A NOVEL APPROACH OF HUMAN EMOTIONAL ESTIMATION SYSTEM VIA MULTISENSORY DATASETS FUSION METHODS

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ABSTRACT

Human emotional understanding has become one of the most rapidly emerging fields developed over the years since the emotional state is created and influenced by several neither easily measured and nor predicted factors. The proposed novel approach is based on the mixture of the processed acceleration data of several designed activities and processed heart rate data under several emotional states, recorded by the application of`smart band devices. Since the processed acceleration and heart rate data are running on different dimensionalities and recorded by different types of sensors, some machine learning-based methods applied to fusing these two kinds of data. The results of the data fusion methods are defined as the new fused datasets for Multi-Layer Perceptron and Support Vector Machines classifiers based on a selected criterion. At last, the accuracy results of the selected classifiers running under the defined machine-learning-based fusion dataset compared to each other to find out the effectiveness of the proposed fusion method.

Keywords: datasets fusion algorithm, emotional state estimation, human-robot interaction, heart rate variability, machine learning

I. INTRODUCTION

IN [12][14][15][17][19], the estimation of emotions is using classification methods (e.g., Support Vector Machines (SVM) and others) by involving several kinds of data like raw heart rate, HRV, skin conductance data; to estimate a limited number (e.g., 3 to 5) of emotional states, with the accuracy varying 57-84%. Based on our understanding, all previous works used the stimulated-user procedures by involving some emotion-induced videos and or music during the experimental tests with a data recording period of 3 hours up to 2 weeks.

A new parameter or feature measured on personal activity information is added to improve the performance of the human emotional state estimation system based on the knowledge of the person's movement correlated indirectly with the emotional states through the brain-heart autonomic nervous system (ANS) mechanism or by the heart rate management mechanism has unique personal patterns differ by activity based on the medical perspective [21]. Instead of using this feature only, a novel approach by combining it with the heart rate data on purpose to improve the effectiveness of the estimation system by applying some machine learning-based data fusion algorithms. Two methods of classifiers are used in this paper to find the effect of this mechanism on the activity, heart rate, and emotional states.

In the first proposed approach, some machine learning algorithms were applied for each dataset of accelerometer data together with the frequency domain-based HRV data to find the mutual information of the activity and emotional states, then fused these datasets under specific criteria. For the second proposed approach, two machine learning-based classifiers are used for this fusion dataset to find the accuracies of the fusion dataset on defined activity and emotional states. The proposed method's data was obtained via smart band under certain specific conditions in approximately 5 minutes of recording times by each participant and combined activity and emotional states.

II. METHODOLOGY

A. The Principles of the Relations of Physical Activity, Heart Rate Condition, and Emotional State

As described before, human physical activities are correlated indirectly with emotional states through the heart rate parameters by incorporating the autonomous nervous system (ANS) principles. This nervous system is a division of the peripheral nervous system that supplies smooth muscle and glands and influences the function of internal organs, controlled by the spinal cord parts of the human brain [31].

The autonomic nervous system is a control system that acts unconsciously and regulates bodily functions, such as the heart rate, digestion, respiratory rate, pupillary response, urination, and sexual arousal [32]. The integrated reflex regulates the autonomic nervous system through the brainstem to the spinal cord and organs. Autonomic functions include control of respiration, cardiac regulation (the cardiac control center), vasomotor activity (the vasomotor center), and reflex actions such as coughing, sneezing, swallowing, and vomiting. Those are then subdivided into other areas and linked to autonomic subsystems and the peripheral nervous system. The hypothalamus, just above the brainstem, acts as an integrator for autonomic functions, receiving autonomic regulatory input from the limbic system [33].

