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Inference of Mood State Indices by Using a Multimodal High-Level Information Fusion Technique

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ABSTRACT Mood state assessment (MSA) is increasingly important for diagnosis and treatment of depression. Recent years, many approaches have been proposed for the process of MSA. When using a single approach for MSA, the user often has to deal with possible noisy data and unacceptable error rates. **Novelty:** In order to improve the accuracy of MSA, in this paper, we propose a novel high-level information fusion method for determining the MS of users by fusing physiological data, such as heart rate and brainwave information collected through a wearable device, and psychological data collected through a monthly mood chart. The multifaceted information must be collected and analyzed simultaneously. **Contribution:** In the inference process of proposed framework, we adopted a Bayesian Network (BN) to perform high-level information fusion. We exploited various evaluation approaches to evaluate the performance of the proposed approach. **Result:** We have conducted experiments using two datasets and evaluated the performance using various factors. The results show that the proposed method (7-M Bayesian Fusion) is superior to other methods averagely 9.48 % improvement in most evaluation factors. It reveals that the proposed approach is efficient in fusing the MS information required for accurate diagnosis of depression compared with those approaches without fusion approach or with few information fusing.

INDEX TERMS Mood state inference, high-level information fusion, psychological, physiological, Bayesian network.

I. INTRODUCTION

Advances in economy and industry have resulted in increasing occurrence of mental disorders and depression-related diseases in the world. According to the statistics of the World Health Organization (WHO) [1], millions of people suffer from depression or mental disorders every year. Depression is a very common illness, and millions of people suffering from depression commit suicide every year. Considerable research has indicated that mood state (MS) is an important attribute of depression or mental disorders [2]–[5]. Therefore, MS assessment (MSA) is an essential process in depression diagnosis and treatment. Traditionally, questionnaires such as the Center for Epidemiological Studies Depression Scale (CES-D) are carefully designed and used for screening depression. A well-known MSA process [6] adopts the Profile of Mood State questionnaire, which is a psychological rating scale for assessing transient and distinct MSs. Mood charts [7] are also used [8]–[10] to assess an individual's MS. As for the clinical treatment of depression, the MS diagnostic modality mostly involves consultations or interviews to figure out how a patient is feeling. However, such consultations and interviews cannot be performed daily. A monthly mood chart (MMC)[1] is used to assess the daily association

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[1] http://ocpsychiatrymd.com/monthlymoodchart.pdf

between a patient's mood status and the drugs taken by them. The MMC is also used to observe the effectiveness of medical treatment. Some MMC-related apps, such as Mood Tracker[2] and Moodkit,[3] have been developed to record and assess individual MSs online. These apps can be used to record a patient's mood status daily. Users themselves input their MS and feelings. Psychiatrists can use this information to assess patients' MSs as well as the effectiveness of the treatment.

Each of the MSA processes mentioned above mainly uses only one assessment system for its specific purpose. However, it is common that the performance of a single assessment system may be affected by the reliability of the assessment system and the subject's current circumstances. For example, when using the MMC for assessing a patient's MS, the user may intentionally or unintentionally hide or exaggerate certain factors. This reduces the accuracy of assessment. In addition, according to Ross and Jain's claims [11], when using a single biometric indicator, one often has to deal with noisy sensor data, restricted degrees of freedom, non-universality of the biometric trait, and unacceptable error rates. Therefore, it is high time to improve the accuracy of MS estimation and assessment.

Numerous studies have highlighted certain physiological signals that can reflect a person's MS, such as the heart rate variability (HRV) [12]–[14] and brainwave information (captured with an electroencephalogram (EEG)) [15]–[19]. Therefore, the use of biofeedback physiological signals with the MMC may result in the improvement of MSA. However, the various feelings expressed in an MMC represent an MS at a certain time. These feelings consist of various mood indicators, such as the MS, irritability, anxiety, energy, drug taken, weight, daily sleep hours, and activity event. Most of the MS-associated data are represented in the numerical form (e.g., 1–5). The HRV signal is represented as the average value of the heart rate variation during a certain time period. The HRV is used to assess the autonomic nervous system, which can be divided into the sympathetic nervous system and the parasympathetic nervous system [20].

In addition, brainwaves are electrical signals of neural activity occurring in the brain. EEG is a noninvasive method to record the brainwaves detected on the scalp in the form of a physiological-signal-amplification graph. EEG signals comprise various waves, which represent certain physiological states.

In the past decade, the information fusion technique [21]–[23] has been successfully used to integrate various data or information. According to the classification highlighted in [21], the elements of a basic data fusion system can be divided into low-level and high-level fusion processing elements. Low-level information fusion involves numerical data integration, whereas high-level information fusion involves feature and decision integration [24]. The MMC, EEG, and HRV are different models and distinct methods for identifying the MS of individuals. Low-level fusion cannot be used to fuse the signals from distinct modalities, such as the MMC, EEG, and HRV, which provide different types of data or signals. Integrating multimodal and distinct types of data and directly presenting them as an MS is difficult. The fusion of high-level multimodal information has been successfully achieved in the last decade [24]–[34]. Multimodal information fusion techniques have been applied in biometrics [26], [27], [29], [33]–[38] to systematically recognize individuals. There are also other methods, such as weighted fusion, which are used to fuse multi-complex-valued information [64] to ensure the quality of the multiple sources data fusion and its fault diagnosis.

To the best of our knowledge, such fusion techniques have not yet been applied for fusing psychological and physiological data in MSA. Therefore, to propose a multimodal high-level information fusion technique for MSA is an important issue.

In this paper, we propose a Bayesian Network (BN)-based [39] high-level information fusion framework [21]–[23] to integrate and fuse multimodal psychological and physiological data into unique MS indices for evaluating a user's MS. In the proposed framework, we consulted the clinical experience of psychiatrist at Taipei Medical University Hospital to define the conditional probability of the BN and conduct experiments on volunteers to evaluate the performance of the proposed fusion technique. The results indicate that multimodal high-level information fusion can be suitably applied in the fusion of psychological and physiological data. A more noticeable improvement is achieved in the evaluation of the MS when using the proposed framework than when using only a single assessment method.

The contributions of the study are as follows.

