [3], [4].

For this group of users, accessing conventional light switches is often a challenge. Simple actions such as turning on or off lights can be difficult, even impossible to do without assistance [5], [6]. Therefore, a voice-based lighting control system can improve their independence, safety, and quality of life, in line with the concept of universal design and the development of inclusive technology [7], [8].

Template matching is a lightweight method that does not require training, simply by matching voice input with a pre-recorded voice template [9], [10]. This method uses Mel-Frequency Cepstral Coefficients (MFCC) for voice feature extraction and Dynamic Time Warping (DTW) to measure the similarity of Time patterns [11]. This approach is very suitable for IoT devices such as Raspberry Pi, which have limited power, memory, and computing performance [10].

However, this method also has challenges, such as variations in voice characteristics between users, environmental noise, and the need for a clean and representative voice dataset [12]. However, this method is very useful in conditions without an internet connection, because the system can work locally, without relying on the cloud—increasing privacy and reducing latency [13], [14].

Several previous studies have developed voice control systems for home automation. Haq et al. (2020) developed a home automation system using MFCC and DTW, but it was not specifically intended for people with disabilities [13]. Isyanto et al. (2020) used Google Assistant as an intermediary for voice control in a smart home, but this approach relies on an internet connection because it uses cloud services [13]. Darabkh et al. (2018) developed a computer control system for users with hand disabilities [14], Utomo et al. (2023) designed a smart stick for blind children [15], while Hariharan et al. (2025) designed a voice-based smart wheelchair for blind and physically disabled users [2].

Despite much progress, there is still a gap in research on the development of a lighting control system that works locally, uses a combination of template matching methods (MFCC + DTW), and focuses on people with physical disabilities and blind people.

Therefore, this study aims to answer this gap by building an efficient, inclusive, and internet-independent voice control system to support accessibility in a smart home environment. This study focuses on the application of template matching methods based on voice feature extraction using MFCC and time pattern matching with DTW, which are specifically intended to support the accessibility needs of people with disabilities in daily household activities. This system is expected to provide a technological solution that is easily accessible to users with physical and visual limitations, and can be applied to low-power IoT devices commonly used in smart home environments.

II.METHOD

The method used in this study is template matching, a pattern recognition technique without training, which matches input voice with a reference voice template. The recognition process begins with recording the user's voice, which is then feature-extracted using Mel-Frequency Cepstral Coefficients (MFCC) [10]. MFCC simulates the way human hearing captures sound information. After feature extraction, the voice features are compared to the template using Dynamic Time Warping (DTW), which allows for matching two voice signals despite differences in duration or speed.

The process is carried out in two stages: training and testing. In the training stage, users record several voice samples which are analyzed and stored as templates. In the testing stage, a new voice input is compared to the template, and the system determines a match based on the similarity score. This method is speaker dependent, meaning it only recognizes the voice of users who have been registered in the system.

2.1 Pre-processing of Voice Data

a. Bandpass Filtering

Sound signals are filtered using a bandpass filter with a frequency limit between 500 Hz and 3000 Hz. This range was chosen because it covers most of the frequency components of the human voice, and is effective in reducing both low (e.g. hum) and high (e.g. hiss) frequency disturbances.

This filter process was created using functions from the scipy.signal.butter library. The filter used is a 5th order filter, with the calculation of digital coefficients done through bilinear transformation.

b. Noise Reduce

After the frequency filtering process, noise reduction is performed using the spectral gating method from the noisereduce library. The main goal is to eliminate background noises such as fan noise, wind blowing, or room noise, so that the main voice (from the user) can be heard more clearly and dominantly.

c. Pre-emphasis

This stage aims to amplify high-frequency signals that are usually weak in human voice signals. This process is done using a pre-emphasis filter with the following formula:

Formula:

$$y[n] = x[n] - \alpha . x[n-1] \qquad (1)$$

Where:

x[n]: input signal

y[n]: pre-emphasis result signal

α : pre-emphasis coefficient (usually between 0.95 - 0.97)

d. Signal Normalization

The last step is to normalize the signal amplitude so that all sound signals have an equal maximum scale. Normalization is important so that differences in volume or distance from the microphone do not affect the feature extraction process, so that each signal has an equal weight of influence.

