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D-Talk: Real Time Communication Powered By AI For Specially Abed.

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ABSTRACT

Communication plays a significant role in making the world a better place. Communication creates bonding and relations among the people, whether persona, social, or political views. Most people communicate efficiently without any issues, but many cannot due to disability. They cannot hear or speak, which makes Earth a problematic place to live for them. Even simple basic tasks become difficult for them. Disability is an emotive human condition. It limits the individual to a certain level of performance. Being deaf and dumb pushes the subject to oblivion, highly introverted. In a world of inequality, this society needs empowerment. Harnessing technology to improve their welfare is necessary. In a tech era, no one should be limited due to his or her inability. The application of technology should create a platform or a world of equality despite the natural state of humans.

On the other hand, technology is the most innovative thing on Earth for every time the clock ticks, researchers, software engineers, programmers, and information technology specialists are always coming up with bright ideas to provide convenience to everyone. This paper shows how artificial intelligence is being used to help people who are unable to do what most people do in their everyday lives. Aligned with communication, D-talk is a system that allows people who are unable to talk and hear be fully understood and for them to learn their language easier and also for the people that would interact and communicate with them. This system provides detailed hand gestures that show the interpretation at the bottom so that everyone can understand them. This research allows the readers to learn the system and what it can do to people who are struggling with what they are not capable of and will provide the technical terms on how the system works.

Key words: Machine learning, disability application, sign language, image processing, neural networks, artificial intelligence

1. INTRODUCTION

Communication should be universal without any barriers or limitations. This paper establishes a method for providing equality, turning the disabilities of the hearing and, or speech impaired individuals to abilities, creating a base where both the disabled and the able can communicate without any barrier. Our objective is to blend deaf and dumb within society and make them able to use their personal computers more effectively and efficiently. Our idea is to create sign assistance, like many applications which is using voice assistance such as Siri on iOS and Cortana on windows. There is need to develop an application that will create an interactive platform where the sign language can be translated to voice output and writing, and voice and writing input can also be converted to sign language. The bigger picture is creating an interactive model of communication for deaf and dumb people. Developing an app will support this vulnerable society of impaired people and enhance communication among people. The application will allow ease in communication, improving their interaction, and hence better life. This project will be a noble cause and translating the sign language into understandable words is the goal. Microsoft Windows will come in handy to enhance the actualization of this application.

According to the World Health Organization, the world population experiencing hearing and speech challenges approximates over 466 million people globally [1,2]. With such disability, instead unequally distributed resources, these people are vulnerable to discrimination [3]. The fact that every human being, abled or disabled, is entitled to a good life with equal opportunities calls for affirmative action [4,10]. This society requires attention from all quarters, especially on technological enhancement, to ensure the disabled get a comfortable life [5,16,20]. With the number increasing significantly, something needs to be done. The deaf and dumb are introverts, remaining engraved in their thoughtful world. Communication, which is essential in human life, is challenging. Humans are social beings, and effective communication is necessary [6, 22,24]. The development of technology should, therefore, serve to improve their lives as well [7]. The introduction of an application that can be used by the deaf and dumb will be a great innovation. It will not only make life easier but will as well increase their life opportunities, including employability. The deaf and dumb category must be involved within technology on PC experience as they involved in technology on smartphones. D-talk application provides this experience for them by reading their hand movements and displays a certain function. This

application will be as a competitor for Cortana on Windows, Siri on iOS, and Alexa on Amazon and Google Assistant on android for doing some tasks in their smart devices. Healthy people use these technologies [8,9], but D-talk will be specifically for deaf and dumb using PCs. D-talk will be built by using the Spyder program because it is an open-source, good on reading images, and easy to find the codes on the web [11, 12]. The application will help the user to perform frequent tasks, which can include opening a web. So far, there is no project for dumb people like D-talk that is for PC functions with unique hand gestures created by the developer instead of the regular sign language. This society has for a long-time used sign language. However, most people are unable to understand this language making communication intricate. The application will bridge this gap by translating various signs used to actual words. A web camera will take up the sign and send images to the app that will translate it through command prompts to words. These words will be arranged simultaneously to create a fathomable sentence. Globally acceptable signs in this language will be identified through codes that shall subsequently be translated appropriately for reading. Though the development of the app shall be complicated, its eventual outcome will be more comfortable and efficient to use. A camera will be vital in identifying the various signs of language movements. Analyzing the same after coding them will be essential for accurate interpretation and translation into words. The user manual will be developed to enhance the quick learning of the application. This manual shall clearly show every sign and interpretation of the same in words. During the implementation, there might be several changes and enhancements in this application.