1) A novel multimodal high-level information fusion framework is developed to fuse psychological and physiological data for MSA.
2) A BN is constructed to infer multimodal data for MS assessment.
3) The results of the experiments, which is conducted to evaluate the performance of the proposed framework, revealed that a more noticeable improvement in MSA is achieved when using the proposed framework than when using a single assessment method.

In this paper, there are many acronyms. In order to make it easier for readers to read, we collect these acronyms into Table 1.

The remainder of this paper is organized as follows. Section II includes a description of related studies and the background of this research. Section III presents the proposed framework for fusing multimodal information. Section IV includes the experimental design, results, and discussion. Finally, Section V presents the concluding remarks and scope for future research.

[2]https://www.moodtracker.com
[3] https://www.facebook.com/MoodKit/

TABLE 1. Meaning of the acronyms used in the paper.

Acronyms	Meaning of the acronym
MSA	Mood State Assessment
BN	Bayesian Network
MMC	Monthly Mood Chart
HRV	Heart Rate Variability
EEG	electroencephalogram
DS	Depressive State
HAM-D	Hamilton Depression Scale
MDD	Major Depressive Disorder
CPT	Conditional Probability Tables
SDNN	standard deviation of all NN intervals
RMSSD	square Root of the Mean of the Sum of the Squares of Differences between adjacent NN intervals
MSI	Mood State Indices
SD	Standard Deviation

II. BACKGROUND AND RELATED WORK

This section describes the background of this research (including the use of the HRV and EEG for MSA) and well as related studies.

A. PHYSIOLOGICAL DATA FOR MS EVALUATION

1) EEG FOR MSA

EEG can be used as a significant indicator of the MS [15]. According to previous reports, a person's relaxation level may be related to the alpha wave. A strong alpha wave is expressed as a low brain behavior index. Stable alpha behavior indicates high brain activity [40]. The beta wave, on the other hand, is associated with the state of thought, which is prominent in frontal cortex and the surrounding area. According to [41], the beta/alpha ratio may reflect the mood and identified depressive situation. A low beta/alpha ratio indicates a low rate of negative emotions, whereas a high rate is a reflection of the active state. In addition, the alpha and beta activities of depressed patients and those of healthy subjects are compared in [42], and the results indicated that the depressed patients are found to have more alpha and beta activities.

In [43], the authors conducted experiments and claimed that the alpha waves of a person (measured using EEG) may serve as a biomarker in differentiating healthy and depressed people in the future. In addition, Hinrikus *et al.* [44] used the spectral asymmetry (SA) of the EEG spectrum to distinguish depressive and healthy subjects. They claimed that the SA values are positive for depressive subjects and negative for healthy subjects. The authors of [45] reported that depressed patients exhibited an increased overall relative beta power. Furthermore, they observed that depressed patients exhibited an increased absolute beta power and higher mean of the total spectrum frequency at the bilateral anterior regions. The aforementioned studies indicate that EEG can be used to evaluate the MS of people with depression.

2) HRV FOR MSA

The HRV is used to assess the autonomic nervous system, which can be divided into two systems: the sympathetic system and the parasympathetic system. HRV analysis can be divided into two types: time-domain analysis and frequency-domain analysis. In time-domain analysis, the adjacent R wave represents the cycle of the heartbeat, and the R–R interval represents the heartbeat period (Fig. 1). The heartbeat period can also be calculated based on a normal-to-normal (NN) interval when the normal heartbeats are emphasized [46]. In clinical practice, the most commonly used time-domain analyses are the standard deviation of all NN intervals (SDNN), standard deviation of average NN intervals index, and square root of the mean of the sum of the squares of differences between adjacent NN intervals (RMSSD).

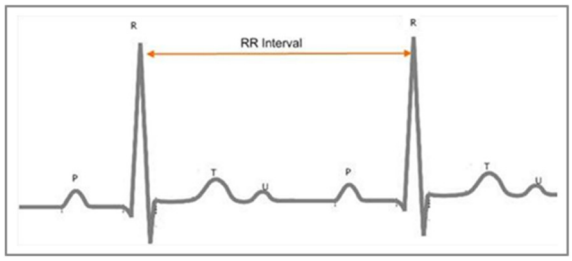

FIGURE 1. R–R interval of an electrocardiogram [20].

The factors highly correlated with the HRV include heart rate, age, circadian rhythm, and acute psychological stress. As mentioned in [47], high-frequency HRV analysis is usually used to predict major depression in patients. Pizzi *et al.* [48] claimed that depression and the HRV have independent relevance and may increase the possibility of a patient suffering from heart disease. Agelink *et al.* [49] demonstrated that there exists a significantly negative correlation between the Hamilton Depression Scale (HAM-D) scores and the vagal HRV indices, which suggests a direct association between the severity of depressive symptoms and modulation of cardiovagal activity. The authors of [50] have conducted experiments to assess the feasibility of using HRV biofeedback to treat moderate and severe depression. They reported that the HRV biofeedback appears to be a useful adjunct for the treatment of depression, which is associated with increases in HRV. The authors of [51] and [52] have highlighted that physically healthy patients with mood and anxiety disorders and alcohol dependence display reduced HRV. Thus, the lower the HRV, the more likely is the occurrence of depression. The authors of [53] claimed that patients with major depressive disorder (MDD) exhibit decreased HRV. They suggested that the reduction in the HRV is a psychophysiological marker of MDD. Patients with MDD and comorbid generalized anxiety disorder exhibit the highest reductions in the HRV.

There exist various methods for MSA, but the use of a single assessment method may affect the reliability of assessment. Therefore, a high-level information fusion technique is used in this study to fuse the signals extracted from tools so as to obtain a unified MS score. Table 2 summarizes the existing work and used tool for MSA. Our proposed method exploits the fusion method expecting to improve the reliability.

TABLE 2. Existing works and its tool for MSA.

