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A MOBILE-BASED COVID-19 DECISION SUPPORT SYSTEM USING DEMPSTER-SHAFER THEORY

Indra Sujadi[1], Friska Natalia[1,*], Ferry Vincenttius Ferdinand[2]
Sud Sudirman[3] and Chang Seong Ko[4]

[1]Department of Information Systems
Universitas Multimedia Nusantara
Scientia Boulevard, Gading Serpong, Tangerang, Banten 15811, Indonesia
indra.sujadi@student.umn.ac.id; *Corresponding author: friska.natalia@umn.ac.id

[2]Department of Mathematics
Universitas Pelita Harapan
Tangerang, Banten 15811, Indonesia
ferry.vincenttius@uph.edu

[3]School of Computer Science and Mathematics
Liverpool John Moores University
Liverpool L3 3AF, UK
s.sudirman@ljmu.ac.uk

[4]Department of Industrial and Management Engineering
Kyungsung University
309, Suyeong-ro, Nam-gu, Busan 48434, Korea
csko@ks.ac.kr

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Abstract. *COVID-19 testing hesitancy is problematic but prevalent in many developing countries. Because of this, many governments face difficulties in limiting the rate of spread of the disease since it will impact adversely on the effectiveness of the track-and-trace program. This problem is a result of the relatively high cost of the test in these countries compared to the income of the population which has put off many people in getting the test. While the majority of the population recognize the importance of getting the test, many do not want to spend their money because they are unsure if they should, based on the symptoms they are experiencing. Also, ideally, people should be able to consult their General Practitioners to discuss their symptoms but to many people in developing countries, this may also be unaffordable. In this paper, we detail our solution that can improve this situation by developing a COVID-19 decision support system that is deployed as a mobile application. This application allows its user to enter the type of symptoms they are experiencing and provide a recommendation on whether to seek further medical advice or not. The application uses the Dempster-Shafer Theory and statistical inference based on the knowledge database developed through opinions gathered from medical experts. The process considers the similarity of symptoms of COVID-19 disease with several other diseases. The mobile application has also several features that are designed to help increase the understanding and awareness of its users about the disease and educate them about how to maintain their health and safety during the pandemic.*

Keywords: COVID-19, Dempster-Shafer Theory, Decision support system, Mobile application

1. **Introduction.** COVID-19 testing is an important and integral part of a solution to combat the spread of the disease. However, the availability and affordability of testing vary between countries. This can be seen by the large differences between the number of

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tests carried out in developed and developing countries. As an example, as of July 14^{th}, 2021, the UK had conducted 3,311 tests per 1,000 population compared to Indonesia which only managed 55 tests per 1,000 population [1]. The reason for this discrepancy is because, in most developed countries, COVID-19 tests are readily and freely available in hospitals, pharmacies, GP surgeries and can be ordered online. On the other hand, in many developing countries such as Indonesia, COVID-19 tests are expensive and limited to hospitals. This has put off many people in getting the test. Although the majority of people recognize the importance of getting the test, many do not want to spend the money because they are unsure if they should, based on the symptoms they are experiencing.

In this paper, we detail our solution that can improve this situation by developing a COVID-19 decision support system that is deployed as a mobile application called WAVID. This application allows its user to enter the type of symptoms they are experiencing and uses the Dempster-Shafer Theory (DST) and statistical inference to provide a recommendation on whether to seek further medical advice or not. In addition, the application also provides a more general information about how to stay safe and healthy during the pandemic.

The organization of this paper is as follows. Section 2 contains a review of the most current and relevant approaches in the literature on this topic. We present the problem statement and description of the methodology in Section 3. In Section 4, we describe one representative scenario where the Dempster-Shafer method is used to predict a COVID case and the implementation of the methodology as a mobile application. This is followed by the paper conclusion in Section 5.

