[EN] Tanrida Utari - Talk to Me Paper rev

by Hanif Fakhrurroja

Talk to Me: Artificial Intelligence "Virtual Friend" For Depression Sufferers Using Term Frequency – Inverse Document Frequency (TF-IDF) and Finite State Machine Method

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ABSTRACT

Depression refers to mental health in which a person experiences a bad mood and has a decreased quality of life. In Indonesia, there are quite a lot of challenges in dealing with depression problems such as lack of education on how to treat depression, lack of mental health personnel, and the emergence of a bad stigma against depression sufferers. Voice-based artificial intelligence technology for people with depression was developed to play a role in filling the gap by acting as a support system. In this research, the Natural Language Processing (NLP) method is used to enable computer to be able to understand the user's input. The Term Frequency - Inverse Document Frequency (TF-IDF) method is also used to weight documents and the Finite State Machine (FSM) method used to classify the results of document weighting against a predetermined dialogue scenario. To be able to interact with the system, the author uses the Google Cloud Speech API technology to convert speech and text. As for testing of this system, it is done by calculating the level of accuracy of the answers given by the system to users. The level of accuracy of the system answers obtained from the test results is 96.5%. The accuracy value indicates that the answer given by the system is in accordance with what the user's input.

Keywords: Depression, Artificial Intelligence, NLP, TF-IDF, FSM.

INTRODUCTION

Depression is a mental health disorder related to mood. A person who is depressed will feel unmotivated, hopeless, and lose interest in activities (Sumarsono, 2020). Some people think that depression is a trivial thing and will go away by itself, but the fact is that depression is a form of disorder that is more than just a temporary emotional change (Dirgayunita, 2016). According to the World Health Organization, there are more than 264 million people in the world suffering from depression, and nearly 800,000 people each year choose to end their lives because of their depression. The effects of depression itself can last for a long time and repeat itself, which will result in a decrease in the function of one's body. The causes of depression include the complex interactions between social, psychological, and biological factors. Unattended depression will lead to sufferers suicidal thoughts. In 2015, suicide was ranked number two in the cause of death for a person aged 15-29 years (World Health Organization, 2020).

In Indonesia, based on the results of the Basic Health Research of the Ministry of Health in 2018, the prevalence rate of depression for the age group ≥ 15 years is 6.1%. According to that, only 9% of people with depression undergo medical treatment (Kesehatan, 2018). There are many challenges in dealing with depression, such as the stigma for people with depression being labeled abnormal and often associated with mystical things. Moreover, the health services provided ranging from facilities to practitioners are not yet qualified. Indonesia only has 773 psychiatrists and 451 clinical psychologists centered on the island of Java, a very small number when compared to Indonesia's population of approximately 260 million people. This means that 1 (one) trained psychiatrist must handle 300,000-400,000 people. WHO determines that the ratio of the number of psychologists and psychiatrists to the total population should be 1 per 30 thousand people. That means, Indonesia still lacks around 24,000 mental practitioners (Apriyani, 2019). Time and cost limitations are also an obstacle for depression sufferers to get help from psychologists (Rahmadhani et al., 2020).

Anyone can experience depression. In fact, everyone has a different pattern of depression. For example, some people experience major depression for a short time, but some people experience mild depression for a very long time (Borrill, 2001). Therefore, based on the background provided, the authors are interested in developing an artificial intelligence technology in Bahasa using the Natural Language Processing method, Term Frequency-Inverse Document Frequency (TF-IDF), and Finite State Machine where these methods focus on natural language processing and answer classification so that later it allows the computer to be able to understand the language entered by the user and be able to provide answers in accordance with what the user inputs. For the development of the system itself, the author adds a voice-based conversation mode so that when used, users can more easily tell what they are thinking and feeling.