Existing Study	MMC	HRV	EEG
MoodTracker	V		
Moodkit	V		
Peng et al. [41]			V
Begić et al. [42]			V
Kan et al. [43]			V
Hinrikus et al. [44]			V
Knott et al. [45]			V
Rottenberg et al.[47]		V	
Pizzi et al. [48]		V	
Agelink et al. [49]		V	
Siepmann et al. [50]		V	
Kemp et al. [51]		V	
Nahshoni et al. [52]		V	
Chen et al. [53]		V	
Proposed method	V	V	V

Since the MMC, EEG, and HRV have different ways to evaluate MSA, there are also different models of data representation. In order to achieve high-level information fusion, we first translate emotion-related attributes (Mood state, Irritability, Anxiety, Energy, Sleep) in the MMC into numerical data at different scales. The HRV and EEG attributes are also calculated as numerical data according to its characteristic. We then set up different conditional probabilities based on the advice of the professional physician. Finally, we use BN to derive possible probability values.

The following subsection demonstrates how the high-level information fusion is obtained using BN.

B. BAYESIAN NETWORK

A Bayesian Network (BN) is a probabilistic graphical model (a statistical shape model) that displays the dependencies of a random variable through a directed acyclic graph [39]. The basic element of a BN is a random variable, which is considered as an initial event in an unknown environment.

In general, the Bayesian theorem is used to determine the probability of tracing the causes, that is, the a priori probability. The Bayesian classifier assumes that all variables (property) are useful for the classification and that these variables are independent of each other. A BN allows us to specify certain properties subject to conditional independence. A BN has two important elements: the directed acyclic graph that displays the correlation dependencies between variables and the probability table records for each node and its immediate parent nodes [54].

In a BN, each node represents a variable in the Bayesian sense. The represented variables may be observable quantities, latent variables, unknown parameters, or hypotheses. Each edge represents a dependency relationship between two variables, where unconnected nodes represent variables that are conditionally independent of each other. Each node is associated with a probability function, the input of which is a particular set of values for the node's parent variables and the output of which is the probability of the variable represented by the node. The conditional dependencies in the graph are often estimated using known statistical and computational methods. For discrete random variables, the conditional probabilities are often represented by a table, which lists the local probability that a child node takes each of the feasible values for each combination of values of its parents. The unique joint distribution of a collection of variables can be determined using such local conditional probability tables (CPTs). The joint probability of several variables can be calculated from the product of the individual probabilities of the nodes, which are calculated using Eq. (1). A formal definition of a BN is given in [42].

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | parent(X_i)) \tag{1}$$

Although there are other ways to fuse three multimodalities, such as weighted voting or multimodal neural networks [61], [62], [63], the reason for using the current method in this study is that the BN method is similar to weighted voting because each piece of information has its own probability. As for the method that does not use Artificial Neural Network (ANN), it is because data collection is not so easy. At this stage, it is impossible to collect a large amount of information to train the neural networks model. Therefore, the method of ANN is not suitable for training the model before collecting more data.

III. BN-BASED PHYSIOLOGICAL AND PSYCHOLOGICAL INFORMATION FUSION

A. BN MODELING

The fusion of multimodal information (information from MMC, HRV, and EEG) into unique indices involves the construction of a BN and the determination of the associated conditional probability of one factor on another for inferring the MS score (e.g., conditional probability of anxiety for depression). In this study, CPTs are created according to references [55], [56], [57] and [24] as well as suggestions and reports from psychiatric physicians at Taipei Medical University Hospital. We consulted professionals about how the conditional probabilities should be determined. In addition, to simplify the complexity of DS inference, we assumed the factors to be independent. The BN is modeled as displayed in Fig. 2. The following subsections present the BN modeling for the three types of information considered. Below are the three types of BN modeling for information fusion.

B. DEPRESSIVE STATE (DS) MODELING FOR THE MMC DATA

The MMC comprises five major factors: the MS, irritability, anxiety, energy, and hours of sleep associated with a DS. The data are represented as numerals ranging from 1 to 5 or from −3 to 3. The purpose of converting these parameters of anxiety, irritability, and energy to numbers is mainly to facilitate the inference of adding these parameters to the BN. It can help the experiment more easily than without convert.

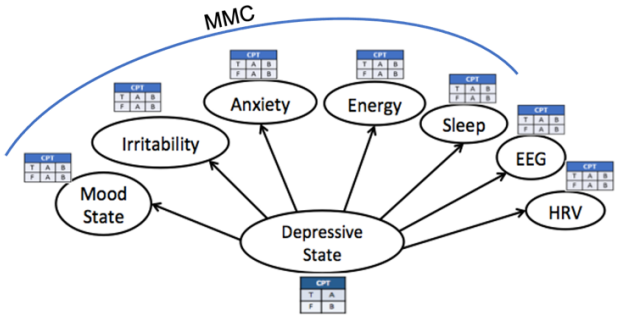

FIGURE 2. Modeling the BN for fusing psychological and physiological data.

TABLE 3. (A) DS probability for sleep hours. (B) DS probability for anxiety. (C) DS probability for irritability. (D) DS probability for energy. (E) DS probability for the MS.

(A)

Depressive State	< 6 Hours	> 6 Hours
T	0.8	0.2
F	0.2	0.8

(B)

Depressive State	0-2	3-5
T	0.25	0.75
F	0.8	0.2

(C)

Depressive State	0-3	4-5
T	0.67	0.33
F	0.9	0.1

(D)

Depressive State	0-2	3-5
T	0.8	0.2
F	0.5	0.5

(E)

Depressive State	+3	+2	+1	0	-1	-2	-3
T	0.0	0.0	0.0	0.1	0.35	0.35	0.2
F	0.0	0.01	0.09	0.8	0.04	0.04	0.02

And after consulting the psychiatrist, we defined the probability of the DS being caused by various factors according to psychiatrists' experience (Table 3(A)–(E)) because the MMC has been used for diagnosis of depression for many years.

C. DS MODELING FOR THE HRV DATA

In this modeling, we adopted the SDNN to analyze the HRV and conducted experiments to evaluate the SDNN value for determining the probability of a factor causing a DS. The authors of [58] presented the estimated mean values (standard error) in terms of the SDNN for subjects with MDD and healthy subjects [mean = 33.71 and 38.57, respectively; standard deviation (SD) = 2.23 and 2.22, respectively]. Two observations can be made from the results. First, most of the HRV values of healthy subjects are larger than those of the subjects with MDD. Therefore, we assume that the larger the HRV, the lower is the probability of the DS. Second, from the statistics of [59], the HRV values had roughly a Gaussian distribution. Therefore, we could calculate the probabilities of the DS and healthy state by using Eq. (2).

$$f\left(x|\mu,\sigma^2\right)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \tag{2}$$

where μ is the mean and σ is the SD. According to the aforementioned two observations, we can deduce the following: The lower the HRV, the higher is the value of P(HRV|DS = True), and the higher the HRV, the higher is the value of P(HRV|DS = False). For example, P(HRV = 33|DS = True) = 0.17005645143 and P(HRV = 33|DS = False) = 0.00771947569, whereas P(HRV = 39|DS = True) = 0.01073119717 and P(HRV = 39|DS = False) = 0.17636415613.