2. **Literature Review.** Due to the pressing nature of the pandemic, there has been a flurry of research that relates to COVID-19. The application of computer science as a tool for managing the pandemic ranges from diagnosis systems to disease spread visualization [2,3]. Several studies have been reported in the literature that developed applications to assist the diagnosis or detection of COVID-19 based on the user's list of symptoms. Priyantono et al. [4] used the forward chaining method in an application that can predict COVID-19 disease based on its early symptoms whereas Al Hakim et al. [5] used the certainty factors in their COVID-19 detection application. Liu et al. developed a mobile-based decision support system for COVID-19 risk assessment for General Practitioners [6]. The system is composed of three parts: mobile terminal apps for the patient-end and GP-end, and the database system. The data used in the calculation is the patients' demographic information, clinical symptoms, contact history, blood test results, and CT scan. The paper reported an average value of above 0.71 for the macro-area under the curve for the classification results. Rahmanita et al. [7] conducted a comparison study to assess the effectiveness of the DST method and the forward chaining method in diagnosing digestive tract diseases. The DST method has been proven to be able to help diagnose several diseases based on their symptoms. Pratama and Natalia [8] developed a mobile application that can diagnose measles, dengue fever, and typhus using the DST method. Sembiring and Sinaga [9] developed an application that can diagnose diseases caused by the Treponema Pallidum bacteria using the DST method. These show the popularity and success of using the DST method in assisting the diagnosis of a disease. The DST is a numerical method for evidential reasoning which was developed by Shafer [10] using a method proposed by Dempster [11] that serves as a mechanism for reasoning under knowledge uncertainty. It can be considered as an extension to the Bayes probability theory with special advantages in its treatment of ambiguous data and the ignorance arising from it. The method has become popular, and the basic model has been extended in several directions in recent years [12,13].

3. **Problem Statement and Methodology.** The decision support system designed in this study attempts to categorize the symptoms that are experienced when a person is infected with one or more of the following diseases: the Flu, Typhoid Fever, Dengue Fever, and COVID-19. The decision is inferred using the DST method by considering the evidence which is the displayed symptoms to assess the likelihood of a proposition or hypothesis using the belief factor of medical experts on the importance of each symptom in diagnosing certain diseases. Formally, the DST concerns the following preliminary notations.

Let Θ be a finite set of elements which member is a hypothesis. In our case, each hypothesis is a positive diagnosis of a disease. The power set of Θ, denoted as $\Omega(\Theta)$, is a set that consists of all possible subsets of Θ, including the null set. As an example, in our case, we consider four types of diseases namely the Flu (F), Typhoid Fever (T), Dengue Fever (D), and COVID-19 (C). Therefore, the set Θ and its power set $\Omega(\Theta)$ are defined as

$$\Theta = \{F, T, D, C\} \tag{1}$$

$$\begin{aligned}\Omega(\Theta) = &\{\{F\}, \{T\}, \{D\}, \{C\}, \{F, T\}, \{F, D\}, \{F, C\}, \{T, D\}, \{T, C\}, \\ &\{D, C\}, \{F, T, D\}, \{F, T, C\}, \{T, D, C\}, \{F, T, D, C\}, \emptyset\}\end{aligned} \tag{2}$$

where $\emptyset$ is the null set signifying no disease detected and $\{F, T, D, C\}$ is a set that signifies a hypothesis where all four diseases were detected. The method then uses the basic probability assignment, often referred to as the mass function, m_e that maps the elements of $\Omega(\Theta)$ to a number between 0 and 1, i.e., m_e: $\Omega(\Theta) \to [0, 1]$. A value of zero and one for e signify none and the complete importance of an evidence (or a set of evidence), respectively. The function $m_e(A)$ expresses the importance of that particular evidence to support the claim of a set of hypotheses A where $A \in \Omega(\Theta)$. The values of $m_e(A)$ should be normalized for $\forall A$ which means when $A = \Omega(\Theta)$, then $\sum_A m_e(A) = 1$. The value of $m_e(A)$, in our case, contributes to the degree of belief held by a medical expert regarding a certain diagnosis based on specific evidence. Furthermore, different information or evidence can produce different degrees of belief with respect to a given disease diagnosis. The notation of belief that was mentioned previously can be mathematically described as follows. The belief function Bel: $\Omega(\Theta) \to [0, 1]$ measures the total amount of probability that must be distributed among the elements of the set. The function $Bel(X) = \sum_{A \subseteq X} m_e(A)$ signifies the total degree of belief of the set X and constitutes a lower limit function on the probability of the set. On the other hand, the plausibility function Pls: $\Omega(\Theta) \to [0, 1]$ measures the maximal amount of probability that can be distributed among the elements in the set. It describes the total belief degree related to the set and constitutes an upper limit function on the probability of the set. The relationship of belief and plausibility functions is governed as