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The motor neurons of the brain-muscles nervous system influence human physical activities. Motor neurons of physical activity also belong to the autonomic nervous system founded in the autonomic ganglia sections. The ganglia parasympathetic branches are close to the target organ, while the ganglia of the sympathetic branch are close to the spinal cord. A single motor neuron may innervate many muscle fibers, where a muscle fiber can undergo many action potentials in the time taken for a single muscle twitch. The innervation process of the muscle fibers takes place at a neuromuscular junction. The muscle trembles can become superimposed in the interest of summation or a tetanic contraction. The individual muscle trembles can become indistinguishable [34].

Based on [34], the human spinal cords of the nervous system have different purposes and are segmented, where each connects to the specific parts of bodily movement-capable muscles in the human body. Based on the medical-based understanding described above, it could be found that physical activities are related to and influence heart rate conditions, including affecting the human emotional states in many conditions and situations.

B. The Principles of Heart Rate Variability Analysis

Heart Rate Variability (HRV) can be analyzed using several methods, including time-domain, frequency-domain, nonlinear, and time-frequency analysis methods [1, 2, 11, 15]. There are several methods for measuring heart rate measurement techniques based on smart wearable devices or smart device applications, and they mostly produce a time-based series of data. The most widely used method for measuring the heart rate signal is by monitoring and analyzing the differences of the applied electrodes' voltages in several positions of the user's chest as used in the electrocardiogram (ECG) device; and produces a heart rate signal under a specific time of measurement period. In this case, a specially trained person or a cardiologist is needed. The use of chest-placed measurement devices is omitted to eliminate the needs of the specially trained person or cardiologist and also to ease the uncomfortableness of the users. The change of the chest-placed sensors into a wrist-based measurement device such as the smart band or smartwatch with wireless connectivity capability improves both the flexibility and comfort of the user.

The change or variability of the heart rate for a given time is regarded as one of the most effective measures of autonomic nervous system function. In the part of the human nervous system, the autonomic nervous system consists of the sympathetic nervous and parasympathetic nervous systems. These systems act in tandem; the parasympathetic system slows down the blood circulation to the muscles, while the sympathetic system facilitates the blood circulation to the muscles. In other words, the sympathetic nerves allow our bodies to elevate responses under conditions of physical and mental stress. This situation would cause an increase in the heart rate. In contrast, parasympathetic nerves regulate body functions under relaxing conditions and therefore slow down the heart rate. This knowledge yields that the personal stress level is assessed based on the heart rate data [1, 4, 5].

The human heart rate is calculated by the number of heartbeats per minute or beats per minute (bpm) and changes over time according to the needs of the body. By emphasizing HRV as a priority measure, the HRV method could analyze the differences between each heart rate value or beat-to-beat variability during a specified time. HRV parameters apply as a measurement of how many times the heart rate changed or the differences in heart rate value during each period. There are two widely used methods to compute the HRV value [4, 5, 11], first by detecting the beat-to-beat intervals and secondly by computing time differences between the peaks of the heart rate (known as R-value) called R-R interval or inter-beat-interval (IBI).

In the implementation of the proposed human emotional estimation system, only the frequency-domain-based HRV analysis is used and described, where the frequency domain-based techniques convert this time-based series data into a frequency domain where a discrete Fourier transform for the non-parametric method or auto-regressive model estimation for the parametric methods applied.

The benefits of using the frequency-domain analysis compared with the time-domain analysis can be summarized as the spectral signal analysis could be used for analyzing some frequency oscillations that usually occur during the measurement periods, the spectral signal analysis involves the decomposition of the series of Inter-Beat Interval (IBI) or R-R interval into some differences in sinusoidal amplitudes and frequencies functions, and the result of signal analysis could be represented as the variability of the function of frequency (or as power spectrum), shows the fluctuations of heart rate amplitude in different oscillating frequency.

