IDENTIFICATION OF MENTAL HEALTH WORKERS IN LAMONGAN WITH MACHINE LEARNING

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ABSTRACT

COVID-19 has caused a global health crisis, with increasing numbers of people being infected and dying every day. Various countries have tried to control its spread by applying the basic principles of social aggregation and testing. Experts agree that physical and mental health are interrelated and must be managed and balanced. The government must pay attention to balancing physical and mental health during a pandemic. The Ministry of Health has issued a guidebook for Mental Health and Psychosocial Support (DKJPS) during the COVID-19 pandemic. Based on the mental health conditions of the community or medical personnel, we are trying to create a system for mental health analysis for medical professionals based on the results of questionnaires using the machine learning method (Naive Bayes, Decision Tree, k-NN, SVM, Backpropagation, and Logistic Regression). A total of 24 question questionnaires were submitted to respondents. This study aimed to create a machine learning model (Naive Bayes, Decision Tree, k-NN, SVM, Backpropagation, and Logistic Regression) to identify the mental health of medical personnel during the COVID-19 pandemic. The results of this study are machine learning models that have the highest accuracy in identifying health workers' mental health and are 100% SVM.

Keywords*: identification, mental health, medical personnel, machine learning.*

I. INTRODUCTION

Some research that has been done before [1] using a questionnaire to determine the factors that affect mental health during the COVID-19 pandemic and how to analyze it using correlation statistics. Research [2] statistically analyzed questionnaire data shows that gender can affect mental health during the COVID-19 pandemic. Previous studies processed questionnaire data by looking for correlations to find out the factors that affect mental health during the COVID-19 pandemic [3], [4], [5], [6], [7], [8], [9], and using binary logistic regression to determine the correlation between variables [10], used multivariate logistic regression to determine the factors that influence mental health [11], [11], [12]. Research using Twitter data to analyze mental health during the COVID-19 pandemic, namely modelling text to produce a mental health index system using machine learning [13], [14]. We will use machine learning (Naive Bayes, Decision Tree, k-NN, SVM, Backpropagation, and Logistic Regression) to analyze questionnaire data from medical personnel. Therefore we need an analysis of features that affect the mental health of medical personnel during the COVID-19 pandemic and a model for early identification of the mental health of medical personnel.

II. LITERATURE REVIEWS

Coronavirus Disease-19 (COVID-19) is a respiratory disease caused by the SARS-CoV-2 virus (World Health Organization (WHO), 2020a). This disease was first detected in China and has now spread globally, including in Indonesia. As of July 4 2021, the World Health Organization (WHO) reported an increase in the number of positive cases of COVID-19 by 3 per cent (2,668,561 points) globally. WHO says that in the Southeast Asia region, as of July 4 2021, there was an increase in positive cases of 7 per cent (612,933 points) compared to the previous week's data (World Health Organization (WHO), 2020a). The graph of the distribution of positive cases of COVID-19 in Indonesia per day compiled by the COVID-19 Distribution Map shows that until July 10 2021, there were the most additional cases in the province of the Special Capital Region (DKI) Jakarta, namely 649,302 cases (Satgas COVID-19, 2021). Based on the surveillance data graph released by WHO, the trend of positive instances of COVID-19 in Indonesia has increased (World Health Organization (WHO), 2020a). COVID-19 data, as of July 4 2021, states that the number of active cases still shows an increasing trend. During one week from June 28 to July 4 2021, the incidence rate of COVID-19 in Indonesia was 46.9 per 100,000 Indonesian population (World Health Organization (WHO), 2020a).

The coronavirus disease 2019, or COVID-19, caused a worldwide pandemic from 2020 to 2021. This pandemic outbreak has hurt the physical and psychological health of the community [15], [16], [17]. According to Brooks et al. (2020), psychological effects during a pandemic include post-traumatic stress disorder, confusion, anxiety, frustration, fear of infection, difficulty sleeping, and helplessness. Several psychiatrists and psychologists have noted that almost all types of mild to severe mental disorders can occur during this pandemic.