D. DS MODELING FOR THE EEG DATA

To model the DS for the EEG data, we adopted the SA of the EEG spectrum (from the method of Hinrikus *et al.* [44]) to distinguish between depressive and healthy subjects. The SA is defined as follows:

$$SA=\frac{W_{hmn}-W_{lmn}}{W_{hmn}+W_{lmn}}$$

where W_{lmn} refers to the lower EEG frequency band $(\theta-\alpha)$ and W_{hmn} refers to the higher EEG frequency band $(\gamma-\beta)$. Both of the frequency bands are expressed in Hz.

In [30], the authors claimed that the SA value is positive for subjects with depression and negative for healthy subjects. Therefore, we consulted the professional psychiatrist and defined the probability of the DS for EEG's SA (Table 4).

TABLE 4. DS probability for The EEG data.

Depressive State	>0	<0
T	0.67	0.33
F	0.22	0.78

TABLE 5. DS probability.

Depressive State	
T	0.2
F	0.8

Finally, we consulted a psychiatrist regarding the definition of the conditional probability of the DS in the BN. According to the psychiatrist's experience, the ratio between the number of subjects in the depressive and healthy states is approximately 1/4. The conditional probability table is presented in Table 5. We therefore adopted Tables 3–5 to infer the DS from the given parameters. An illustration will be used to demonstrate how the inference can be validly performed.

E. INFERENCE OF MS INDICES (MSI) BY USING A BN

According to the aforementioned modeling, a BN is used to fuse multimodal psychological and physiological data for inferring the MSIs. To compute the probability of obtaining the MS, we extended Eq. (1) into Eq. (3), as shown at the bottom of the page, for MS inference, where X_{DS} (the probability of the DS in Fig. 2) is the inferred DS, which is calculated in the BN by using the CPT of all the nodes; X_i is the node associated with the DS, and X_i is the associated probability. X_i may be one of following nodes: MS, irritability (I), anxiety (A), energy (E), sleep (S), EEG (SA), or HRV (H) (Fig. 2).

The following example illustrates how the probability or MSIs can be obtained. Consider the following psychological and physiological data for a person: MS $= -1$, I $= 1$, E $= 2$, A $= 2$, S $= 8$, H $= 33$, and EEG (SA) $= 0.275$. The probability of the DS can be calculated as equation, shown at the bottom of the page.

IV. EXPERIMENTAL DESIGNS, RESULTS AND DISCUSSION

A. EXPERIMENTAL DESIGNS

For the experiments, a mood chart app is built using HTC Butterfly with Android 4.4.2. a NeuroSky Mindwave[4] Mobile is used as the EEG recorder, and a Fitbit Charge HR[5] is used as the HRV recorder.

For the evaluations, initially we tried to adopt a well-known dataset to evaluate the performance of proposed framework. But after examining some datasets exhaustedly, we decided to develop a more efficient fusion process we need, so that we can get personal MMC (Mood state, Irritability, Anxiety, Energy, and Sleep), EEG, and HRV from the same individual at the same time. There is no given dataset that includes these three kinds of data simultaneously. If these data are not obtained as we stated, we could not fuse the data together. Therefore, in the work we could only test the performance of the proposed framework using two data sets we collected as follows. 1) Twenty students are invited and categorized into two groups, namely groups A and B. The 10 students in group A had been struggling to obtain their MS degree for a few months. They expressed that they often felt depressed in the past few months. In group B, the 10 students either had just started their MS studies or are undergraduate students. These students expressed that they felt normal in the past few months. The detailed information of the subjects is presented in Table 6. 2) In order to strengthen the results, we have added another new experiment. The data of this experiment is collected from mentally abnormal patients in the hospital of Taipei Medical University. We collected 40 data from

[4] https://store.neurosky.com

[5] https://www.fitbit.com/tw/home

$$
\begin{aligned}
&P\left(X_{MS} = True | X_i = x_i, each\ X_i\ symptom\ that\ patient\ has\right) \\
&= \frac{P\left(\begin{array}{l} X_{DS} = True, X_i = x_i, for\ all\ symptoms\ X_i\ of \\ Depressive\ State \end{array}\right)}{P\left(X_i = x_i, all\ x_i\ is\ all\ nodes\ of\ BN\ of\ Depressive\ State\right)} \\
&= \frac{\begin{array}{l} P\left(X_{MS}|DS = T\right) P\left(X_I|DS = T\right) P\left(X_E|DS = T\right) P\left(X_A|DS = T\right) \\ P\left(X_S|DS = T\right) P\left(X_H|DS = T\right) P\left(X_{SA}|DS = T\right) P(DS = T) \end{array}}{\begin{array}{l} P\left(X_{MS}|DS = T\right) P\left(X_I|DS = T\right) P\left(X_E|DS = T\right) P\left(X_A|DS = T\right) \\ P\left(X_S|DS = T\right) P\left(X_H|DS = T\right) P\left(X_{SA}|DS = T\right) P\left(DS = T\right) \\ +P\left(X_{MS}|DS = F\right) P\left(X_I|DS = F\right) P\left(X_E|DS = F\right) P\left(X_A|DS = F\right) \\ P\left(X_S|DS = F\right) P\left(X_H|DS = F\right) P\left(X_{SA}|DS = F\right) P(DS = F) \end{array}}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
&\frac{\begin{array}{l} P\left(MS = -1|DS = T\right) P\left(I = 1|DS = T\right) P\left(E = 2|DS = T\right) \\ P\left(A = 2|DS = T\right) P\left(S = 8|DS = T\right) P\left(H = 33|DS = T\right) \\ P\left(SA = 0.275|DS = T\right) P(DS = T) \end{array}}{\begin{array}{l} P\left(MS = -1|DS = T\right) P\left(I = 1|DS = T\right) P\left(E = 2|DS = T\right) \\ P\left(A = 2|DS = T\right) P\left(S = 8|DS = T\right) P\left(H = 33|DS = T\right) \\ P\left(SA = 0.275|DS = T\right) P\left(DS = T\right) + P\left(MS = -1|DS = F\right) \\ P\left(I = 1|DS = F\right) P\left(E = 2|DS = F\right) P\left(A = 2|DS = F\right) \\ P\left(S = 8|DS = F\right) P\left(H = 33|DS = F\right) P\left(SA = 0.275|DS = F\right) \\ P(DS = F) \end{array}} X100\% \\
&= \{[0.35 \times 0.67 \times 0.8 \times 0.25 \times 0.2 \times 0.62490379 \times 0.67 \times 0.2] \\
&\quad /[(0.35 \times 0.67 \times 0.8 \times 0.25 \times 0.2 \times 0.62490379 \times 0.67 \times 0.2) \\
&\qquad + (0.04 \times 0.9 \times 0.5 \times 0.8 \times 0.8 \times 0.00605352 \times 0.22 \times 0.8)]\} \times 100\% \\
&\approx 98.47\%.
\end{aligned}
$$