HRV analysis components in the frequency domain for the short-term recording could be divided into several categories such as:

- 5 minutes of total power (measured in ms^2)
- Very Low Frequency (VLF) components, where the range is ≤ 0.04 Hz (measured in ms^2)
- Low Frequency (LF) components, the range is 0.04 ~ 0.15 Hz (measured in ms^2)
- Normalized LF (LFnu) components is the normalized unit of the Low Frequency (LF) components, calculated $\frac{LF}{(TotalPower-VLF)} x100$ and measured in $n.u$
- High Frequency (HF) components, the range is 0.15 ~ 0.4 Hz (measured in ms^2)

- Normalized HF (HFnu) components is the normalized unit of the High Frequency (HF) components, calculated in $\frac{HF}{(TotalPower-VLF)}x100$ and measured in $n.u$
- LF/HF ratio, is the ratio of the Low Frequency (LF) components and High Frequency (HF) components, calculated $\frac{LF}{HF}ratio = \frac{(LF(ms^2))}{(HF(ms^2))}$

The LF/HF ratio shows the overall balance between the sympathetic and parasympathetic responses in the autonomic nervous system (ANS). A high value of this ratio shows the domination in the sympathetic system, meaning that there is a change in the emotional state. On the other hand, a lower value in this ratio shows the domination in the parasympathetic system or means there is little or no change in the emotional state [3].

HF power spectrum shows the parasympathetic response and fluctuations caused by spontaneous respiration called Respiratory Sinus Arrhythmia (RSA). In other words, the LF power spectrum shows the increased sympathetic response in the human autonomous nerve systems [1, 2]. The VLF power spectrum is defined as a representation of negative emotions, worry, and others [1, 2]. Based on the references and standards [1, 2, 3, 4, 5, 11], the minimum period or windowing for heart rate monitoring under HRV analysis is approximately 5 minutes and can be up to 24 hours.

III. Human Physiological Data Recording And Processing

The photoplethysmogram (PPG) or electrocardiogram (ECG) and accelerometer sensors of *Empatica E4* [9] smart band are applied for human physiological data recording. This device connects to a proprietary Bluetooth server program as an interface between the smart band and the machine learning-based estimation system. The specification of the smart band is for the heart rate ECG sensor capturing a time pair based on the recorded inter-beat interval (IBI) data, and for the accelerometer function, it has a tri-axial accelerometer sensor with 32Hz of output data rate with 6 bits per axis for the sensitivity; where Fig. 1 shown the human physiological data recording and processing scheme.

A. The Parameters of the Participants during the Human Physiological Data Recording Procedures

The procedures of the data recording are realized under specific conditions to limit the effects of external factors from the environment. All the data are obtained from 25 participants (15 males and 10 females aged from 25 to 35 years old) doing the three activities of *Sitting*, *Standing*, and *Walking* under the influences of the four emotional states of *Happy*, *Neutral*, *Worry*, and *Sad*, where all participants were situated in the same conditioned rooms with temperatures around 24 to 26 degrees *Celsius* in the activities of *Sitting* and *Standing*.

In the activity of *Sitting*, the participants are sitting in one direction or freely moving left or right as long as still in the sitting position. The participants standstill or pretend to have phone calls in the activity of *Standing*. In the activity definition of *Walking*, the participants are free to move without changing altitudes. The defined condition in the activity definition of *Walking* is the outdoor environment with temperatures of around 31 to 32 degrees *Celsius* with some emotional-related movie scenes and or music proposed by each participant based on each emotional state used as inducements. All the acceleration-based and heart rate-based data are recorded with a smart band for each participant's data in the pre-defined specific conditions under a 5-minute interval by each combined activity and emotional state.

The *Empatica Bluetooth Low-Energy (BLE)* Server [10] is used to connect the smart band and the personal computer through the *SiliconLabs BlueGiga BLED112-v1* BLE module [8] under the *Transfer Control Protocol/Internet Protocol* (TCP/IP) interfaces by our own-developed Python language-based program to access and recording the participant's data from the accelerometer and PPG sensors of *Empatica E4* smart band.

On the final, the procedures of the human physiological data recording for the participants on the defined situation and conditional parameters, as explained above produce two kinds of datasets; the acceleration-based dataset recorded from the pre-defined physical activities and the heart rate-based dataset recorded under the effects of specific predefined emotional states.