RELATED WORKS

The rapid development of technology has succeeded in encouraging humans to create many things to facilitate their work, including in the field of mental health. In fact, everyone always tells about what they feel when they get happiness or face sadness in their immediate environment (ROKOM, 2017). In the case of depression, at least the sufferer needs someone to listen to all the complaints they have. However, based on the background that has been described there are many challenges in meeting these needs. Along with the times, nowadays many technologies have been developed for human mental health. For the example, Expert System Application for Diagnosis of Levels of Depression in Teenage based on Android (Nurabsharina et al., 2020). This study is conducted to assist psychologists in making treatment decisions for depressed patients. The expert system application developed focuses on early detection of the level of depression that occurs in a person. As for the depression category, researchers used four levels, that is Mood Disorders, Mild Depression, Moderate Depression, and Major Depression. The application developed consists of several stages, one of which is the Forward Chaining method. The Forward Chaining method itself is one of the main methods of reasoning in using an inference engine (decision making machine) and can logically be described as a repetition application of the modus ponens (a set of inference rules and valid arguments) (Akil, 2017). In general, this expert system application works by receiving input in the form of symptoms of depression experienced by users. Then the system will process the data and produce output in the form of depression levels and a large percentage of depressive symptoms using the Forward Chaining method. The results of the study using 15 sample data. It was found that the level of accuracy resulting from the application of this method was 93%, where these results prove that the application of Forward Chaining method for expert system applications is very accurate.

Expert System Determines Depression Levels of Layed Workers Using Certainly Factor Method (Siregar et al., 2019). Termination of employment by companies is a frightening specter for employees. The emergence of various emotions when experiencing layoffs will certainly affect a person's mental health greatly. A person who is laid off can experience various changes that are in stark contrast, such as deep sadness, disappointment, hopelessness, and even separation from his social life. This study develops an expert system application that can detect the level of depression in laid-off workers by using the Certainly Factor method. Meanwhile, the Certainly Factor method is a clinical parameter value given by MYCIN to show the amount of trust (Yulianti et al., 2019). In the case study, the level of depression used was divided into three parts, namely Mild Depression, Moderate Depression, and Major Depression. From the results of testing conducted on case studies of workers A, B, and C, it was found that the percentage of depression suffered by worker A was 29%, worker B was 44%, and worker C was 47%.

Expert System to Determine Student Anxiety Levels in Writing Thesis Using the Multi Factor Evaluation Process and Tsukamoto Fuzzy Inference Method (Ismunu et al., 2020). In Indonesia, writing a thesis is an absolute requirement for bachelor students to obtain a Bachelor's degree. For final semester students, the frustration of working on their thesis always appears. The frustration when working on this thesis can cause symptoms of depression (Andra Arivianda, 2019). This research was made to develop a prototype expert system to detect the level of anxiety in final year students who are compiling their thesis. This research uses the Multi Factor Evaluation Process (MFEP) and Fuzzy Tsukamoto Inference method. According to Render B and Stair, the MFEP is a quantitative method that uses a weighting system. In multi-factor decision making, decision makers subjectively and intuitively weigh various factors or criteria that have an important influence on the alternative choices (Sina et al., 2018). Meanwhile, fuzzy logic is used to translate a quantity that is expressed using language. During the rule evaluation process in the inference engine, the Fuzzy Tsukamoto method uses the MIN implication function to get the α-predicate value for each rule (Irfan et al., 2018). The results of the study using 52 test data, both system prototypes and experts have results that 42 data (81%) are suitable and 10 data (19%) are not suitable. The system prototype designed by implementing the MFEP method and Fuzzy Tsukamoto Inference can be used to assist in determining the level of student anxiety in compiling a thesis with a success rate of 81%.

PROPOSED METHOD

The dialogue management system design architecture used in this study can be seen in the figure below.