TABLE 6. Detailed information of the groups of subjects.

Parameter	Group A	Group B
Subjects	10 students	10 students
Claimed state	Depressive	Not depressive
Age (average)	23-30 (26.1)	20-24 (22.7)
Gender (male/female)	8/2	8/2

20 people. The age is distributed during 23-60 years old. Twenty patients who suffered from (moderate or severe) MDD and are diagnosed to have improved after treatment are also invited. Their psychological and physiological information before and after the effective treatment are collected for comparisons in the experiment. In addition, the temporal information serves as important attribute while adopting BN to fuse various models of physiological and psychological data. The temporal information is not dealt with in these experiments because it could be ignored if the MMC, EEG, and HRV are collected at the same time.

There is a total of five types of psychological information and two types of physiological information that are considered to be associated factors of the depressive MS. The psychological information included self-reported MS, degree of irritability, degree of anxiety, degree of energy, and hours of sleep; and the physiological information included EEG signals and HRV signals. In the experiment, all the psychological information is reported through a mood chart template provided by the psychiatrist. The MS is rated from -3 to 3, whereas anxiety, irritability, and energy are rated from 0 to 5. EEG signals are collected during a 15-minute period according to the SA method [44]. As reported in [44], positive and negative SA values indicated the presence and absence of the DS with high probabilities. HRV signals are collected in the same 15-minute period as the EEG signals. The HRV signals are collected according to the SDNN method. Clinical studies have reported that the HRV values of people with depression are smaller than those without depression [49], [53].

The novel MSI proposed in this experiment is referred to as 7-M Bayesian fusion. To demonstrate the advantages of the proposed MSI, it is compared with traditional indices (such as the subject's self-reported state, EEG, and HRV) and other indices that fused only a part of data (called the 3-M voting fusion, 3-M Bayesian fusion, and MC Bayesian fusion, which will be explained in details later). These newly-developed indices evaluated the presence or absence of the DS in subjects according to different measurements.

(1) Self-reported state: This index is based on the reported MS in the mood chart.

(2) EEG (SA): According to [44], the sign of the SA values is used to evaluate the presence or absence of the DS.

(3) HRV (SDNN): This index is solely based on the conditional probability distributions of the HRV given the presence or absence of the DS.

(4) 3-M voting fusion: This index is based on the voting results of the reported MS, EEG signals, and HRV signals.

(5) 3-M Bayesian fusion: In this index, the judgments of the reported MS, EEG signals, and HRV signals are fused according to the BN theory.

(6) MC Bayesian fusion: In this index, the judgments of the five types of psychological information reported in the mood chart are fused according to the BN theory.

Indices (1) – (3) rely on pure measurements, whereas indices (4) – (6) rely on fusion results.

For quantitative comparisons, all the aforementioned indices are evaluated according to the following aspects:

1) Positive predictive value (generally known as the precision)

$$Positive\ predictive\ value = \frac{\sum true\ positive}{\sum test\ outcome\ positive}.$$

2) Negative predictive value

$$Negative\ predictive\ value = \frac{\sum true\ negative}{\sum test\ outcome\ negative}.$$

3) Sensitivity (also known as the recall)

$$Sensitivity = \frac{\sum true\ positive}{\sum condition\ positive}.$$

4) Specificity

$$Specificity = \frac{\sum true\ negative}{\sum condition\ negative}.$$

5) Accuracy

$$Accuracy = \frac{\sum true\ positive + \sum true\ negative}{\sum total\ population}.$$

6) f1 score

$$f1score = \frac{2 \times precision \times recall}{precision + recall}.$$

B. RESULTS

First, we show the results regarding the first data set from different aspects. Table 7 presents the collected psychological and physiological information. The information in the first three columns represents the measurements of the three single-function models used for the judgment of the presence or absence of the DS. The information in the remaining columns is used as a reference. As expected, the distributions of the measured indices are different for the two groups. In group A, six subjects explicitly said that they felt depressed and five subjects had SA values smaller than 0. The SDNN of all the 10 subjects is significantly deviated from the normal mean value [58]. On the other hand, in group B, no subjects reported feelings of depression. Only one subject had an SA value smaller than 0, and the SDNN of five subjects is marginally biased away from the normal mean value.

Fig. 3 illustrates how the four indices: (a) 3-M voting fusion, (b) 3-M Bayesian fusion, (c) MC Bayesian fusion, and (d) 7-M Bayesian fusion revealed the possibility of which

TABLE 7. Psychological and Physiological measurements of two groups of graduate students.

