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Comparing Classic Machine Learning with Deep Learning for Stress Detection Using Wearable Sensors

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ABSTRACT

Based on conducted research, stress can have a significant impact on human relationships and human-related incidents. By identifying stress during daily activities such as driving, some incidents and accidents can be prevented. In this study, the PhysioNet database pertaining to drivers' heart rate during driving was utilized, and their features were extracted. Subsequently, the features underwent reduction using PCA and were compared using two artificial intelligence methods. The results, including accuracy, error, and validation credibility with fold-10 in four classes, were obtained for both neural network and deep learning approaches. In the feature extraction phase, 7 spatial features, 16 frequency features, and 64 wavelet features were employed. The classification result for the neural network achieved an accuracy of 90.8%±0.8. In the deep network, comprising one-dimensional CNN and Dense layers, with a fusion of raw signals and extracted features, the accuracy reached 96.3%±0.6. These findings indicate the superiority of deep learning over neural networks in this domain. This diagnostic system is suitable for portable and compact applications in individuals' daily activities.

1. Introduction

Life is invariably accompanied by numerous stresses that may go unnoticed from individuals' perspectives and attention. Stress, when experienced by individuals, can be detrimental to their health and may lead to the death of nerve cells [1], Parkinson's disease [2], and weakening of physical strength in coping with cancer [3]. With the increase in daily life challenges, individuals

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are exposed to stress [4]. Daily life challenges are minor upsetting events that may not seem significant when considered individually. However, when these challenges occur together or during times of high pressure, although not as noticeable as major life crises, they also contribute to a type of stress known as minor or micro stress [5].

With the rapid advancement of technology, sensors have the capability to accurately capture vital signals [6]. These sensors, aided by advanced devices, can analyze individuals' conditions in terms of sleep disturbances [5], stress, and diseases. A sensor is a detector, derived from the word "sens" meaning to perceive, and it can convert quantities such as pressure, temperature, humidity, and so on into continuous (analog) or discrete (digital) electrical quantities. Sensors are used in various measurement devices, analog and digital control systems such as PLC [7]. The performance of sensors and their ability to connect to various devices, including PLCs, have made sensors an integral part of automatic control device components. Depending on the type and function defined for them, sensors send information to the control system, which operates according to the defined program [8]. The main goal is to improve the accuracy and reliability of stress detection and classification using wearable sensors and to reduce simulation time. Wearable sensors can be utilized by employing signal processing methods in stress detection clinics and studying their changes to improve the disease process and the effects of medications.

2. Wearable Sensors

Wearable sensors refer to all types of sensors that can be worn by humans. These sensors should have features such as portability and lightness, and on the other hand, consume minimal energy. These conditions are not mandatory; rather, most common sensors in this field meet these conditions. Some wearable sensors are illustrated in ***Figure 1***.

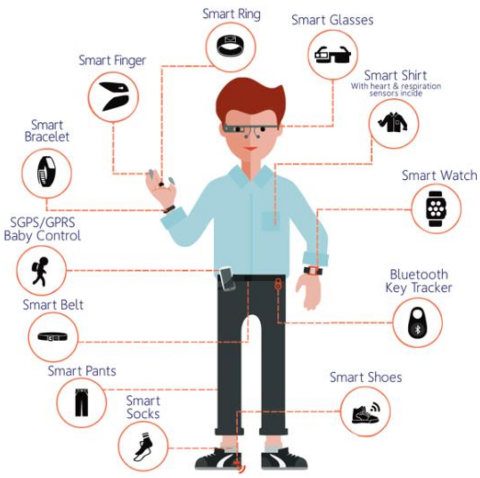


Figure 1. Sensors with their respective placements [9]

3. Classification of Wearable Sensors

From an operational perspective, sensors can be classified into two distinct categories: active and passive. The categorization is contingent upon their capability to function. Pulse oximeter sensors are positioned within the active classification owing to their operational capacity, whereas thermometers exemplify passive sensors, necessitating no functional power. As diverse methodologies for exhibiting energy effects emerge, sensors are systematically classified based on the energy they are subjected to during testing [9]. In a broader classification, temperature sensors are subdivided into two primary types: digital and analog. ***Figure 2*** delineates a comprehensive classification framework for wearable sensors. It portrays the potential for single-purpose or multi-purpose functionality. Structurally, sensors may either be active or passive. In terms of deployment, sensors can be either invasive or non-invasive [10]. In this particular project, single-purpose, passive, non-invasive acquisition sensors, tethered to the body via wires, were employed.