1.1 Research Question

The process of this application can be daunting, but the value is priceless. Being able to create something to serve people in need is uncountable. The focus of this research is to answer questions related to sign recognition. Therefore, we narrow the research question to align with this application that will be developed by machine learning and artificial intelligence to make the right decisions. These trees will be based on images in the database to define our system in a more efficient and effective method to reach the optimal decision. Several questions considered as research questions, which are:

What will happen when the application recognizes the image?
What is the process of recognition of the image by the application?
How the image recognized by the application?

The next section 2 will provide theoretical background, section 3 methodology, section 4 results, and lastly section 5 conclusion.

2. THEORETICAL BACKGROUND

This section provides a theoretical background for D-talk to have a better understanding of the process to be used in the application [13,30, 32]. This application can provide a helpful tool for communication between the deaf and the external world. The sign language recognition program, which is required to understand sign languages, has been studied extensively for years [25,27]. The studies are focused on various input sensors, gesture segmentation, feature extraction, and classification methods. This paper is aimed at evaluating and comparing the methods used in the sign recognition systems, classification methods used and identifies the most promising approach for this project. Despite recent advances in classification methods, many of the recent works proposed to apply primarily to classification methods, such as deep learning [23, 34, 40, 42]. This paper focuses on the classification methods used in the prior recognition scheme for sign Recognition. Based on our research, HMM-based methods, including its modifications, have been thoroughly discussed in prior studies.

2.1 Machine Learning

It is essential to choose the right strategy; Machine-learning techniques are often used to do this. Machine learning is part of artificial intelligence (AI). It can be defined as an algorithm that focuses on computer program development [14, 15, 35, 43]. Machine learning considered an application that use to increase computer ability to learn from previous experiences [16, 17, 44].

There are three types of ML:
•Supervised:
The application has previous experience of new data using labeled examples to predict future events [18, 19].
•Semi-supervised:
Data can be labeled and unlabeled for training [29, 36].
•Unsupervised:
Data that unlabeled from experience. The system cannot figure out the right input so that the result will be wrong [20, 21, 37].

2.2 Deep Learning

Compared to standard algorithms, neural networks can solve somewhat complicated issues at a much easier level about the complexity of algorithms. Neural networks can solve somewhat complicated issues at a much easier level concerning the complexity of algorithms [26, 30]. The neural network builds to mimic human brain neural function but with the mathematical functions [31, 33,38]. One of the neural networks is the multi-layer network as shown in figure
1. It includes three layers, the input layer, many hidden layers, and the output layer [21,39]. The input layer passes data

without modification. Hidden layers process the data, and the output layer converts hidden layers to output as a classification. Collecting datasets for training takes time to process [41, 45]. As the number of configuration increases, training samples increase. Most data in the world not uniformly distributed. An image recognition model using neural networks in figure 2.
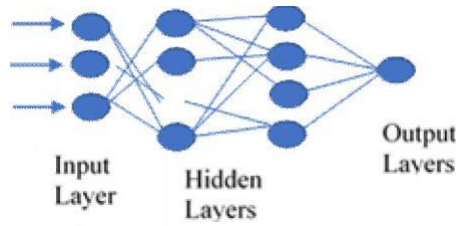

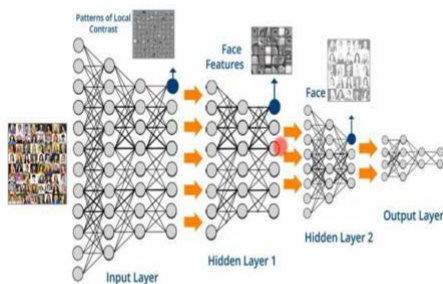**Figure 1:** Multilayer Network

Figure 2: Image Recognition using Neural Network

2.3 Decision Tree

A decision tree uses datasets that include attribute vectors that contain a collection of classification class [16, 20]. This technique builds the dataset on attributes that split the data to different existing classes until the criterion is reached [20, 31]. The decision tree has an excellent representation form to have an idea of data quickly due to easy visualization format. The structure of the decision tree contains nodes that separated into root node, inner node, and end node 'leaf'. The root node is the start of the decision has no incoming edges [32, 40]. Inner nodes include one incoming edge and at least more than one outgoing edge. A decision tree is a tool that uses most of the time to support decisions because it shows the rule of sequential decisions [16]. Marketing people can use it to predict customers purchased by their age; for example, if the consumer age is between 30 and 45, they prefer to rent Kia cars. End nodes will get the answer as an output as a decision to the forecasting [18].