User ID	Self-Reported State	EEG (SA)	HRV (SDNN)	Irritability	Anxiety	Energy	Hour of Sleep
A1	-2	1.00E-01	11.19025467	3	4	2	5
A2	-1	0.216062	23.00478557	0	4	2	5
A3	-1	-0.01448	13.13810573	4	3	1	6
A4	-2	0.081124	13.47687768	1	3	2	5
A5	0	-0.0995	8.822521139	1	1	3	6
A6	1	-0.0856	8.951154776	1	1	3	6
A7	0	-0.00012	18.54319975	2	1	1	5
A8	-1	0.01954	14.65132727	0	2	2	5
A9	1	-0.01988	12.25906973	0	1	5	7
A10	-1	0.12551	12.86327976	2	2	1	4
B1	2	-0.342218	33.69981654	1	1	4	6
B2	2	-0.01195	53.93400489	0	1	1	7
B3	0	-0.0954	32.81963344	0	1	3	5
B4	1	-0.09514	34.24290013	1	1	4	6
B5	0	0.00442	30.38283064	1	0	1	2
B6	1	-0.1477	55.46981763	0	1	2	7
B7	0	-0.05014	38.28137837	1	0	3	7
B8	0	-0.0884	55.50628488	0	1	2	5
B9	0	-0.344512	33.46209636	1	1	3	6
B10	0	-0.45186	28.5810553	0	1	4	8

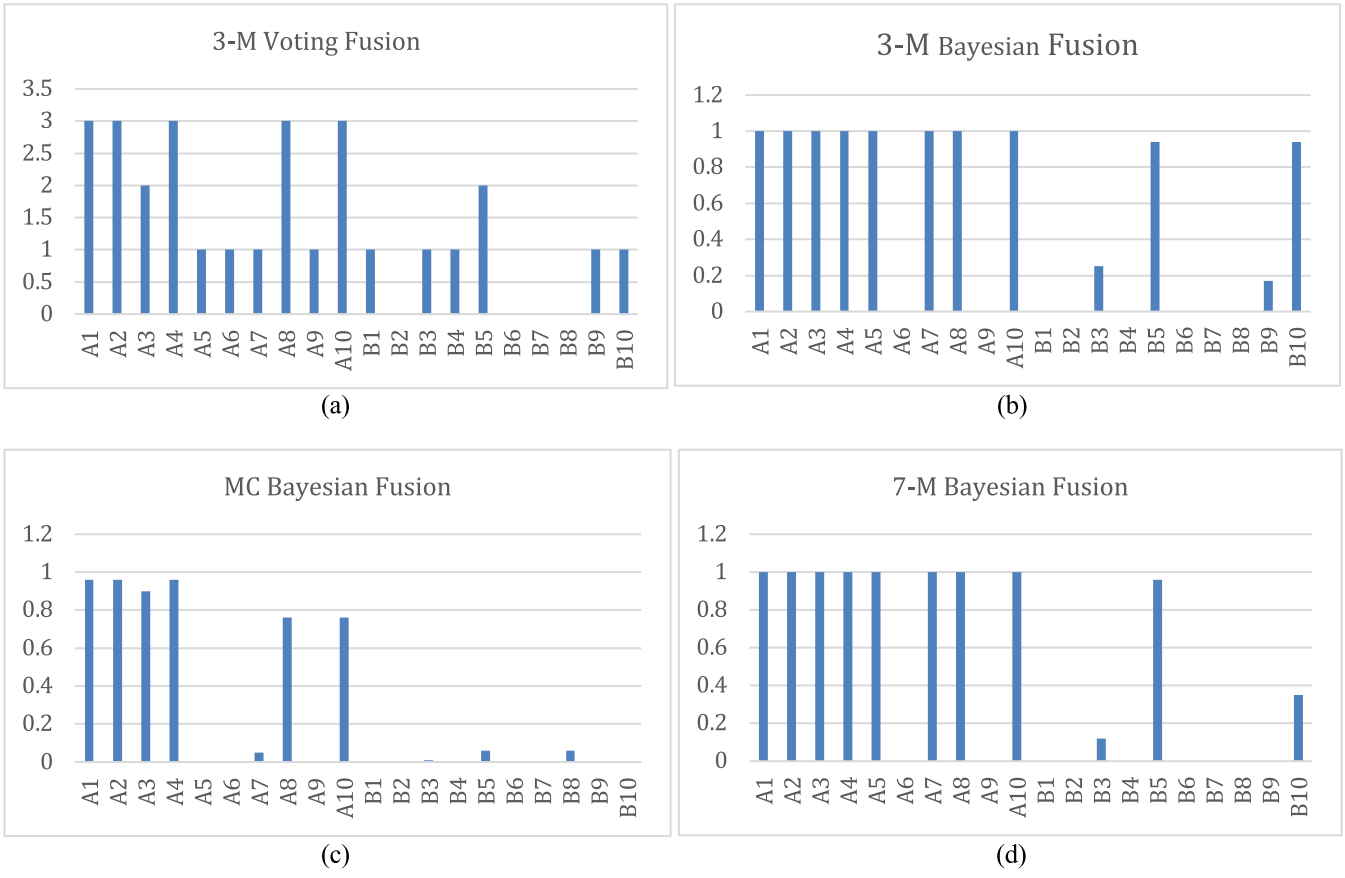

FIGURE 3. Psychological and physiological measurements.

subject in the two groups might be in the DS. The indices depending on pure measurements as well as the index of 3-M voting fusion (Fig. 3(a)) tended to exhibit a high percentage of subjects falling in the area indicating high possibility of the DS. However, the presence or absence of the DS could not be clearly determined by the existing models. On the other hand, the indices fusing multiple measurements according to using) the BN theory (Fig. 3(b)–3(d)) provided highly reliable probabilities that clearly indicated the presence or the absence of the DS.

TABLE 8. Quantitative performance comparisons among reported state, EEG signals, HRV signals, 3-M voting fusion, 3-M Bayesian fusion, MC Bayesian fusion, and 7-M Bayesian fusion on the first data set.