$$Pls(X) = 1 - Bel\left(\bar{X}\right) \tag{3}$$

where $\bar{X}$ is the complementary set of X.

To start with, we need to have as many mass functions as there are evidence or symptoms and the number of mass functions will grow as multiple evidence is considered. The DST method also provides a framework on how to combine multiple pieces of evidence. Suppose $m_1(X)$ and $m_2(Y)$ are two mass functions that are based on evidences 1 and 2 that support two hypotheses X and Y, respectively. We can combine the two mass functions to create one combined mass function $m_3(Z)$ that supports the intersection hypotheses $Z = X \cap Y$ using the unnormalized Dempster's orthogonal rule [11]:

$$m_3(Z) = \sum_{X \cap Y = Z} m_1(X) \cdot m_2(Y) \tag{4}$$

This combination process will need to be performed iteratively until all symptoms or evidence has been considered. When the calculation process is complete, it will generate one suspected disease that is likely to be experienced by the user based on the highest confidence value of the several suspected diseases generated. An overview of the proposed COVID-19 decision support system is elucidated in Figure 1. The description of each step in the diagram is as follows. Step 1) collects the list of symptoms of the four diseases from the medical experts, step 2) collects the weights of the symptoms signifying each symptom's importance to the diagnosis process, step 3) aggregates the weights to obtain the value to be used to determine the mass function and store them in a knowledge database, in step 4) the user enters a list of felt symptoms, step 5) retrieves relevant information from the knowledge database, step 6) performs the evidence reasoning using DST, step 7) predicts the most likely type of disease(s), steps 8) and 9) retrieve and display the recommended action to take to the user, respectively. The list of disease symptoms and the weight of disease symptoms that will be used to carry out the disease detection process can be seen in Table 1.