The COVID-19 outbreak has caused changes to the hospital work system. The more confirmed cases mean, the higher the demand for health services [18]. Anxiety is the most common psychological impact due to the COVID-19 pandemic. Anxiety is most commonly found in health workers who work in hospitals [19]. Health workers experience anxiety caused by the new situation they have to face, causing changes in routines at work and in daily life [20]. Anxiety experienced by health workers is a psychological disorder still in its early stages, so it is still possible to treat it [21]. These things make health workers at health service facilities (Fasyankes) on the front line work tirelessly and continue to provide services to the point that they cause physical fatigue and have the potential to cause psychological stress, both anxiety, fear of stress and depression [22].

Distress and anxiety are normal reactions to threatening and unexpected situations like the coronavirus pandemic. Possible stress-related reactions in response to the coronavirus pandemic can include shifts in concentration, irritability, anxiety, insomnia, reduced productivity and interpersonal conflict. Still, these are especially true for directly affected groups (e.g. healthcare professionals). Apart from the threat posed by the virus, there is no doubt that the quarantine measures implemented in many countries have a negative psychological effect, further increasing stress symptoms. The severity of symptoms depends in part on the duration and extent of quarantine, feelings of loneliness, fear of infection, adequate information and stigma in more vulnerable groups, including psychiatric disorders, healthcare workers and people of lower socioeconomic status [16].

Experts agree that physical and mental health are interrelated and must be managed and balanced. The government must pay attention to balancing physical and mental health during a pandemic. The Ministry of Health has issued a guidebook for Mental Health and Psychosocial Support (DKJPS) during the COVID-19 pandemic. Referring to the policies of the World Health Organization (WHO), this book is one of the guidelines for medical personnel in providing mental health and psychosocial support for healthy people, people with monitoring (ODP), people without symptoms (OTG), and patients with supervision (PDP), COVID-19 patients, and vulnerable groups.

COVID-19 has caused a global health crisis, with increasing numbers of people being infected and dying every day. Various countries have tried to control its spread by applying the basic principles of social aggregation and testing. Health professionals have become frontline workers globally in preparing for and managing this pandemic [23].

III. METODOLOGI PENELITIAN

The data was taken through a questionnaire by the Lamongan district medical personnel. The total data obtained was approximately 2149 correspondents. There are three classes of mental health, namely normal, moderate distress, and severe distress, based on research [1], [2], [8], [23], [24]. The features analyzed were 24 questionnaire questions and were analyzed using the feature selection method.

The overall research stages are shown in Figure 1. The first step is to collect data by distributing questions through the Google Form with a total of 24 questions referring to previous research [1], [2], [8], [23], [24]. The next stage is data analysis or looking for correlations of factors that affect the mental health of medical personnel during the COVID-19 pandemic. The following process is conducting experiments and implementation related to identifying the mental health of medical personnel in the COVID-19 pandemic. The data is divided into 80% training data and 20% testing. The total number of questions is 24 in Table 1.

TABLE I
QUESTION

Question 1: Compared to usual, I feel more nervous and anxious.
Question 2: I feel insecure and buy a lot of masks, medicines, sanitisers, gloves and or other household items
Question 3: I can't stop imagining myself or my family being infected and feeling scared and anxious about it.
Question 4: I feel helpless in whatever I do.
Question 5: I feel sympathy for COVID-19 patients and their families.
Question 6: I feel helpless and angry about the people around me, the government and the media.
Question 7: I have lost faith in the people around me.
Question 8: I collect information about COVID-19 all day long. Even if it's not necessary, I can't stop myself.
Question 9: I will trust COVID-19 information from all sources without any evaluation.
Question 10: I prefer to believe negative news about COVID-19 and be sceptical about good news.
Question 11: I constantly share news about COVID-19 (mostly negative information).
Question 12: I have avoided watching the COVID-19 news because I am too scared to do so.
Question 13: I am more irritable and often have conflicts with my family.
Question 14: I feel tired and sometimes even exhausted.
Question 15: When I feel anxious, my reactions become sluggish.