Index	Positive Predictive Value	Negative Predictive Value	Sensitivity (Recall)	Specificity	Accuracy	F1 Score
Self-Reported State	1	0.7143	0.6	1	0.8	0.75
EEG (SA)	0.8333	0.6429	0.5	0.9	0.7	0.625
HRV (SDNN)	0.625	1	1	0.4	0.7	0.7692
3-M Voting Fusion	0.8571	0.6923	0.6	0.9	0.75	0.7059
3-M Bayesian Fusion	0.8	0.8	0.8	0.8	0.8	0.8
MC Bayesian Fusion	1	0.7143	0.6	1	0.8	0.75
7-M Bayesian Fusion	0.8889	0.8182	0.8	0.9	0.85	0.8421

The presence of a DS is assumed if the self-reported mood state had a value smaller than 0, the EEG had an SA value smaller than 0, the HRV had an SDNN value with a higher probability for the presence of the DS than that for its absence, 3-M voting fusion (Fig. 3(a)) had at least two votes for the presence of the DS, and the Bayesian-fusion-based (Fig. 3(b)–3(d)) indices deduced the presence of the DS with a probability larger than 0.5. Table 8 compares the quantitative performances of these indices from the following six aspects: the positive predictive value (precision), negative predictive value, sensitivity/recall, specificity, accuracy, and f1 score. In terms of the positive predictive value, the self-reported mood state and MC Bayesian fusion exhibited the highest value, 7-M Bayesian fusion exhibited the second-highest value, and HRV exhibited the lowest value. In terms of the negative predictive value, the HRV had the highest value, 7-M Bayesian fusion had the second-highest value, and EEG exhibited the lowest value. In terms of the sensitivity or recall, the HRV had the highest value, 3-M Bayesian fusion and 7-M Bayesian fusion exhibited the second-highest value, and EEG exhibited the lowest value. In terms of the specificity, the self-reported state and MC Bayesian fusion exhibited the highest value; EEG, 3-M Bayesian fusion, and 7-M Bayesian fusion exhibited the second-highest value; and HRV exhibited the lowest value. In terms of the accuracy, 7-M Bayesian fusion exhibited the highest value; the self-reported state, 3-M Bayesian fusion, and MC Bayesian fusion exhibited the second-highest value; and the EEG and HRV exhibited the lowest values. In terms of the f1 score, 7-M Bayesian fusion exhibited the highest value, 3-M Bayesian fusion exhibited the second-highest value, and the EEG exhibited the lowest value. Overall, 7-M Bayesian fusion exhibited the best or the second-best performance for all of the six aspects, which indicated the advantages of using the BN theory to fuse psychological and physiological information.

Next, Table 9 compares these indices in evaluating the improvement of depression for the subjects in the second data set. As these indices reveal the possibility of a subject in the DS according to the psychological and/or physiological information, a subject might be said to have improved if the possibility decreases after the treatment. 7-M Bayesian fusion has the best performance, and Self-Reported State, 3-M Bayesian Fusion, and MC Bayesian Fusion follow and are comparable. EEG (SA) exhibited the lest value, which is even smaller than 0.5.

TABLE 9. Comparisons in evaluating the improvement of depression.

Index	Precision
Self-Reported State	0.75
EEG (SA)	0.25
HRV	0.55
3-M Voting Fusion	0.5
3-M Bayesian Fusion	0.75
MC Bayesian Fusion	0.75
7-M Bayesian Fusion	0.8

C. DISCUSSION

In this study, we proposed a fusion technique for determining MSIs by using both psychological and physiological information. As reported in previous study [60], the presence of the DS generally tends to affect the psychological and physiological information of a person to different degrees. Thus, as presented in Table 7, the MSIs based on different types of information may provide inconsistent results regarding the presence of the DS. For example, the indices using the mood chart, EEG, and HRV reported inconsistent judgment for subjects A3, A5–A7, A9, B1, B3–B5, B9, and B10. However, to the best of our knowledge, limited research has been conducted on how to suitably integrate the judgment of these indices. In reality, the final judgment highly relies on psychiatrists' experiences. Consequently, for the same subjects, psychiatrists with different experiences may report inconsistent judgments. Many psychiatrists have used measurements such as the irritability, anxiety, energy, and hours of sleep (Table 7) as references. Nevertheless, situations in which inconsistent results are obtained always cause confusion to subjects and sometimes to psychiatrists as well. Therefore, the fusion technique for determining MSIs by using both psychological and physiological information can solve the problems mentioned above.

In addition, the results displayed in Fig. 3 indicate the usefulness of MSIs that fuse multiple measurements. For the inconsistency problem, naive 3-M voting fusion (Fig. 3(a)), which is based on the votes of three judgments, is an effective solution. This index provides expected judgments in

most cases. However, the degree or risk of the presence of the DS obtained with naive 3-M voting fusion is somewhat inaccurate. For example, according to the naive 3-M fusion index, subjects A5–A7 and A9 had an equal degree or risk of DS (Fig. 3(a)). However, the self-reported MS and other measurements (i.e., irritability, anxiety, energy, and hours of sleep) for A6 and A9 had higher values than those for A5 and A7. Similarly, subjects B1, B3, B4, B9, and B10 are also reported to have an equal degree or risk of the DS according to the naive 3-M fusion index; however, the self-reported MS and other measured values for B1 and B4 are higher than those for the other subjects. This inaccuracy is observed because the naive 3-M voting fusion method (1) treated the judgments of the self-reported state, EEG signals, and HRV signals equally and (2) did not consider the referring measurements (i.e., the irritability, anxiety, energy, and hours of sleep). The comparisons between naive 3-M voting fusion and 3-M Bayesian fusion (Fig. 3(a) and (b), respectively) supported the first point. According to the 3-M Bayesian fusion index, the risk or possibility of DS for subjects A6 and A9 is smaller than that for subjects A5 and A7. Furthermore, subjects B1 and B4 had a smaller risk or possibility of being in the DS than subjects B3, B9, and B10 did.

The results of this experiment indicated the advantage of Bayesian fusion over naive voting fusion, which met our expectation. Moreover, the comparisons between 3-M and 7-M Bayesian fusion (Fig. 3(b) and (d), respectively) supported the second point explaining the inaccuracy of naive 3-M voting fusion. 3-M and 7-M Bayesian fusion reported similar judgments for most of the cases except B5 and B10. In Fig. 3(b), B5 and B10 are judged to have a similar risk of falling in the DS, whereas in Fig. 3(d), B5 is judged to have a higher risk than B10. According to the measurements shown in Table 8, 7-M Bayesian fusion provided more accurate results than 3-M Bayesian fusion did. These results indicated that referring to the measurements of the irritability, anxiety, energy, and hours of sleep for judgments is helpful. In addition, the comparisons between the MC Bayesian fusion and 7-M Bayesian fusion (Fig. 3(c) and 3(d), respectively) indicated the advantages of considering physiological information, such as EEG and HRV signals, in the judgment of the presence of the DS. In particular, 7-M Bayesian fusion identified the presence of the DS in subjects A5 and A7; however, MC Bayesian fusion (Fig. 3(c)) could not identify the presence of DS in the same subjects. The self-reported state of A5 and A7 is 0, which indicated that the subjects are unaware of their depression.