B. The Procedures of the Acceleration-based Dataset Preparation and Processing

The acceleration data based on the *x*, *y*, and *z*-axis from the smart band are captured in the one-second interval at the same time as the heart rate data recording and used as the input data for the activity estimation. All the acceleration data is recorded under each axis, pre-processed, and used in the classification system. The method of the heart rate data recording is similar to the one in the acceleration data recording process, where it connects through a TCP-based socket message protocol to record the tri-axial accelerometer sensor data.

From the acceleration-based human physical activities data recording process, the raw data of each axis are processed under specific conditions:

- The Mean Absolute Derivatives (MAD) or P_n from each *x*, *y*, and *z*-axis calculated from their raw acceleration data, recorded by the smart band accelerometer sensor. The formula of P_n for processing the raw acceleration values in *x*-axis data or P_x, where a_x is the value of

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acceleration captured by the sensor in x-axis and t is the time constant needed by the sensor, is:

$$P_x = \frac{\sum \quad |a_{x(i+1)} - a_{x(i)}|}{t}$$

This equation applies to the raw acceleration values in the y-axis and z-axis data. These processed values represent 3 features based on each axis, defined as P_x for the x-axis, P_y for the y-axis, and P_z for the z-axis in the dataset.

- The minimum and maximum values of the accelerometer sensor data by each x, y, and z-axis; for example for x-axis data are x_{min} and x_{max}. These data represent 6 features, where each axis has two values consisting of minimum and maximum values, where defined as x_{min}, x_{max}, y_{min}, y_{max}, z_{min}, z_{max} in the dataset.

Both of the processed acceleration data represent the 9 features used in the acceleration-based dataset.

C. The Procedures of the Heart Rate-based Dataset Preparation and Processing

The *HRVAnalysis* API [16] is used to retrieve the Heart Rate Variability (HRV) analysis values of the Inter-Beat Intevals (IBI) data recorded from the Empatica E4 smart band. This analysis tool produces the HRV analysis results in two domains; the time-domain and the frequency-domain. This API is capable of processing the heart rate signal into several kinds of domains; such as time-domain, frequency-domain, geometrical-domain, and non-linear-domain. For example, in the time-domain analysis, the raw data of the heart rate originally recorded in the time-based R-R interval signal is processed into several components like *MeanNNI*, *SDNN*, *SDSD*, *NN50*, *pNN50*, *NN20*, *pNN20*, *RMSSD*, *MedianNN*, *RangeNN*, *CVSD*, *CVNNI*, *MeanHR*, *MaxHR*, *MinHR*, *STDHR* where *NN* has the same meaning of *RR*. In the frequency-domain analysis, the raw time-domain-based heart rate signal is converted using the Fourier transform based on Welch's method [2] and produces several parameters like *LF*, *HF*, *VLF*, *LF/HF* ratio, *LFnu*, *HFnu*, and *TotalPower*. In the implementation, only the frequency-domain-based heart rate analysis results were applied. Several parameters produced by the analysis tool and used in the implementation are the *LF/HF* ratio, *VLF* value, *LF* value, normalized LF (*LFnu*), *HF* value, and normalized HF (*HFnu*) value. These analysis data represent the six features used in the heart rate-based dataset. In total, the number of feature types in the dataset when combined are nine features of the accelerometer-based dataset and six features of the heart rate-based dataset, becoming 15 feature types in the combined dataset.

IV. Acceleration and Heart Rate-Based Datasets Fusion Approach

The dataset of participants' physiological data consists of the acceleration and heart rate under certain combined activities and emotional states recorded at the same time through the *Empatica E4* smart band. During the data processing procedures, these two kinds of data have two different dimensionalities, where the processed acceleration data are running under the time domain while the processed heart rate or heart rate variability data are running under the frequency domain.

Several methods based on machine learning algorithms were applied to create a fusion of these two different dimensional data, where each of these algorithms worked under each kind of data; the acceleration dataset defined as the *ACC* dataset and the heart rate variability dataset defined as the *HRV* dataset.