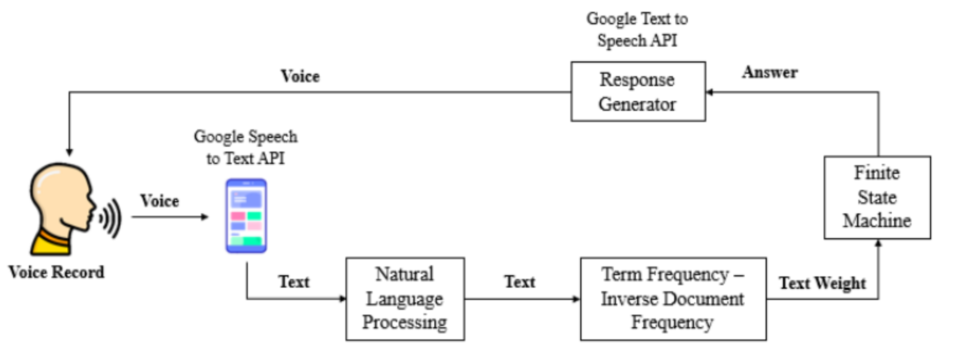


Figure 1. Talk to Me system design

In this study, the authors designed a dialogue management system with six dialogue scenarios based on three categories of speech. The following are the dialog categories that have been designed.

Table 1.

Dialogue scenario.

Categories	**Dialogue Classification**	**Keyword of Dialogue Scenario**
Putus Asa Desperate	*D1 Kehidupan* D1 Life	*Aku ingin mati* I want to die
	D2 Bullying	*Aku dibully* I am being bullied
Stress	D3 Bullying	*Aku diperlakukan tidak baik* I was mistreated
	D4 Keluarga	*Keluargaku hancur*

	D4 Family	My family is broken
Trauma	*D5 Percintaan* D5 Love	*Aku putus dengan pacarku* I broke up with my boyfriend/girlfriend
	D6 Bullying	*Aku dihina* *I was insulted*

The dialog scenario above will then be described in a dialogue session between application users and the Talk to Me system. The following is an example of a dialogue session for the Despair category, the D1 Life dialog classification that has been created for app users to chat with the Talk to Me system.

Table 2.

Dialogue Scenario 1 (D1).

Dialogue Scenario 1 (D1)		
User	:	*Aku merasa putus asa* I feel desparate
Talk to Me	:	*Apakah kamu mau cerita?* Do you want to talk about it?
User	:	*Aku cape dengan hidup ini* I am tired of this life
Talk to Me	:	*Ada banyak alasan yang bikin kita cape. Apa kamu sering merasa seperti ini?* There are so manyreasons to feel tired. Do you always feel like this?
User	:	*Aku merasa seperti ini jika aku sedang sendirian* I feel like this when I am alone
Talk to Me	:	*Aku ada disini untukmu, jangan pernah merasa sendirian* I am here for you, do not feel that you are alone
User	:	*Aku ingin mati saja* I want to die

Talk to Me	:	*Apakah kamu berpikir untuk mengakhiri hidup?* Are you thinking to end your life?
User	:	*Ya* Yes
Talk to Me	:	*Aku tidak bisa membayangkan betapa menyakitkannya perasaan itu, tapi aku ingin mencoba untuk memahami situasimu saat ini. Tidak ada yang lebih penting selain apa yang kamu rasakan. Jangan pernah menyerah, aku yakin banyak sekali orang yang peduli terdahapmu. Kami tidak ingin kehilangan seseorang yang berharga seperti dirimu. Mari kita berjuang untuk menghadapi semua ini.* I can't imagine how painful that feeling is, but I want to try to understand your current situation. Nothing is more important than how you feel. Don't ever give up, I'm sure a lot of people care about you. We don't want to lose someone as precious as you. Let's fight for all of this.

Speech Recognition using Google Cloud Speech API

Speech Recognition is the process of converting a digital signal that converts sound waves into a set of numbers which are then matched with a pattern stored on a device (Arifin et al., 2016). The system designed in this study is a dialogue management system using the Indonesian language for human interaction with voice-based applications so that speech recognition uses the Google Cloud Speech API. The author chooses to use the Google Cloud Speech API because it can be accessed for free for the cloud-based speech recognizer (Patrick & Suendermann-Oeft1, 2014). In addition, the Google Cloud Speech API itself has experienced rapid development by having 120 language options including Indonesian. The main purpose of this voice recognition technology is to enter commands in the form of a voice into the machine so that the machine is able to understand and process it directly (Gozali & Suharto, 2019).