Thus, the physiological information is important for determining the presence or absence of the DS. Subject B5 said that he/she did feel depressed in the past few months. As expected, his/her psychological and physiological measurements deviated from normal values and indicated a high potential for being in the DS. Thus, physiological information (i.e., the EEG and HRV signals) can indicate the presence of the DS, especially when a person does not understand their MS. In summary, the aforementioned results indicated the advantages of our system, including the advantages of using (1) Bayesian fusion (Fig. 3(b)-3(d)) over the naive voting fusion and (2) psychological2021-10180 and physiological information fusion over a single type of information.

The comparisons presented in Table 8 provided profound insights into the indices using different fusion techniques for different kinds of information. First, the self-reported state tended to exhibit an improvement for the positive predictive value and specificity than for the negative predictive value and sensitivity/recall. This result is observed because the self-reported state indicated a person's awareness of the presence of the DS. If a person feels depressed, in most cases, they experience an MS of depression, which results in a high positive predictive value. On the other hand, if a person is not truly in a DS, they should not suffer from depression, which leads to a high specificity. Because the EEG and MC Bayesian fusion also reflected a person's consciousness, these two indices exhibited a good performance for the positive predictive value and specificity. By contrast, the HRV index also tended to exhibit improvement for the negative predictive value and sensitivity/recall because the HRV measures the physiological state of bodies. This leads to a high sensitivity/recall.

If tests on the physiological state of bodies report normal values, it usually indicates that the subject does not have a DS, which results in a high negative predictive value. 3-M voting fusion exhibited improvement for positive predictive value and specificity than for negative predictive value and sensitivity/recall due to its equal treatment of the self-reported state, EEG, and HRV. When the psychological and physiological information is treated with different weights and fused according to the Bayesian theory, 3-M Bayesian fusion and 7-M Bayesian fusion exhibit an equivalent performance in two aspects: positive predictive value and specificity/recall. These two indices exhibited the best performance in the accuracy and f1 score. 7-M Bayesian fusion always outperformed 3-M Bayesian fusion in all aspects of the evaluations because 7-M Bayesian fusion considered and fused more types of information than 3-M Bayesian fusion did.

Obviously, the accuracy is improved by (0.85-0.8)/$0.8 \times 100\% = 6.25\%$, and the F1 Score increased by $(0.8421-0.7692)/0.7692 \times 100\% = 9.48\%$, which shows that this has a good improvement. It can be used for improving the mood state inference.

In addition, according to the statistics of [59], the HRV values have roughly a Gaussian distribution. Therefore, if the HRV value is between two means (such as between 33.71 and 38.57), the probability of DS state will be approaching 0.5. This will be difficult to distinguish the DS state if the HRV is between 33.71 and 38.57. Such case will increase the error rate and decrease the inference accuracy; and decrease the inference performance of full system accordingly.

Besides, because the mean of HRV of MDD subject is 33.71 and the SD is 2.23, the mean of HRV of Healthy subject is 38.57 and the SD is 2.22. If the HRV value is in between the means of MDD subjects and of healthy subjects, the certainty

of DS becomes more confusing. In other words, if the HRV value is between 35.94 (33.71 + 2.23) and 36.35 (38.57 − 2.22), it will cause the confusion error of BN inference, and decrease the inference performance accordingly.

As mentioned above, exploiting HRV data to model DS state may have the confusion error of BN inference. Therefore, the proposed framework makes use of high-level information fusion to improve the inference performance. When HRV data may cause inference confusion error, there are two kinds of information in this framework that can improve this problem.

Furthermore, as these indices can reveal the possibility of a subject in the DS, Table 9 shows a reliability that these indices might be used as a reference for the improvement of depression after treatment by comparing the possibilities before and after the treatment. From the results of this experiment, it indicates similar observations: 1) the advantage of Bayesian fusion over naive voting fusion, and 2) the physiological information is important for depression diagnosis. However, it also indicates that EEG (SA) can help the detection of the present of DS, but EEG (SA) alone is not sufficient for evaluating the depression degree, since the correlation among DS and EEG is not yet clear under the researches.

Finally, regarding to the computation complexity of the proposed method, this method mainly uses BN technology to fuse various information. The BN model used in the work has only one layer, so the computational complexity is relatively simple. The calculation of each test data is O(1).

V. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a high-level information fusion method for determining the MS of users by fusing physiological data, such as heart rate and brainwave information collected through a wearable device, and psychological data collected through a monthly mood chart. A hybrid cloud is used to collect, store, and fuse daily mood data and brain wave information from a private cloud as well as heart rate data from a public cloud. The fusion of multimodal data types ensured practicality and convenience for the user. Most importantly, the proposed method eliminated the need for spending considerable time in pre-integration for analyzing different patterns of different data types. It shows that to fuse these data and to infer the MS indicator with a probability value can provide doctors and other users a reliable reference. In addition, we also conducted experiments to evaluate the performance. The results revealed that there is a great improvement in MSA when using the proposed information fusion framework than when using only one single assessment method.

Since the methodology is a novel approach for assessing the MS, continuously improving the accuracy of assessments is an important mission. In the future, we would like to implement a cloud platform, combined with the Internet of Things, so that each user can collect psychologically and physiologically related data on a daily basis. Then, through precise analysis, each user can adjust the conditional probability to achieve better accuracy. We therefore plan to design a new system that can automatically collect, process, and analyze the collected user data in order to achieve the goal of precision medicine. This system requires a cloud platform, an Internet of Things that collects HRV and EEG information, and a user's APP. With these devices, users can collect relevant data by themselves.

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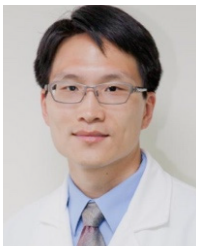

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