Question 16: I need help concentrating.
Question 17: I find it challenging to make decisions.
Question 18: During this COVID-19 period, I often feel dizzy or experience back pain and chest pain.
Question 19: During COVID-19, I often experience stomach pain, bloating and another stomach discomfort.
Question 20: I feel uncomfortable when communicating with other people.
Question 21: Recently, I rarely talk to my family.
Question 22: I often wake up at night because I dream about my family being infected with COVID-19.
Question 23: I have a change in my eating habits.
Question 24: I have constipation or frequent urination.

The research proposal analyzes the factors that affect the mental health of medical personnel during the COVID-19 pandemic by selecting features. The second proposal is to create a machine-learning model to identify the mental health of medical personnel during the COVID-19 pandemic. We use machine learning algorithms, including Naive Bayes, Decision Tree, k-NN, SVM, Back-propagation, and Logistic Regression.

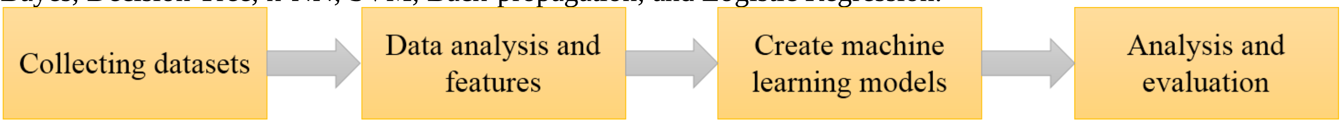

Figure. 1. Research Stages

IV. Results

The questionnaire we gave via the Google form asked 24 things, as shown in Table 1. Each question had five answers: never, sometimes, occasionally, often, and always. Answers to questions are processed first by converting them to 0 (never), 1 (occasionally), 2 (sometimes), 3 (often), and 4 (always). Then add up the 24 questions answered by respondents were then added up to get the total value of the CPDI (COVID-19 Peritraumatic Distress Index). The total score is in the range of 0 to 100; 0-27 is normal, 28-51 is moderate distress, and >52 is severe distress [2], [8], [23]. The total number of normal respondents was 1605, moderate distress was 534, and severe distress was 10 (Table 2 explains the probabilities). For all questions, the probability calculation of each answer is never, sometimes, occasionally, often, and always in Table 3. Based on Table 2, only 10 respondents experienced severe distress, so making machine learning models and checking correlations only using two classes, namely normal, and moderate distress. Table 4 shows the correlation value of each question or feature to the mental health class (normal and moderate distress).

TABLE II
CPDI CLASS PROBABILITY QUESTIONNAIRE

Class	CPDI	Total	Probability
Normal	0-27	1605	0.747
Moderate Distress	28-51	534	0.248
Severe Distress	>52	10	0.005
Total		2149	

TABLE III
PROBABILITY QUESTIONNAIRE ANSWERS

Questions	Never	Occasion-ally	Sometimes	Often	Always
Q1	0.375	0.370	0.203	0.040	0.012
Q2	0.246	0.266	0.193	0.180	0.115
Q3	0.283	0.334	0.238	0.102	0.043
Q4	0.656	0.166	0.158	0.013	0.006
Q5	0.030	0.150	0.050	0.355	0.415
Q6	0.523	0.232	0.215	0.026	0.005
Q7	0.639	0.169	0.172	0.017	0.003
Q8	0.481	0.220	0.251	0.034	0.014
Q9	0.611	0.181	0.147	0.034	0.027
Q10	0.701	0.129	0.108	0.026	0.035
Q11	0.670	0.134	0.141	0.038	0.016
Q12	0.541	0.228	0.189	0.029	0.013
Q13	0.743	0.098	0.149	0.007	0.002
Q14	0.265	0.337	0.310	0.081	0.007