2.2 Feature Extraction Analysis (MFCC)

a. MFCC calculation

Feature extraction is performed using MFCC (Mel-Frequency Cepstral Coefficients) via the librosa library. This process takes 13 main coefficients from the pre-processed speech signal (including normalization, bandpass filtering, and noise reduction), with a sample rate of 16,000 Hz.

b. Dynamic Time Warping (DTW)

After the MFCC is extracted, the features are compared with a reference template using DTW (Dynamic Time Warping) to measure the similarity of time patterns. DTW calculates the distance between the input MFCC and the template despite the difference in duration.

If the DTW value is within the threshold range (4100-5200), then the voice is recognized as belonging to the user.

2.3 Design System

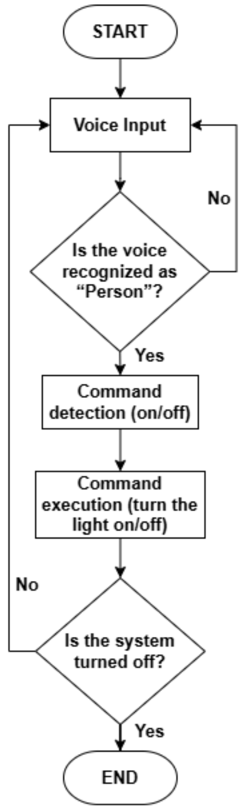

FIGURE 1. Flowchart

The flowchart above illustrates the workflow of the voice-based light control system. The process starts with the system receiving voice input from the user. Next, the system will check whether the voice received matches the predefined voice template - in this case, only one user, "Person". If the voice is recognized as the voice of "Person", then the system will proceed to the command detection process, i.e. whether the spoken command is "turn on the light" or "turn off the light".

However, if the voice received is not "Person", the system will return to the beginning to receive a new voice input. Once the command is recognized, the system will execute the command. If the command received is "turn on the light", the system will turn on the light. Otherwise, if the command is "turn off the lights", the system will turn off the lights. After the command is executed, the system will check if the system is manually turned off. If not, then the system will return to the beginning to receive the next voice input. If the system is turned off, then the process will stop (completed).

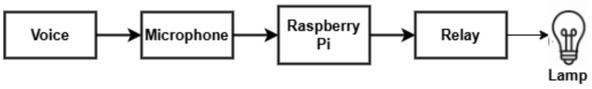

FIGURE 2. Design System

The designed system uses voice control as the main method to turn lights on and off, specifically for users with disabilities. The workflow of this system starts from the voice input given by the user. The voice is then captured by a microphone, which is directly connected to the Raspberry Pi. Raspberry Pi functions as the main processing unit. It contains a voice recognition program that will identify the commands spoken by the user. After the voice is recognized and validated, the Raspberry Pi will send a signal to the relay module. The relay module serves as an electronic switch. When receiving a signal from the Raspberry Pi, the relay will channel or cut off the electricity to the lamp. Thus, the lights will turn on or off according to the voice commands given. This system does not use WiFi-based smart lights, but uses ordinary lights that are controlled through relays, so the implementation is more cost-effective and still effective for users with special needs.

II.RESULT AND DISCUSSION

3.1 Pre-processing of Voice Data

a. Bandpass Filtering

The voice signal filtering process using a bandpass filter successfully isolated the main frequency range of human voice, which lies between 500 Hz and 3000 Hz. This result indicates a significant reduction in noise components outside this range, such as low-frequency hums (<500 Hz) and high-frequency hisses (>3000 Hz). Figure 3 shows a comparison of the voice signal before and after bandpass filtering.