2.4 Object Detection

For this application, object detection will be involved. It is one of the classical problems of computer vision because it depends on different elements, such as the level of lighting and the position of the user. It is difficult to have an idea where the object is located and how the image is segmented.

We need to know what the shapes of the fingers are, where they are located. The software will use a saliency map to guide for locating the object. The location and size will be defined by a bounding box, rectangle shape, which located on corner coordinates. Figure 3 shows the example of object detection.
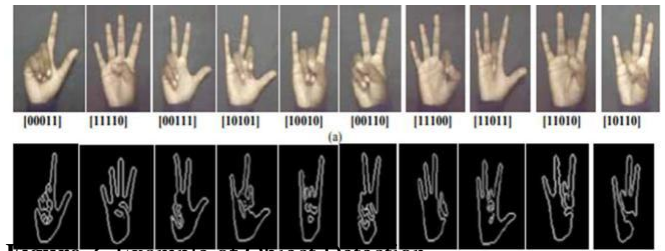

Figure 3. Example of Object Detection

The webcam will try to capture the sign that the user will gesture by size and location. Then, the software will use algorithms above and get the right output to depend on the input that will be produced by the user. Moreover, several conditions can help the application to give the best result, such as lightning, positioning, mirroring, and scale. Lightning and shadows condition could affect image recognition, but the system must be able to recognize the objects. Object position can be changed, the application must be able to identify the object position. The object recognition system must recognize mirrored images of the object.

2.5 Image Recognition Process

The image recognition process is a process that enables the input of the sign language into the application for necessary processing [20,31,46]. The process requires a sign to be made in front of the webcam. The computer captures the sign made via the webcam and stores the different images made. Images that come from the camera will be resized, and the resolution will change. The colors will change to grayscale image and then to black and white images while editing the images [25, 33,47]. There several techniques used to extract the image, such as SIFT, SURF, BRISK, and HSV algorithms.

Scale Invariant Feature Transform "SIFT" is used to extract features vectors that define local patches of the image [35]. These features are invariant to translation, rotation, and illumination, not only vectors scale-invariant. There are several advantages to the SIFT descriptor [36]. For example, this descriptor is accurate than any other descriptor. It can describe the key points in the image for any object. It allows an individual feature to define the correct match with the best probability in a huge database of features [37]. Also, it can cover the full range scales and location of the image, and it is close to real-time performance.

Speed Up Robust Features "SURF" is used in computer vision tasks, and it used for object detection purposes. SURF is based on determinant of the Hessian Matrix (square matrix of second ordered partial derivatives of a scalar function), and it

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exploits integral pictures to improve feature detection speed [19,48].

For any point, $X=(x,y)$ in the image L that needs to be matched, the Hessian matrix H (X,σ) is defined by vector σ as shown in equation (1):

$$H(X,\sigma)=\begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \quad (1)$$

SURF contains two steps, feature extraction and feature description [6]. Feature extraction is a method for interest point detection that uses basic Hessian matrix calculation [10]. On the other hand, the feature description contains two steps [12]. The first step lies in fixing a reproducible orientation based on information from the circular region around a key point. Second, create a square area aligned to the selected orientation and extract the SURF descriptor from it [14].

Because SURF is based on the Hessian matrix, it is faster than SIFT. It has widely used in computer vision applications, and it is suited to our application. Finally, it has been high repeatability and distinctiveness [16].

BRISK stands for Binary Robust invariant scalable key points. It based on defining the characteristic direction of all features for reaching rotation invariance [20]. BRISK has two steps, namely scale space key point detection, and keypoint description. Identify the operation on the panoramic picture using the idea of image registration and implement the different methods for several applications [22]. Moreover, identify the various kinds of methods and techniques of picture registration with the effective demonstration of their proposed algorithm.

Hue Saturation Value Color Model "HSV" is a color space that describes colors of Hue, Saturation, and value. The HSV model preferred more than the RGB model (red, green, blue). The HSV can describe colors similar to how human eyes can perceive colors. RGB describes primary colors, but HSV describes colors by more familiar comparisons such as brightness, vibrancy, and color [19].