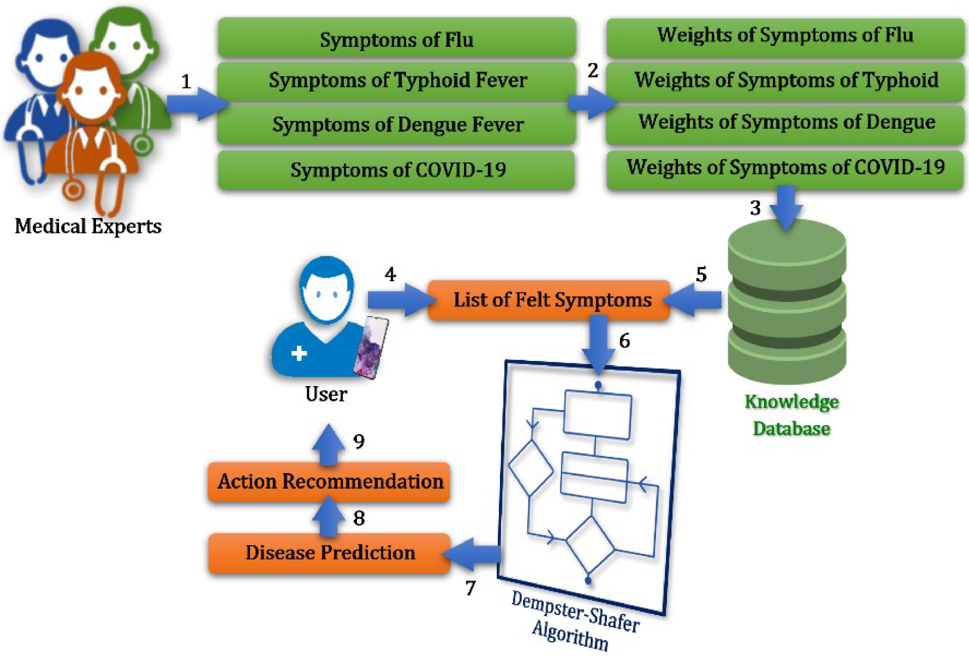


FIGURE 1. An overview of the proposed COVID-19 decision support system

4. **Scenario Discussion and Implementation.** To illustrate the process that takes place during the calculation of the DST, in this section, we provide one scenario where the user identifies four symptoms to the algorithm.

4.1. **Example scenario.** In this scenario, the user identified fever, dry cough, tiredness, and loss of ability to taste and smell. The summary of the symptoms with their weight and focal elements is shown in Table 2. The focal element of each symptom is defined as a set that consists of the diseases that have non-null weight values in Table 1.

The DST calculation starts by considering the first two symptoms.

a. The first symptom, s_1: Fever

Based on Table 1, fever is a symptom of Flu, Typhoid Fever, Dengue Fever, and COVID-19.

$Bel(\{F,T,D,C\}) = \sum m_1(\{F,T,D,C\}) = 0.94$

$Pls(\emptyset) = m_1(\emptyset) = 1 - Bel(\{F,T,D,C\}) = 0.06$

TABLE 1. Knowledge database of symptoms with weight values. The last column is calculated as the mean of all weight values for each symptom.

Symptoms	**Flu**	**Typhoid fever**	**Dengue fever**	**COVID-19**	**Weight**
Fever	0.85	1.00	1.00	0.90	0.94
Dry cough	0.75	0.45		0.50	0.57
Tiredness	0.55	0.65		0.60	0.60
Loss of ability to taste/smell				0.70	0.70
Runny/stuffy nose	1.00			0.40	0.70
Sore throat	0.75			0.70	0.73
Headache		0.70		0.50	0.60
Muscle/joint pain	0.65		0.80	0.70	0.72
Skin rashes			0.90		0.90
Nauseous vomit			0.75	0.50	0.63
Diarrhea		0.80		0.20	0.50
Chills/dizziness				0.55	0.55
Hard to breathe				0.65	0.65
Loss of appetite		0.85	0.80	0.80	0.82
High body temperature ($> 38°$C)				0.50	0.50
Depression				0.25	0.25
Sleep disorder				0.15	0.15
Stomachache		0.75			0.75

TABLE 2. The table extracted from the knowledge database given the user input list of symptoms

Symptoms (s)	**Focal element**	**Weight (m)**
Fever (s_1)	$\{F, T, D, C\}$	0.94
Dry cough (s_2)	$\{F, T, C\}$	0.57
Tiredness (s_3)	$\{F, T, C\}$	0.60
Loss of ability to taste or smell (s_4)	$\{C\}$	0.70

b. The second symptom: s_2: Dry cough

Based on Table 1, dry cough is a symptom of Flu, Typhoid Fever, and COVID-19.

$Bel\left(\{F, T, C\}\right) = \sum m_2\left(\{F, T, C\}\right) = 0.57$

$Pls\left(\emptyset\right) = m_2\left(\emptyset\right) = 1 - Bel\left(\{F, T, C\}\right) = 0.43$

After determining the belief and plausibility values of symptom s_1 and symptom s_2, we can calculate the new mass function m_3 by first creating a combination rule table which can be seen in Table 3.