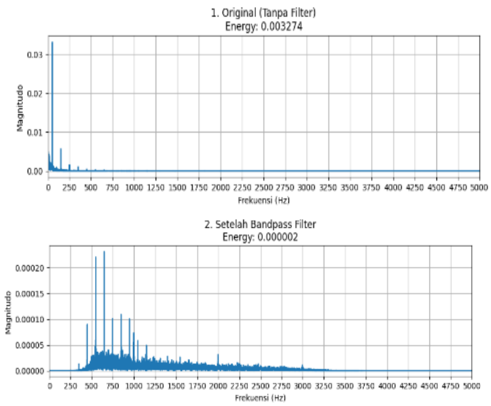

FIGURE 3. Voice Signal Before and After Bandpass Filtering

b. Noise Reduce

After frequency filtering, background noise such as fan sounds and room noise was successfully reduced using the spectral gating method from the noisereduce library. As a result, the main voice signal becomes clearer with an increased signal-to-noise ratio (SNR). Figure 4 illustrates the voice spectrum before and after the noise reduction process.

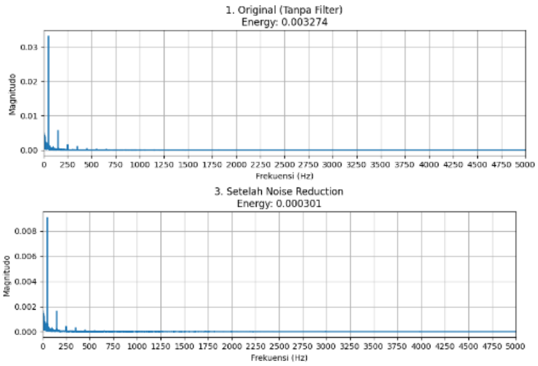

FIGURE 4. Voice Spectrum Before and After Noise Reduction

c. Pre-emphasis

The application of pre-emphasis with a coefficient of $\alpha = 0.97$ successfully enhanced the high-frequency components in the voice signal. This adjustment helps improve signal sharpness during feature extraction.

d. Signal Normalization

The last step is to normalize the signal amplitude so that all sound signals have an equal maximum scale. Normalization is important so that differences in volume or distance from the microphone do not affect the feature extraction process, so that each signal has an equal weight of influence.

An example of the effect of bandpass filtering and noise reduction to reduce background noise in speech recognition. There are four graphs, the original sound, the sound after bandpass filtering only, the sound after noise reduce only, and the sound after bandpass filtering and noise reduce.

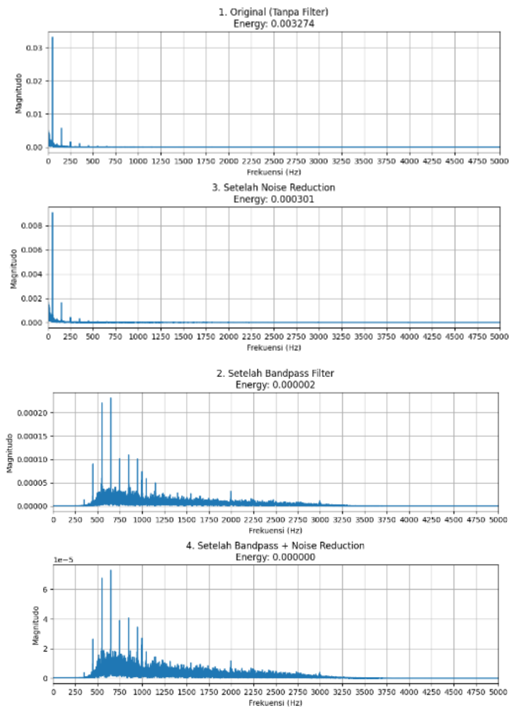

FIGURE 5. Frequency Spectrum of No Noise

In Figure 5 is the result of the no noise condition. In graph two, the results are clean and retain the shape of the Person sound pattern. In graph three, it almost does not affect the quality because there is no noise. In the fourth graph, it can be seen that the quality of the voice signal has decreased slightly due to the use of a combination of bandpass and noise reduction.