Hue:

Hue is the color portion of the model [30], expressed as a number from 0 to 360 degrees:

> Red: between 0 and 60 degrees.
> Yellow: between 61 and 120 degrees.
> Green: between 121-180 degrees.
> Cyan: between 181-240 degrees.
> Blue: between 241-300 degrees.
> Magenta: between 301-360 degrees.

Saturation:

Saturation describes the amount of gray, from 0 to 100 percent. Reducing this component toward zero introduces the grayer and produces a faded effect. Sometimes, saturation appears as a range from just 0-1, where 0 is gray, and 1 is a primary color [2].

Value (or brightness):

Value works in conjunction with saturation and describes the brightness or intensity of the color, from 0-100 percent, where 0 is completely black, and 100 is the brightest and reveals the most color [5]. An HSV color model is shown in figure 4.
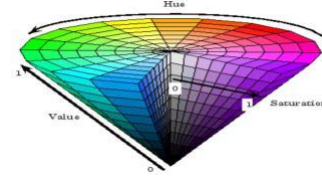

Figure 4: HSV Model

These algorithms will select the hand and finger points to decide which image in the database is related or similar to these points. When the points have the best match, the analysis set matches for correspondence. These techniques work best with rigid objects. The images are subject to a training phase where they are coded with the appropriate interpretations and sent to the testing phase before the output is displayed. The figure 5 shows the process that the D-talk may use for selecting the right image for the task.
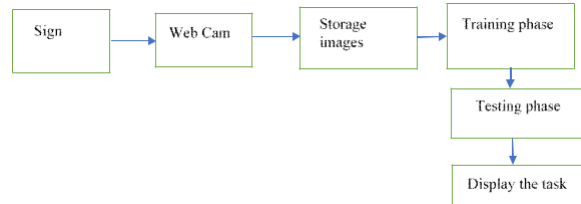

Figure 5: Simple Process for sign detection

3. METHODOLOGY

This paper presents an understanding of complex hand movements. A framework based on Hidden Markov Models (HMMs) [11] is provided for modeling and recognition of complex gesture trajectories. A detection algorithm is used to detect the hand of the user, and a contour-based hand tracker is developed, which combines condensation and partitioned sampling. The proposed approach can attain automated online identification of hand movements and can effectively reject atypical movements. The experimental results indicate that the proposed algorithm can produce better results for recognition than the conventional method of hand recognition [12]. The hand gesture recognition system consists of three major parts: palm detection, hand tracking, and trajectory recognition. Figure 5 provides an overview of the hand gesture recognition process. The hand tracking function is enabled when the device senses an open hand in front of the camera; when the user finishes the gesture, the hand gesture classification based on HMM is disabled. The basic algorithmic structure for our process of recognition is the following: -

Detect the palm from the video and initialize the tracker with the template of hand shape.
Track the hand motion using a contour-based tracker and record the trajectory of the palm center.
Classify the gesture using HMM, which gives the maximum probability of occurrence of observation sequence.
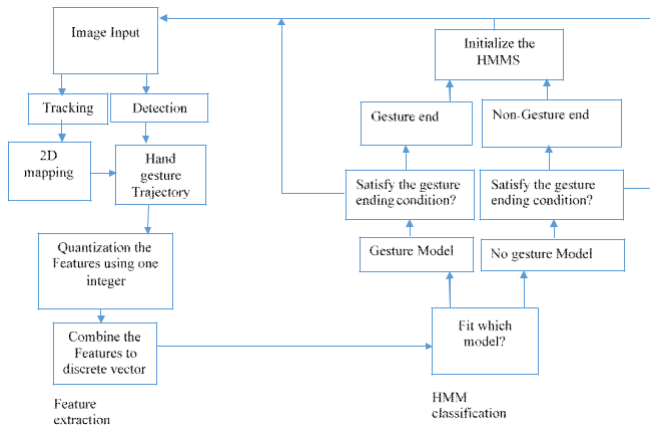

Figure 5: Overview of Hand Gesture Recognition Process

The research aims to provide detection, initially for four unique signs. A dataset of images was made for four unique signs to start the detection process. The dataset contained at least 1000 images. The training images will be for men and women's hands to make the application suitable for both genders. Each sign will have 50 images with different positions and light levels. After the image is taken from the webcam, the application will process the image and compare it with the 1000 images that are in the dataset. The nearest image will be taken as a decision to produce the task. The webcam may take images in the dataset with the distance between the hand and the cam around 3-4 feet.