The machine learning algorithms used in the implementation are the Hidden Markov Model (HMM) [25], *k-means* clustering [26], and *k-nearest* Neighbors (*k*NN) [27]. All of the datasets produced by each algorithm are used in the next classification process under two kinds of classifiers. The detailed descriptions of the machine learning-based fusion methods are shown in Fig. 2.

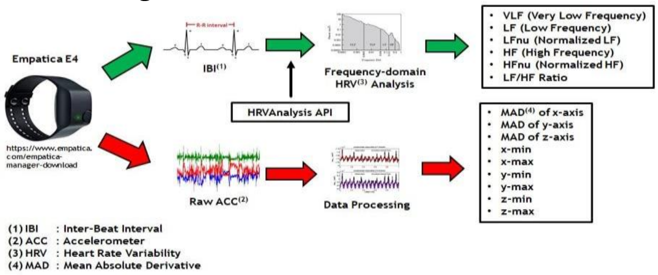

Figure 1. Human physiological data recording and initial processing scheme

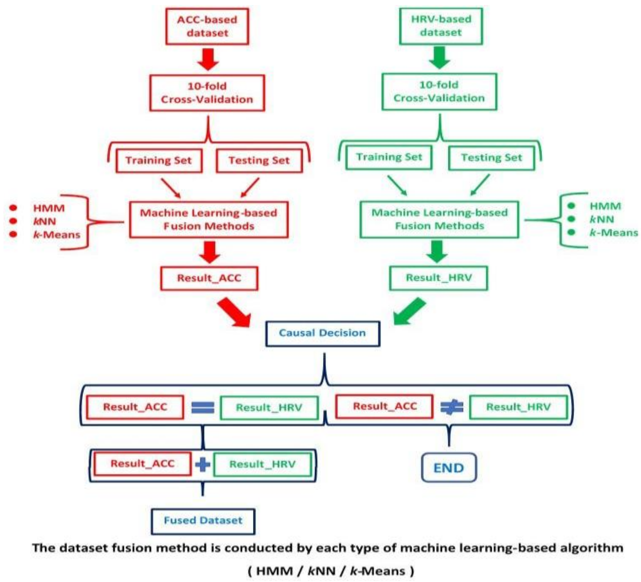

Figure 2. The detailed description of the machine learning-based acceleration and heart rate datasets fusion method

V. Classification Procedures on Fused Acceleration and Heart Rate-Based Datasets

After the acceleration and the heart rate datasets are fused under defined machine learning-based algorithms, the fused dataset goes into several classification procedures to find out if this dataset is applicable in the combined human activity and emotion state estimation system. The classification algorithms used in these procedures are the Multi-Layer Perceptron (MLP) and Support Vector Machines (SVM). The reason for the selection of the classifiers comes from several previous works under this domain; the MLP and SVM classifiers are the most commonly used ones, so these classifiers apply in this experimental test.

A. The Classification Procedures for the Multi-Layer Perceptron-based Fused Dataset

The procedures of the Multi-Layer Perceptron (MLP) classification are running on each previous machine learning-based datasets fusion method, where there are three types of fused datasets such as the Hidden Markov Model (HMM)-based combined dataset, the *k*-Nearest Neighbors (*k*NN)-based fused dataset, and the *k*-Means Clustering-based fused dataset.

Each type of fused dataset is divided again into two parts as the previous one, into the training and testing sets by involving the cross-validation method. The training set of the fused dataset was applied to train the classifier, and the testing set was loaded to find out the accuracy or effectiveness of the classifier based on these three kinds of fused datasets. At last, there will be three values of accuracy metrics of the MLP-based classifier conducted for each type of machine learning-based fused dataset, where these values are compared by each other. As explained before, similar to the MLP-based classifier results, there will be three values of accuracy metrics of the SVM-based classifier procedures based on the three types of machine learning-based fused datasets procedures.