The no-noise results in Figure 5 show that the signal quality is relatively clean and stable as there is no background noise. This causes the bandpass filter and noise reduction process not to change the sound waveform significantly. The filter only smoothens the contours without changing the main pattern of the original signal. The quality degradation in the combination of bandpass and noise reduction occurs due to the loss of some high-frequency details, although the signal is still recognizable. Therefore, under ideal conditions, for example, without noise, additional filter treatment is not really necessary. However, the application of bandpass filters and noise reduction is still done to maintain the consistency of the system, and will be especially important and effective if the signal is subjected to background noise under real conditions.

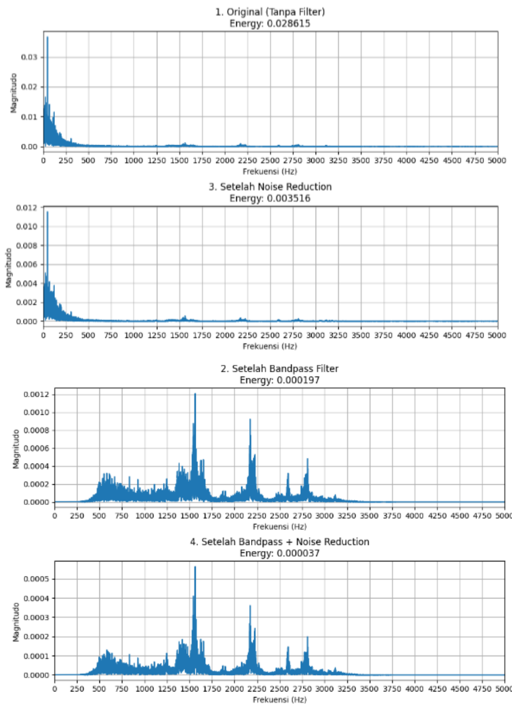

FIGURE 6. Frequency Spectrum of Noise

In the pure noise from the fan and cell phone in Figure 6, the initial energy is very high (0.028615), reflecting the intensity of the noise. The bandpass filter lowers it dramatically to 0.000197, and the noise reduction to 0.003516. The combination is most effective with an energy of only 0.000037.

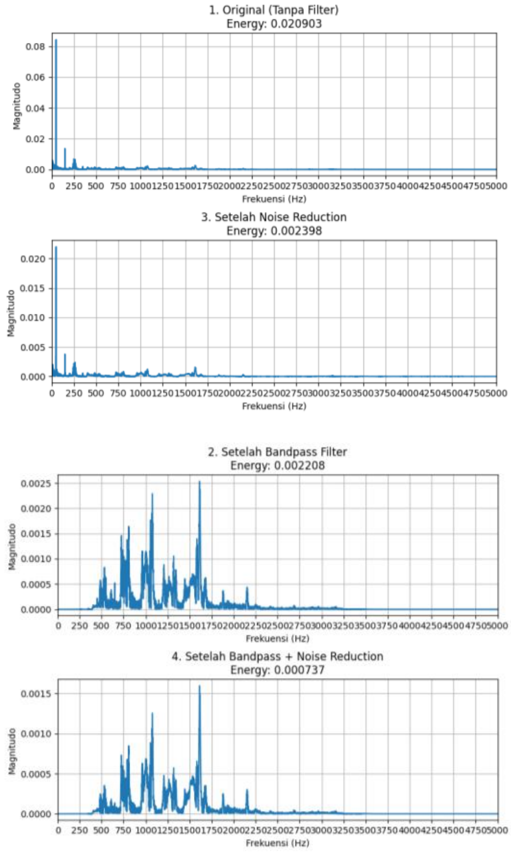

FIGURE 7. Frequency Spectrum of User's Voice with Noise

In User's voice in Figure 7, the initial signal energy of 0.020903 indicates noise contamination. After bandpass filtering, the energy drops to 0.002208, and with noise reduction to 0.002398. The combination of the two resulted in the smallest energy of 0.000737, indicating a very low noise level without disturbing the main sound much. Overall, the combination of bandpass filter and noise reduction proved to be the most optimal in reducing noise, both on signals containing human voices and on pure noise.