Q15	0.350	0.291	0.308	0.040	0.011
Q16	0.428	0.242	0.311	0.017	0.003
Q17	0.460	0.235	0.289	0.014	0.001
Q18	0.605	0.151	0.221	0.021	0.001
Q19	0.631	0.149	0.202	0.016	0.001
Q20	0.559	0.188	0.225	0.021	0.007
Q21	0.883	0.052	0.057	0.005	0.003
Q22	0.875	0.049	0.071	0.004	0.001
Q23	0.633	0.172	0.162	0.026	0.007
Q24	0.720	0.117	0.147	0.015	0.002
Max	0.883	0.370	0.311	0.355	0.415
Min	0.030	0.049	0.050	0.004	0.001
Average	0.538	0.194	0.188	0.048	0.031

TABLE IV
CORRELATION VALUE OF QUESTIONS AGAINST MENTAL HEALTH CLASSES

Questions	Correlation
Q1	-0.336
Q2	-0.271
Q3	-0.403
Q4	-0.471
Q5	-0.139
Q6	-0.388
Q7	-0.409
Q8	-0.381
Q9	-0.322
Q10	-0.309
Q11	-0.320
Q12	-0.359
Q13	-0.445
Q14	-0.360
Q15	-0.418
Q16	-0.444
Q17	-0.410
Q18	-0.412
Q19	-0.388
Q20	-0.486
Q21	-0.311
Q22	-0.385
Q23	-0.449
Q24	-0.386
Max	-0.139
Min	-0.486
Average	-0.375

In Table 4, the average correlation is negative, which means that each question or attribute is inversely related to the mental health class (normal, moderate distress). We used two experiments, the first experiment created a machine-learning model with all questions or attributes (24 input variables), and the second made a machine-learning model with 12 questions or attributes (12 input variables). Based on Table 4, the average correlation value is -0.375, so we use 12 questions with a correlation value of -0.3, namely questions (Q1, Q6, Q8, Q9, Q10, Q11, Q12, Q14, Q19, Q21, Q22, Q24). The total data from normal and moderate distress respondents is 2139, divided by training 80% (1711 respondents) and testing 20% (428 respondents). The evaluation results from the modelling experiment are listed in Table 5. Based on Table 5, the average evaluation results with all attributes (24 questions) have good accuracy compared to 12 questions/attributes. The best accuracy in determining the mental health of medical personnel is the 100% SVM method. If using 12 attributes/questions, the best accuracy is using the 90.4%

Backpropagation method. The Backpropagation method on an architecture with 24 input attributes/variables is 24-58-1, with 24 neurons in the input layer, 58 neurons in the hidden layer, and one neuron in the output layer. The activation function used in the Backpropagation method is Sigmoid. While the Backpropagation architecture on the 12 input attributes/variables is 12-32-1.

TABLE V
MODEL EVALUATION RESULTS

Method	Accuracy (24 Attributes)	Accuracy (12 Attributes)
Naive Bayes	0.916	0.862
Decision Tree	0.881	0.853
k-NN	0.914	0.881
SVM	1	0.89
Backpropagation	0.991	0.904
Logistic Regression	0.981	0.89

V. CONCLUSION

The purpose of this research is to analyze the features or questions that are distributed through a questionnaire. The results of the feature analysis of the questionnaire are in the form of correlation values, with the average correlation between questions on mental health (normal and moderate distress) being -0.375. Based on the correlation value, it shows an inverse relationship. And we make machine learning models (Naive Bayes, Decision Tree, *k*-NN, SVM, Backpropagation, Logistic Regression) to identify mental health. We used two experiments, the first experiment used all questions as input variables, and the second only used 12 questions with a correlation value of -0.3 (Q1, Q6, Q8, Q9, Q10, Q11, Q12, Q14, Q19, Q21, Q22, Q24). The evaluation results of making the best accuracy machine learning model using 24 questions. The highest accuracy is 100% SVM.

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