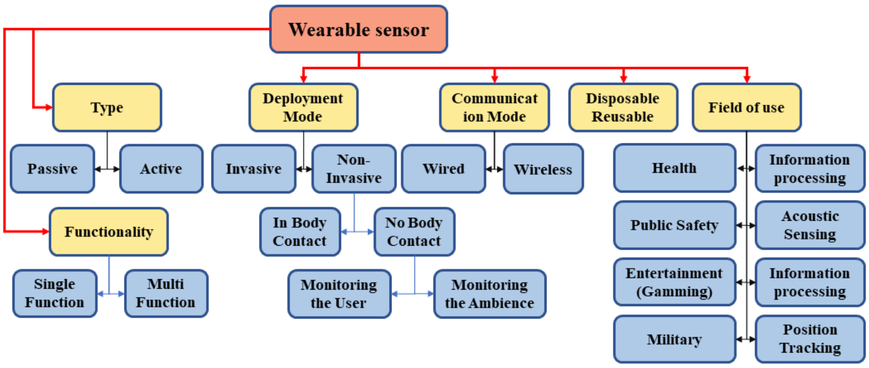


Figure 2. Classification of Wearable Sensors [11]

Health-related data pertaining to individuals is acquired through wireless sensors and transmitted to a caregiver via an information gateway, such as a mobile phone. Numerous studies emphasize the utilization of mobile phones as portable processors [12]. Caregivers can leverage this information to enact interventions as warranted. Nonetheless, during this process, two distinct cohorts from varying societal strata are particularly scrutinized. The first cohort comprises individuals with heightened risk profiles (e.g., pregnant women, the elderly), while the second cohort encompasses laborers engaged in physically demanding occupations [13].

4. Proposed Methodology

For stress identification based on cardiac signals, a general block diagram is employed, as depicted in ***Figure 3***, outlining the overall structure of the processing [14]–[17].

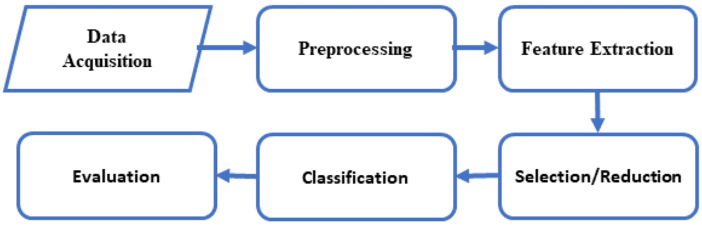


Figure 3. Block diagram of the proposed system for arrhythmia detection using classical methods.

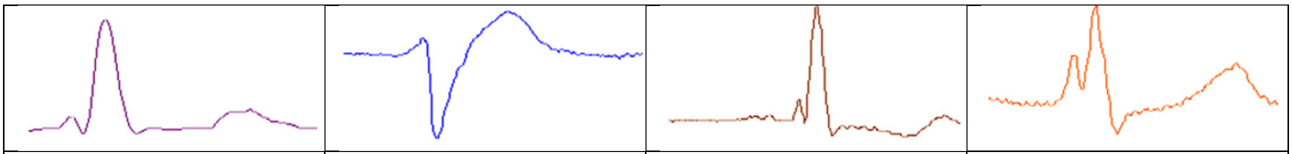
4.1. Vital Signal Acquisition

In the initial block, data is simulated into signals and fed into the program. For this purpose, the Physionet database was utilized, based on articles published in this field. This database, curated by Jennifer Healey on the PhysioNet website, comprises a collection of multi-recorded signals from healthy volunteers driving on specific routes such as streets and highways in Boston, Massachusetts. The aim of this study in gathering these data was to explore the feasibility of automatic stress recognition based on recorded signals, including ECG (Electrocardiogram), EMG (Electromyogram), GSR (Galvanic Skin Resistance) measured on the hands and feet, and respiration. For the training and testing of the neural network, a number of ECG signals were downloaded from the MIT database. This database includes 48 files, each with a duration of 30 minutes and containing 15 types of arrhythmias. The sampling frequency of these signals is 360 Hz. Out of the available files in the mentioned database, 24 were utilized in this study. The lead placement method is triangular on the chest [18], [19]. ***Table 1*** shows the files used and their corresponding classification classes.