Natural Language Processing (NLP)

Natural Language Processing is a computational technique used to analyze and represent text written naturally (human language) at one or more levels of linguistic analysis with to obtain human-like language processing that can be implemented in various fields (Elizabeth D. Liddy, 2001). The series of processes of NLP used in this study include case folding, tokenizing, filtering, and stemming. Case folding is used to change all uppercase letters in sentences to lowercase letters, tokenizing is used to break sentences into pieces of words, filtering is used to carry out the retrieval or filtering steps for words that are important in sentence, and the last is stemming, which is making changes to the whole sentence to become a root word by removing the affix from each document. Stemming in Indonesian itself has a more complex structure than stemming in English (Fakhrurroja et al., 2020). After all the series of processes have been completed, the data will be processed by TF-IDF.

Term Frequency – Inverse Document Frequency (TF-IDF)

Term Frequency-Inverse Document Frequency, abbreviated as TF-IDF, is a statistical calculation method intended to indicate how important a word is to a document in a corpus or database. This method is often used as a weighting factor for information retrieval and text mining. This method serves to give weight to each word that appears and calculate the inverse of the existing sentence frequency. The results of the assessment depend on whether the question term is present or not in the dialogue sentence document zone. It lies in the sentence in the data set that contains more terms in the question and is related to the question, therefore the sentence has a higher score. For *tf* is a local parameter that calculates the frequency of each term *t* in the sentence document *d*, so that *ft,d* means the frequency of occurrence of the terms *t* to *i* in sentences *d* to *j* (PERMATASARI, 2019).

$$tf\,(t_i,d_j) = f_{t,d} \tag{1}$$

The global parameter that is *idf* is the inverse frequency of the sentence, *idf* calculates the inverse of the occurrence of the term in the dialog dataset, where *D* is a set of sentences in the dialogue scenario.

$$idf\,(t_i,D) = 1 + \log \frac{D}{d(ti)} \tag{2}$$

Therefore, the TF-IDF equation is used to give the weight of the sentence document *d* into term *t*.

$$\mathbf{w}(t_i,d_j) = tf(t_i,d_j) * idf\,(t_i,D) \tag{3}$$

The frequency for this term is used to improve memory in search of information but cannot be ascertained to increase precision. Words with a high TF-IDF value imply a strong relationship with the dialogue that appears.

The design of the TF-IDF method is used as a method for giving weight to dialogue sentences in the answer dataset in the Talk to Me system. The following is a flow chart of how TF-IDF works in weighting.

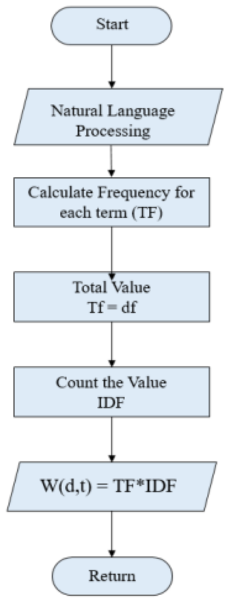


Figure 2. TF-IDF flow chart

In the picture above, after the speech file is processed in NLP, the flow of the TF-IDF calculation itself starts from calculating the frequency of word occurrences (TF) which is similar to what is input by the user. The total of the TF value (df) will be used to calculate the IDF value. From this result, the TF and IDF values were obtained and then multiplied to get the weight value of each word. Referring to Table 2 Dialogue Scenario 1 (D1), the design for the chat in the D1 dialogue scenario, that is "I want to die", TF-IDF calculations are carried out to determine the weight of the sentence. The calculation weights are as follows.

Table 3.

TF-IDF calculation for Scenario D1.