3.2 Feature Extraction Analysis (MFCC)

a. MFCC calculation

The feature extraction process using MFCC produced 13 main coefficients for each signal frame. The extraction was performed on signals that had undergone all pre-processing stages. Figure 8 displays the MFCC representation of one user's voice signal.

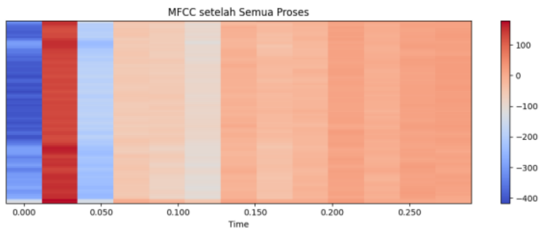

FIGURE 8. MFCC Representation of Voice Signal

From this result, it can be seen that the MFCC patterns for each user have unique characteristics, which can be used as identifiers in a voice recognition system.

b. Dynamic Time Warping (DTW)

DTW was used to calculate the similarity distance between the input voice MFCC features and the reference template. Test results showed that:

- Voices from users matching the template produced DTW values in the range of 4100–4900, indicating high similarity.
- Voices from other users or those not matching the template resulted in DTW values above 5500, indicating dissimilarity.

Table 1 and 2 presents the DTW values from several test trials.

3.3 Testing

The testing process was conducted to evaluate the system's ability to recognize the voice of a user (“Person”) and reject the voice of a non-user (“Not Person”). Three categories of voice were tested, namely two unregistered users (Not Person 1 and 2) and one registered user (Person), each with 22 samples, making a total of 66 voice samples. If the DTW value falls within the threshold range of 4100-5200, the voice is classified as “Person”; if it falls outside this range, it is classified as “Not Person”. The classification results are then divided into four categories: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

Testing was conducted to measure the system's ability to recognize the user's voice (Person) and reject non-user voices. The total test data amounted to 66 voice samples, which were divided into three categories:

a. Not Person 1: 22 samples
b. Not Person 2: 22 samples
c. Person: 22 samples

The system is tested with a minimum DTW (Dynamic Time Warping) value limit of 4100 and a maximum of 5200. If the DTW value between the input voice and the Person template is within the range, the system will accept the voice as Person. If it is outside the range, the system will reject it.

TABLE 1. Testing

File Audio Speaker	DTW		Desc
Not Person 1	7035.17	TN	Not Recognized
Not Person 1	5946.40	TN	Not Recognized
Not Person 1	6082.44	TN	Not Recognized
Not Person 1	8701.66	TN	Not Recognized
Not Person 1	7703.29	TN	Not Recognized
Not Person 1	8092.29	TN	Not Recognized
Not Person 1	6834.96	TN	Not Recognized