B. The Classification Procedures for the Support Vector Machines-based Fused Dataset

Similar procedures of the MLP-based classifier were implemented on the SVM-based classifier also; by applying the SVM-based classification procedures to each type of machine learning-based fused datasets. The accuracy scores of SVM-based classification procedures are measured under each kind of machine learning-based to find the comparisons of both types of fused datasets procedures.

VI. Experimental Results

In the implementation, the numbers of fused features used in the classification process are divided into two kinds:

- 12 features used in the fused dataset, consisting of 6 features of accelerometer *(ACC)*-based and 6 features of heart rate (HRV)-based; where the *ACC* features are $x_{min}, x_{max}, y_{min}, y_{max}, z_{min}, z_{max}$ and *HRV* features are *LF/HF*, *VLF*, *LF*, *LFnu*, *HF*, *HFnu*.
- All 15 features in the fused dataset, consist of 9 features of the accelerometer (*ACC*)-based and 6 features of heart rate (*HRV*)-based; where the *ACC* features are $P_x, P_y, P_z, x_{min}, x_{max}, y_{min}, y_{max}, z_{min}, z_{max},$ and *HRV* features are *LF/HF*, *VLF*, *LF*, *LFnu*, *HF*, *HFnu*.

Both 12-feature and 15-feature types datasets are inputted into two defined classifiers as explained before, the Multi-Layer Perceptron (MLP) and the Support Vector Machines (SVM) classifiers. Instead of dividing the number of the features of the fused datasets used in the classification procedures, two kinds of cross-validation methods; 10-fold and 5-fold cross-validations were implemented for both classification procedures.

As for the comparisons in the 12-features fused datasets results, the lowest score was acquired for the *k*NN-based combined dataset in the 10-fold cross-validation MLP-based and SVM-based classification procedures as the accuracy score is around 33.33% for both the classifiers. While for the 12-features *k*NN-based fused dataset results in the 5-fold classification procedures are 45.83% in the MLP-based classifier and 58.33% in the SVM-based classifier.

As explained before, instead of classifying the 12-feature fused datasets only, another classification procedure is conducted for the 15-feature fused dataset also. The classification procedures for the 15-features fused dataset are the same as the 12-features fused dataset. Each of the three machine learning-based fused datasets (HMM, *k*NN, and *k*-Means Clustering-based fused datasets) was implemented under two kinds of classifiers (MLP and SVM-based classifiers).

Instead of the results of the HMM-based fused dataset, the other MLP and SVM-based classifiers were found to have lower accuracy scores, where it has scores around 16.67% up to 66.67% for both the 10-fold and 5-fold cross-validation procedures. It also can be concluded that the classifications of the 10-fold cross-validation procedures are working better for the 15-features fused dataset or specifically the HMM-based fused dataset.

The results for the *k*-Nearest Neighbors-based fused dataset were found to be the lowest ones in the 15-features fused datasets classification during the 10-fold

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cross-validation procedures compared by the others, either the accuracy scores in the MLP-based classifier as 16.67% and as 33.33% in the SVM-based classifier. In other ways, the accuracy scores of 5-fold cross-validation procedures for the same fused dataset are 58.33% as in the MLP-based classifier and 41.67% as in the SVM-based classifier.

By looking at the classification results above, the HMM-based fused dataset has the best accuracy scores compared to the *k*NN and *k*-Means Clustering-based fused datasets. The reason for this is because the HMM algorithm or the Gaussian-based HMM algorithm could find the probabilities of the predicted labels or classes by using the defined features. Since the HMM algorithm is the Gaussian-based one, there are high chance that the algorithm model finds the highest distribution of specific types of features correlated and or affected by the kinds of predicted classes or labels.