Q	D1	D2	D3	D4	D5	D6	df	idf
Aku I	1	1	1	0	1	1	5	1.079
Mati Die	1	0	0	0	0	0	1	1.778

The table above shows the TF and IDF calculations in the D1 dialog scenario, where Q itself is a query or keyword in the dataset document. Meanwhile for df (df = tf) itself is the number of words that appear from each dialogue scenario. For the results of the IDF itself, it is obtained from the calculation of the formula in II.2, so that the TF and IDF calculations are obtained for each word element, then to get the TF and IDF values, multiplication of the two calculations will be carried out. The following is a calculation table of TF x IDF.

Table 4.

TF x IDF Calculation for Scenario D1.

Q	D1	D2	D3	D4	D5	D6
Aku I	1.079	1.079	1.079	0	1.079	1.079
Mati Die	1.778	0	0	0	0	0
Total	**2.857**	1.079	1.079	0	1.079	1.079

From the calculation of the table above, it can be seen that the total amount obtained is 2,857. The results of these weights will then be processed in the Finite State Machine method to obtain the most appropriate answer.

Finite State Machine

Finite State Machine or FSM is a control system design methodology that describes the behavior or working principles of the system by using three things, that is state, event, and action. At one point in a significant time, the system will be in one of the active states. The system can switch or transition to another state if it gets certain input or events, either from external devices or components in the system itself. This state transition is generally also accompanied by actions taken by the system when responding to the input that occurs. The actions taken can be in the form of simple actions or involve a series of relatively complex processes (Rahadian et al., 2016). After the weighting process is carried out in the TF-IDF method, then the calculation results that have been obtained will be processed in the FSM method to control the flow of dialogue based on the number of states that have been determined and are limited to the dialogue scenario. The FSM method here is structured by following the dialogue scenario and dialogue session. The following is a scenario diagram of ~~a~~ dialogue management on FSM.

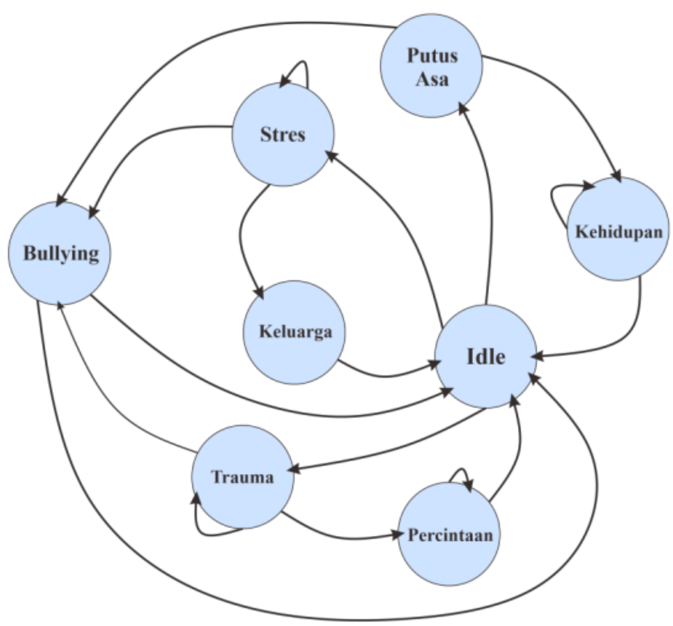


Figure 3. FSM scenario diagram

The picture above shows the structure of the expected FSM diagram in accordance with the previously designed dialogue scenario. In this diagram, eight statuses consist of idle, sad, broken up, bullied, angry, family, depression and life. The direction of the arrow pointing to the status itself indicates if the status will remain in that state when there is the same input. From all of these states, there is a trigger that can cause a change from one state to another, this trigger is called a transition. The purpose of this transition change is that it is triggered by a dialog entered by the user. It can be exemplified for the change in transition 1, that is *I break up x idle* → *Break Up*, where the transition will change from idle to sad status. FSM arranges dialogues based on scenarios that have been designed to be able to interact with its users so that the system is able to respond by issuing answers based on transitions and status.