TABLE 3. Combination rule table for m_3

	$m_2(\{F, T, C\}) = 0.57$	$m_2(\emptyset) = 0.43$
$m_1(\{F, T, D, C\}) = 0.94$	$m_3(\{F, T, C\}) = 0.5358$	$m_3(\{F, T, D, C\}) = 0.4042$
$m_1(\emptyset) = 0.06$	$m_3(\{F, T, C\}) = 0.0342$	$m_3(\emptyset) = 0.0258$

Using the values specified in the table we have

$m_3(\{F, T, D, C\}) = 0.4042$

$m_3(\{F, T, C\}) = 0.5358 + 0.0342 = 0.570$

$m_3\left(\emptyset\right) = 0.0258$

c. The third symptom, s_3: Tiredness
Based on Table 1, tiredness is a symptom of Flu, Typhoid, and COVID-19.
$Bel\left(\{F,T,C\}\right) = \sum m_4\left(\{F,T,C\}\right) = 0.23$
$Pls\left(\emptyset\right) = m_4\left(\emptyset\right) = 1 - Bel\left(\{F,T,C\}\right) = 0.77$

After determining the belief and plausibility values of the third symptom s_3, we can calculate the mass function m_5 by first creating a combination rule table for m_3 and m_4 which can be seen in Table 4.

TABLE 4. Combination rule table for m_5

	$m_4(\{F,T,C\}) = 0.60$	$m_4(\emptyset) = 0.40$
$m_3(\{F,T,D,C\}) = 0.4042$	$m_5(\{F,T,C\}) = 0.2424$	$m_5(\{F,T,D,C\}) = 0.1616$
$m_3(\{F,T,C\}) = 0.570$	$m_5(\{F,T,C\}) = 0.342$	$m_5(\{F,T,C\}) = 0.228$
$m_3(\emptyset) = 0.0258$	$m_5(\{F,T,C\}) = 0.0156$	$m_5(\emptyset) = 0.0104$

Using the values specified in the table we have
$m_5(\{F,T,D,C\}) = 0.1616$
$m_5(\{F,T,C\}) = 0.2424 + 0.342 + 0.0156 + 0.228 = 0.828$
$m_5(\emptyset) = 0.0104$

d. The fourth symptom, s_4: Loss of ability to taste or smell
Based on Table 1, a loss of ability to taste or smell is a symptom of COVID-19.
$Bel\left(\{C\}\right) = \sum m_6\left(\{C\}\right) = 0.70$
$Pls\left(\emptyset\right) = m_6\left(\emptyset\right) = 1 - Bel(\{C\}) = 0.30$

After determining the belief and plausibility values of symptom s_4, we can calculate the new mass function m_7 by first creating a combination rule table which can be seen in Table 5.