3.1 Training Phase
The training phase was based on storing the images in the database. The database contained images of hands, both men and women. The training was based on identifying all possible signs that can be made using one hand. For this purpose, 30 different images with different levels of lights and duration were captured and stored in the database. These images were used as training images that will help in making the right decision for the tasks. The database contained over 1000 images of unique hands and signs.

3.2 Gesture Recognition
We explored one way to identify simple hand gestures and implement two basic gesture controls: movement of the cursor and mouse click.
The figure 6 describes the basic process of hand gesture recognition.
By using vision-based recognition, the computer captures the sign to find the gesture acquisition.

Hand tracking can be done by using clustering algorithms that able to treat each finger as a cluster and delete the empty spaces between them or multi-scale color feature hierarchies that provide users' hand and the different background shades of colors to identify and remove the background. Hand tracking is the computer's ability to track the user's hand and split it from the background or any other objects.
Feature extraction depends on the application. On D-talk, finger status, skin color, alignments of the finger, and the palm position are taken into consideration.
After features extracted, they sent to training and testing classification algorithms to reach the output.
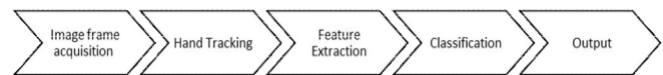

Figure 6: Basic steps of hand recognition process

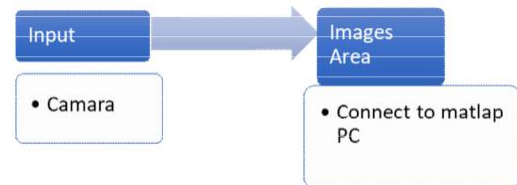The simple operation for testing the system is show below in figure 7.

Figure 7: Simple application operation

Figure 8 explained the gesture acquisition process. Gestures are acquired from the user or image taken as a snap, with the help of the snap comparison is made between input gestures and loaded gestures. When gestures matched, the movement, if gestures did not match, then it will start acquiring the gestures. In this paper, we have designed the model for deaf and dumb people by employing a single compact device. The main advantage is that the device can be removed quickly and weightlessly. A simple coding language was used to make it less complicated. If the training and testing gestures are matched, the corresponding voice will be generated. The gestures are viewed on display. The image will be recognized through a web camera. If the system detects some unrecognizable gestures, it will automatically be refreshed for the user to be able to make proper gestures once again. This

artificial intelligence that was being developed can identify errors on hand gesture matches and will stop as a default.

It will generate corresponding gestures that allow every user to read and be able to understand what the gesture means. It is a very crucial part of the testing phase, wherein it proves the efficiency and effectiveness of the system while it is being used now. The proposed work aids deaf-dumb people to communicate with others. It is a step towards creating further technologies that prove to be the zenith power in helping people with deferent capacities.
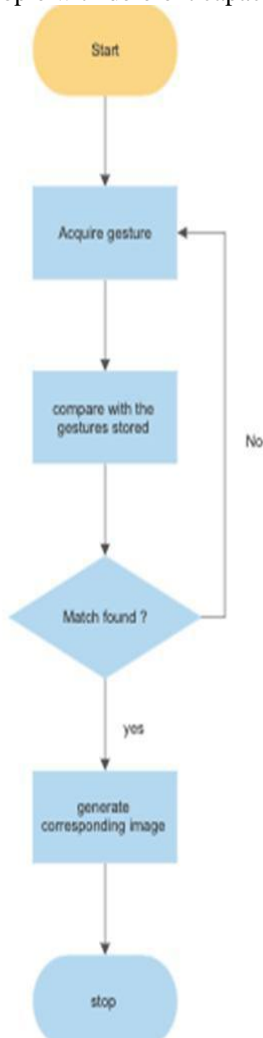

Figure 8: Gesture Acquisition Process

4. IMPLEMENTATION AND RESULTS

In the implementation phase, developers change several tasks that they were planned to do. They notice that they can build the system without preparing any training and testing images as they were plan. The code is depending on skin color and contour to find the right sign. Moreover, developers narrow the tasks to only one task which is browse websites only. Moreover, the result was precise and accurate aligned with the methodology and testing that was used. This signifies that developing modern technology assists disabled individuals specifically deaf-dumb on interacting among people. The measurement variables along with the supporting

evidence from the methodology concluded that the measures taken to evaluate this study were supported all throughout.