Not Person 1	6395.06	TN	Not Recognized
Not Person 1	6694.03	TN	Not Recognized
Not Person 1	8109.01	TN	Not Recognized
Not Person 1	5296.81	TN	Not Recognized
Not Person 1	7647.79	TN	Not Recognized
Not Person 1	9992.27	TN	Not Recognized
Not Person 1	9065.33	TN	Not Recognized
Not Person 1	8451.80	TN	Not Recognized
Not Person 1	7316.53	TN	Not Recognized
Not Person 1	7622.61	TN	Not Recognized
Not Person 1	6393.35	TN	Not Recognized
Not Person 1	9752.55	TN	Not Recognized
Not Person 1	8267.47	TN	Not Recognized
Not Person 1	6047.04	TN	Not Recognized
Not Person 1	4850.50	FP	Identified As Person
Not Person 2	9133.87	TN	Not Recognized
Not Person 2	8290.65	TN	Not Recognized
Not Person 2	7485.92	TN	Not Recognized
Not Person 2	8749.66	TN	Not Recognized
Not Person 2	8481.52	TN	Not Recognized
Not Person 2	8915.67	TN	Not Recognized
Not Person 2	7809.51	TN	Not Recognized
Not Person 2	8622.88	TN	Not Recognized
Not Person 2	8210.46	TN	Not Recognized
Not Person 2	8468.39	TN	Not Recognized
Not Person 2	8465.66	TN	Not Recognized
Not Person 2	9086.84	TN	Not Recognized
Not Person 2	7755.93	TN	Not Recognized
Not Person 2	6918.59	TN	Not Recognized
Not Person 2	8295.16	TN	Not Recognized
Not Person 2	8261.08	TN	Not Recognized
Not Person 2	7653.99	TN	Not Recognized
Not Person 2	8450.52	TN	Not Recognized
Not Person 2	8298.95	TN	Not Recognized
Not Person 2	8271.27	TN	Not Recognized
Not Person 2	9202.43	TN	Not Recognized
Not Person 2	9757.83	TN	Not Recognized
Person	5373.66	FN	Not Recognized
Person	4017.63	FN	Not Recognized
Person	4295.64	TP	Identified As Person
Person	4921.07	TP	Identified As Person
Person	4346.89	TP	Identified As Person
Person	4427.28	TP	Identified As Person
Person	3431.52	FN	Not Recognized
Person	6493.59	FN	Not Recognized
Person	6173.56	FN	Not Recognized
Person	6603.33	FN	Not Recognized
Person	5000.38	TP	Identified As Person
Person	5720.90	FN	Not Recognized
Person	6235.86	FN	Not Recognized
Person	5720.90	FN	Not Recognized
Person	4742.72	TP	Identified As Person
Person	4763.69	TP	Identified As Person
Person	4691.61	TP	Identified As Person
Person	4933.09	TP	Identified As Person
Person	4975.93	TP	Identified As Person
Person	5070.59	TP	Identified As Person
Person	5109.61	TP	Identified As Person
Person	5160.27	TP	Identified As Person

Based on the results of testing 66 voice samples as shown in Table 1, the system correctly classified 13 Person voices (True Positive) and successfully rejected 43 non-Person voices (True Negative). However, there were 13 non-Person voices that were mistakenly accepted as Person voices (False Positive), and 9 Person voices that were not recognized by the system (False Negative).

The system produced a high number of True Negatives (TN), with 43 out of 44 voice samples other than "Person" successfully rejected, indicating that the system only responds to voices that match the predefined template. This accuracy is achieved by implementing template matching that uses specific characteristics of the user's voice, as well as the DTW's ability to recognize different voice patterns from different individuals even when speaking identical words. In addition, pre-processing such as bandpass filters and noise reduction help to improve the signal quality before features are extracted.

TABLE 2. Testing Results

File Audio Speaker	Total Sample	Identified as Person	Rejected as Not Person
Person	22	13 (*True Positive*)	9 (*False Negative*)

Not Person 1	22	1 (*False Positive*)	21 (*True Negative*)
Not Person 2	22	0 (*False Positive*)	22 (*True Negative)*
Total	66		

This section describes how the voice-based light control system works based on the test results. From a total of 66 voices tested, the system was able to recognize 13 out of 22 Person voices correctly, and was also able to reject 43 out of 44 voices that were not Person. However, there was still 1 voice that was not Person but was misrecognized as Person, and 9 Person voices that the system failed to recognize.

Overall, the accuracy of the system is quite good as 56 out of 66 voices were detected correctly, or about 84.85%. Even so, the error in recognizing Person's voice (false negative) was quite high. A total of 13 out of 22 Person voices-or around 59.09%-were not recognized, which can certainly make users feel annoyed that their voices are not being responded to properly.