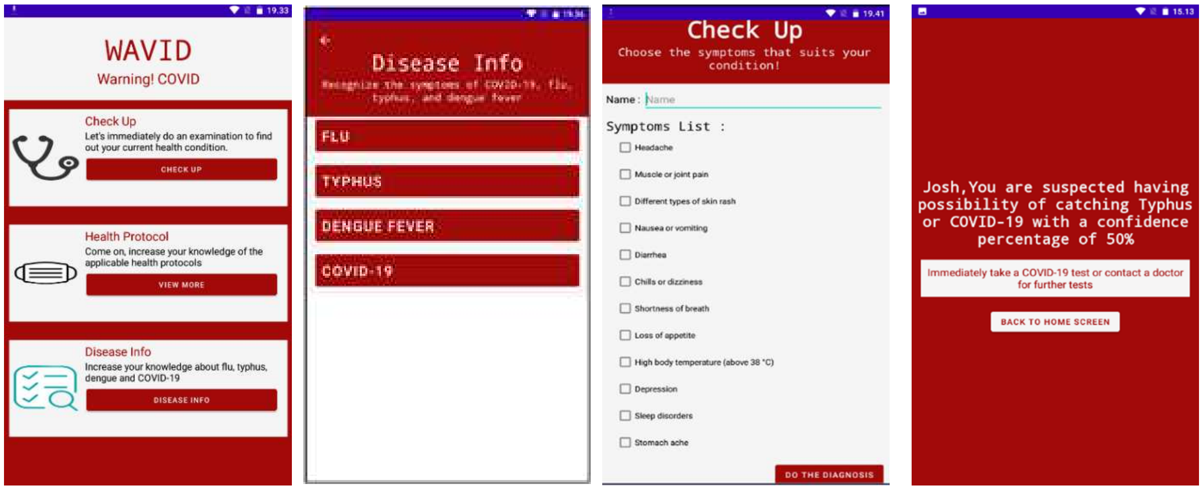
TABLE 5. Combination rule table for m_7

	$m_6(\{C\}) = 0.70$	$m_6(\emptyset) = 0.30$
$m_5(\{F,T,D,C\}) = 0.162$	$m_7(\{C\}) = 0.1134$	$m_7(\{F,T,D,C\}) = 0.0486$
$m_5(\{F,T,C\}) = 0.828$	$m_7(\{C\}) = 0.5796$	$m_7(\{F,T,C\}) = 0.2484$
$m_5(\emptyset) = 0.01$	$m_7(\{C\}) = 0.007$	$m_7(\emptyset) = 0.003$

Using the values specified in the table we have
$m_7(\{F,T,D,C\}) = 0.0486$
$m_7(\{F,T,C\}) = 0.2484$
$m_7(\{C\}) = 0.1134 + 0.5796 + 0.007 = 0.70$
$m_7(\emptyset) = 0.003$

In this scenario, no other symptoms were found, hence the DST calculation process stops here, and the final density value, m_7, is the result of the Dempster-Shafer calculation based on the four symptoms shown in Table 2. Based on the calculation results obtained, it can be said that if the user experiences the symptoms listed in Table 2, the resulting diagnosis is likely to have COVID-19 disease with a confidence percentage of $m_7(\{C\})$ which is 70%.

4.2. **Mobile application development.** Our implementation of the methodology is a bi-lingual mobile application called WAVID which has a user interface elucidated in Figure 2. We opted not to implement the solution as chatbot [14] to achieve simplicity in communicating the important messages to the user. The Java programming language was used to program the front end, the PHP is used to create the API services, and MySQL to store and query the database. At the start, the user is shown the main page (Figure 2(a)). On this main page, the user can access the examination page, disease info



(a) (b) (c) (d)

FIGURE 2. The user interface of WAVID our mobile application: (a) is the home page and (b) is the disease info page. The diagnosis page consists of (c) the information entry page and (d) the action recommendation page.

page, and health protocol info page by pressing the button provided. If the user selects disease info, the page shown in Figure 2(b) will be displayed. On this disease info menu page, the user can choose information about the disease that the user wants to see, such as information on the meaning, symptoms, and modes of transmission of the selected disease. Before proceeding to the inspection page, the user must state that the user has understood the message displayed by the application and decided to proceed. After the user states that the user understands the message displayed and wants to continue to access the examination page, a continue button will appear to access the examination page.

Figure 2(c) shows the page that allows the user to enter all the symptoms that are experienced. On this page, the user will be asked to write a name and enter data about the symptoms experienced by the user into the application. To continue the examination process, the user must press the perform diagnosis button, where afterward the diagnosis process using DST will take place. The examination results page will display the results of calculations and diagnoses performed by the application based on the symptoms that have been selected by the user. The page shows the type of action recommendation given to the user when the system thinks that COVID-19 is likely in Figure 2(d).

5. **Conclusion.** We have detailed in this paper, our solution to the problem of COVID-19 testing hesitancy in many developing countries that resulted from the test's relatively high cost in these countries, through the development of a COVID-19 decision support system which is deployed as a mobile application. This application allows its user to enter the type of symptoms they are experiencing and provide a recommendation on whether to seek further medical advice or not. The application uses the Dempster-Shafer Theory and statistical inference based on the knowledge database developed through opinions gathered from medical experts. The process takes account of the similarity of symptoms of COVID-19 disease with a number of other diseases and illnesses namely the Flu, Typhoid Fever, Dengue Fever, and COVID-19. The mobile application also has additional features designed to help increase the understanding of its users about the disease and educate them about how to maintain their health and safety during the pandemic. With this application, it is hoped that it can help reduce the spread of COVID-19 and help save lives. In the future, we plan to further improve the decision-making process by including

more symptoms and deploy the application to a wider public so that its effectiveness can be measured.

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