Meanwhile, the efficiency and effectiveness of the system provide the utmost benefit of disabled individuals by offering convenience and being able to make their lives easier and better for there are no required training or specificities for them to use the system. Thus, as a result, D-talk allows everyone to determine the hand gestures that are being projected and be able to come up with interpretations on enabled individuals. Hence, communications between deaf-dumb and enabled individuals are way easier and lacks misunderstandings are being prevented this time. This application can catch finger shapes by using the code for Extract skin color and draw lines around the hand. As a result, the system will recognize any element in the frame. The application main screen is shown in figure 9. Thus, users must be careful about what is inside the frame to avoid any other unwanted requests. This system will recognize any element in the box, and the brightness does not matter. D-talk is a dynamic system that includes three gestures in total to browse websites. All that users need to implement this system is WiFi connection and webcam to capture user gestures. The following figures 10 and 11 show the hand gestures that are used for orders that the system can recognize to browse websites. It could be used as a guide for users.

Figure 9: Application main screen

Figure 10: Signs being used by System

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While building this system, there was only one issue. The system is very sensitive. It catches any element in the box. So, the user must be careful to have a blank background. The result was as below when the user signs a gesture, and the system will decide which sign reflect which website.
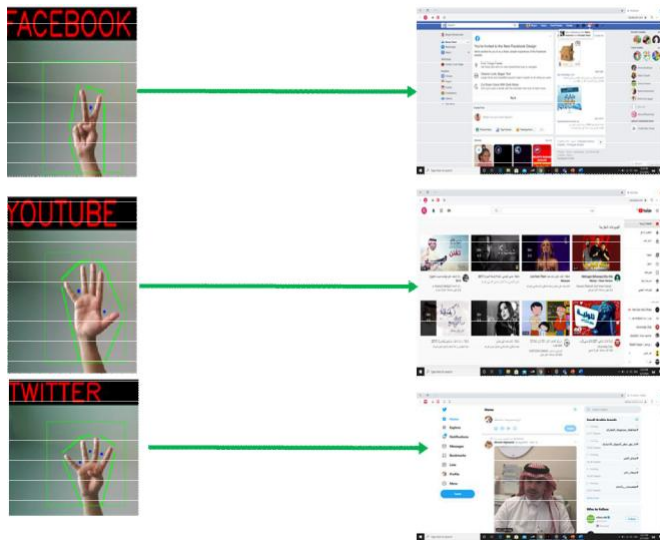

Figure 11: Results of Sign Detection

To validate the method proposed in this paper, we conducted two experiments. The first experiment is men hand region segmentation. We use 50 hand region samples with a different gesture and 50 women hand region samples. We take 70 samples as test data and 30 samples as validation data. The accuracy of segmentation is 60%, where among ten gestures, 6 of them are defined correctly. To sum up, the experimental accuracy can meet actual needs. D- talk as an application for PCs is very useful because it has its signs which consider as easy and understandable signs, they are not complex as regular sign language signs. D- talk use machine learning model accuracy in figuring out which model is best at distinguishing connections and examples between factors in a dataset dependent on the information, or preparing, information. The better a model can sum up to 'concealed' information, the better forecasts, and bits of knowledge it can create, which deliver more application value.

5. CONCLUSION

The main objective of this research has been achieved successfully. Gesture interpretation works best in case users who understand sign language may interact with people who are unfamiliar with sign language. Speech interpretation is helpful for sign language non-speakers who want the accompanying hand sign to be understood. Room conditions such as lighting can play a role in predicting the outcome of poor lighting. The light that is either too bright or too dim will result in inaccurate hand segmentation, resulting in inaccurate gesture prediction. The type of inaccuracy can emerge from the user's peripherals, such as poor web camera

performance or poor microphone quality. In a nutshell, the development of technology is essential, and its deployment in sign language is highly critical. It will serve to bring efficiency in communication, not only to the deaf and dumb but those with the ability to hear and speak as well. In addition to creating opportunities for their career growth, it will enhance their social life through effective communication. Making an impact and changing the lives of the deaf and dump through technology will be an innovation of the year worth the time and resources.

At the beginning of the D-Talk idea, the developers think to have more than one task for this application, but in the end, they narrow the task to have only one. They thought to have an open calendar, lunch Microsoft office word, and browse the website. The final task was to lunch three websites, Facebook, Twitter, and YouTube.

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