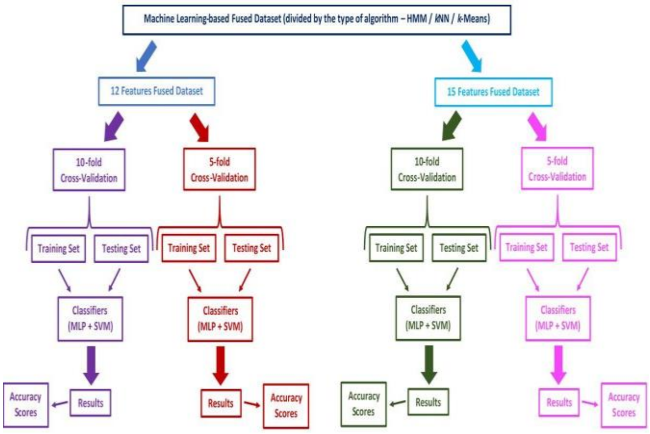

Figure 3. Detailed descriptions of the classification procedures based on the division of the number of features

TABLE I. CLASSIFICATION RESULTS ON THE MACHINE LEARNING-BASED FUSION METHODS FOR THE 12-FEATURES FUSED DATASETS

Types of Fused Dataset	10-fold MLP-based Classifier Results	10-fold SVM-based Classifier Results	5-fold MLP-based Classifier Results	5-fold SVM-based Classifier Results
HMM-based fused dataset	**83.33%**	66.67%	**87.5%**	79.17%
*k*NN-based fused dataset	33.33%	33.33%	45.83%	58.33%
k-Means-based fused dataset	50%	50%	66.67%	58.33%

TABLE II. CLASSIFICATION RESULTS ON THE MACHINE LEARNING-BASED FUSION METHODS FOR THE 15-FEATURES FUSED DATASETS

Types of Fused Dataset	10-fold MLP-based Classifier Results	10-fold SVM-based Classifier Results	5-fold MLP-based Classifier Results	5-fold SVM-based Classifier Results
HMM-based fused dataset	**83.33%**	**83.33%**	50%	54.17%
*k*NN-based fused dataset	16.67%	33.33%	58.33%	41.67%
k-Means-based fused dataset	50%	66.67%	58.33%	66.67%

VII. CONCLUSION

The relation of physical activities, heart rate, and emotional states are discussed in each sensor-based individual, and the removal of several features in the fused dataset-based to estimate the physical activities and emotional states. This relation is found based on the principle of the human physiological systems under the autonomic nervous systems working scheme. To prove this relation, an implementation based on the fusion of the acceleration data of the personal physical activities and the emotional states influenced heart rate data is proposed and found to be proven enough to be applied as one method of estimating the human emotional states together with the physical activities.

By then, the proposed novel approach of multisensory and or multidimensional-based datasets is implemented, discussed, and tested for each type of human physiological signal. This proposed approach is applied by fusing this multisensory data by applying the fusion methods under several criteria and classifiers, where the effectiveness of the implementation is acquired. This effectiveness is measured in the accuracy scores of the selected classification procedures used as the indicator of the best option of the fusion methods.

From the experimental results above, it was found that the Hidden Markov Model-based fusion method is proven to be the best one for the proposed multisensory and multidimensional fusion method based on human physiological data. While for the kinds of the defined classifiers, either in Multi-Layer Perceptron and or in Support Vector Machines found proven enough to be used in this proposed fusion method. By contrast, as shown in the experimental results, the *k*-Nearest Neighbors and *k*-Means Clustering algorithms found not so proven enough to be used for the proposed multisensory and multidimensional data fusion method. In the future, there is a possibility to implement the proposed fusion method for a more advanced system by incorporating various types or kinds of human physiological data, not only the acceleration and heart rate data.

Learned from the experiences during the implementation, especially in the moment of human physiological data recording, there are lots of undefined factors that incorporated the creation of the human emotional states. Based on the findings and experiences and since the proposed system is currently running under the supervised learning scheme, some further advancement of the proposed fusion method is to improve it under the unsupervised learning scheme, as the development of the estimation system for the human emotional states is quite hard to develop due to many uncertainties that highly occur during the implementation procedures.

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