Based on the analysis of the DTW values of all unrecognized “Person” sounds, there are some DTW values that are slightly above the maximum threshold of 5200 (e.g. 5720.90 and 6235.86) while some others are below the minimum threshold of 4200 (e.g. 3431.52 and 4017.63). This shows that the system can still recognize the “Person” sound if the upper threshold of DTW is raised slightly, e.g. to 5500 or 6000. However, in order for the number of False Positives not to increase significantly, retesting the pyeyap is necessary. Therefore, adaptive adjustment of the threshold is more appropriately considered as part of the system development at a later stage.

One of the main causes of this failure most likely lies in the DTW (Dynamic Time Warping) threshold setting used by the system. In this test, the threshold used ranged from 4100 to 5200. In fact, there were several Person votes whose DTW values fell outside this range-some were too low (such as 3431.52 and 4017.63), and some were too high (such as 6493.59 and 6603.33). As a result, the system rejected votes that were actually valid because they were considered mismatched.

III.CONCLUSION

This study shows that the application of the template matching method with a combination of MFCC (Mel-Frequency Cepstral Coefficients) feature extraction and the Dynamic Time Warping (DTW) algorithm in a voice-based lighting control system is proven to be effective in recognizing voices from certain users. This system is designed with the main objective of improving accessibility and convenience for people with disabilities in controlling electronic devices, especially lights, only through voice commands. From a total of 66 voice samples tested, the system managed to achieve an accuracy level of 84.85%. This achievement was obtained by being able to correctly recognize 13 out of 22 voices from registered users and rejecting 43 out of 44 voices from non-users. These results prove that the approach used is quite reliable in distinguishing target voices from other voices, so it has great potential to be applied in a smart home system that is friendly to people with disabilities and based on artificial intelligence.

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SHOLIHAH AYU WULANDARI was born in East Java Province, Indonesia, in 1994. Obtained her Diploma (D3) degree in telecommunication engineering in 2015, and her Applied Bachelor (D4) degree in telecommunication engineering in 2017, both from the Surabaya State Electronics Polytechnic (PENS), Surabaya, Indonesia. She then earned her Applied Master of Engineering (M.Tr.T) degree in electrical engineering from the same institution in 2019. Her main field of study is Digital Signal Processing in Underwater Communication.

Currently, she is a Lecturer in the Department of Information Technology, Jember State Polytechnic, Indonesia. Her research interests include Artificial Intelligence, Digital Signal Processing, and Information System development. She can be contacted at email: sholihah.ayuwulan@polije.ac.id.

ADISTY PRAMUDITA PUTRI RUDI, was born in Sidoarjo, Indonesia in 2003. She is currently pursuing her undergraduate degree in Informatics Engineering at Politeknik Negeri Jember, Indonesia. Her interests revolve around frontend development and UI/UX design, to create intuitive and user-centered digital experiences. As part of her academic research, she is also exploring voice-controlled systems and smart home technologies. She can be reached via email at adistyprmdta@gmail.com.

ADI SUCIPTO, work as a lecturer in the information technology department of Jember State Polytechnic. I have Experienced in Cyber Physical System and Information Technology with a demonstrated history in internet industry, skilled in process control, web, android and Design Control.

BEKTI MARYUNI SUSANTO, was born in Yogyakarta Province, Indonesia, in 1984. He received the Bachelor degree from the Yogyakarta State University, Indonesia in 2010 in Electrical Engineering Education and the Master degree from the STMIK Nusa Mandiri Jakarta, Indonesia, in 2012, in Computer Science. His research interests include cloud computing, internet of things, and machine learning. He can be contacted at email: bekti@polije.ac.id.

DHONY MANGGALA PUTRA, was born in Mojokerto in 1992 and earned a Bachelor’s degree in Management from Trunojoyo University in 2014, followed by a Master’s degree in Management from Diponegoro University in 2016. He specializes in business informatics, with a focus on integrating information technology into business management and decision-making processes. Currently, he is active as a lecturer in his field, and can be contacted via email at dhony_manggala@polije.ac.id.