ANALYSIS AND RESULT

The test system for speech recognition utilizes the Indonesian Language Google Cloud Speech API technology where this testing process is carried out to obtain an overview of the accuracy of the system translation response. This test is carried out by four people by saying sentences that have been designed based on the dialogue scenario. The list of people who conducted the testing is as follows.

Table 5.

Test sample.

Sample Test	Name	Gender	Age
I	Chandra Ramdhan Purnama	Male	22
II	Irwansyah Sudiarna	Male	57
III	Khanha Shandhika	Male	17
IV	Niar Cuniarsyah	Female	52

Each speaker who became the test data spoke 5 times, for each of the six predefined dialogue scenarios with a short distance between the smartphone and the speaker and in a room with minimal noise. The following are the test results for speech recognition accuracy using Google Cloud Speech.

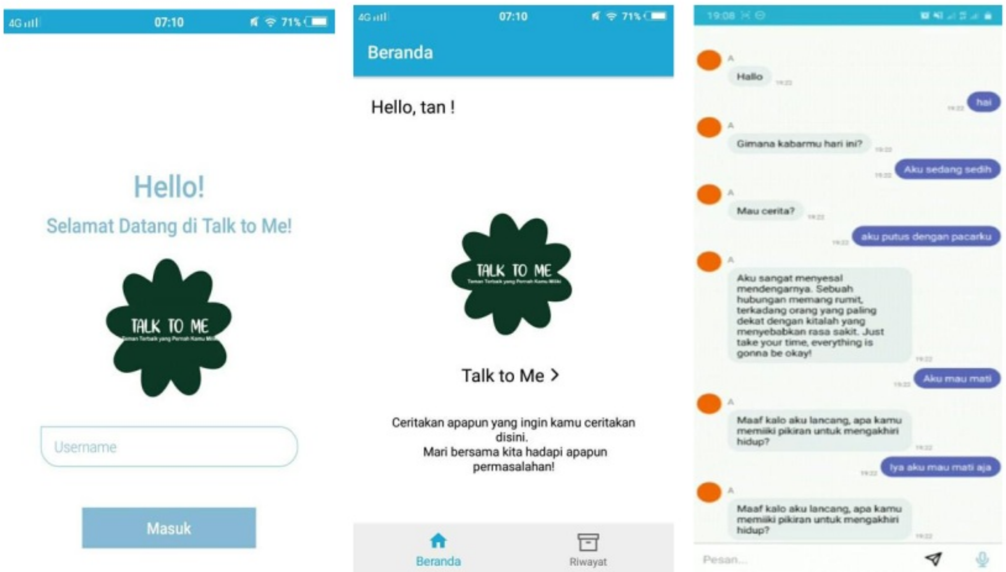
Table 6.

The following is the result of testing the accuracy of the system answer.

Dialogue Scenario	Accuracy (%)				Average Accuracy
	Sample Test 1	Sample Test II	Sample Test III	Sample Test IV	
D1	100	100	100	100	100
D2	100	75	100	100	93,75
D3	100	100	100	100	100
D4	100	100	100	100	100
D5	100	100	75	100	93,75
D6	100	100	75	100	93,75
		Average			**96.5**

Application Display

This research produces an android based application for its users. The following is a display of the Talk to Me application.



(a) (b) (c)

Figure 4. Application display (DIGANTI ENGLISH)

CONCLUSION

The Talk to Me application prototype that utilizes Google Cloud Speech API technology to convert speech and text has been successfully implemented so that interaction between users and applications can be carried out easily. The Talk to Me prototype application utilizes Artificial Intelligence technology using the Natural Language Processing method which is used for text processing, the 5 Term Frequency - Inverse Document Frequency method which is used to weight sentences, and the Finite State Machine method which is used to adjust the dialogue flow for interact with users has been designed and implemented successfully. By using this method, the system can understand input from users and can provide the most appropriate answer according to what has been input.

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