Table 1. Used Files and Their Corresponding Classification Classes [17]

Class	Record Numbers
NSB	100-101-103-112-115-117-121-123-202-220-222-234
PVC	200-208-213-233
PJC	212-118-124-217
PAC	109-111-104-107

In the specified database, ECG signals are stored in three files with the formats hea, atr, and dat. ***Figure 4*** presents a labeled display of four different types of heartbeats from PhysioNet data.



A B C D

Figure 4.. Normal Sinus Beat (NSB) (A), Premature Ventricular Contraction (PVC) (B), Premature Atrial Contraction (PAC) (C), and Premature Junctional Contraction (PJC) (D).

4.2. Preprocessing

Preprocessing of ECG signals aims to eliminate various types of noise. The presence of baseline noise can shift the signal downwards up to -0.3. After removing this noise, the resultant signal is depicted in part B of the figure below. Magnification of this figure yields part C. As observed, high-frequency noises still persist. These noises manifest as disturbances and are eliminated using wavelet transform. The resulting signal after removing these noises is depicted in part D of the figure. (In these figures, the horizontal axis indicates the sample number, and the vertical axis indicates the signal amplitude in millivolts).

These aforementioned steps are performed for all records, both during the neural network training and testing stages. By following this process, preprocessed signals are obtained for training and testing the neural network. It's worth noting that all displayed signals are utilized during the neural network testing phase. For instance, because the first 10 seconds of signal 100 (first 3600 samples) are used for neural network training, the next 10 seconds (10-20) of this signal are utilized for neural network testing. As shown in the table above, signal number 100 is categorized under the normal signal class. The output of both trained networks for this test signal is also normal. ***Figure 5*** displays a representation of the initial signal before and after preprocessing.

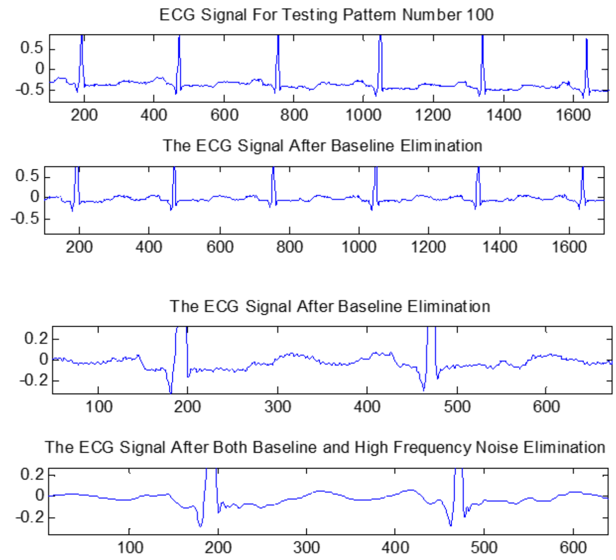


Figure 5: Illustration of the stages of preprocessing for ECG signal number 100.

4.3. Feature Extraction

For signal processing, both MATLAB and Python have been utilized as base software and for classification. The Wavelet Toolbox I, along with wavelet and time-frequency domains, is used to extract signal features. Extracting features from cardiac signals is possible through signal analysis in the time, frequency, and time-frequency domains. Seven time-domain features have been extracted, including the mean and standard deviation of heart rate (mean time between two beats), the number of beats in a specified time interval, the mean and variance of the length of time between two consecutive RR intervals, and the mean and variance of the signal amplitude. Sixteen frequency-domain features are extracted from the mean and variance of the frequency power in 8 equally spaced frequency intervals of Fourier transform coefficients. Sixty-four features are extracted from the mean and variance of the power in the time-frequency domains of the 16-package wavelets for the first Daubechies and Symlet. A total of 87 extracted features are utilized for training the proposed networks is shown in ***Figure 6***.

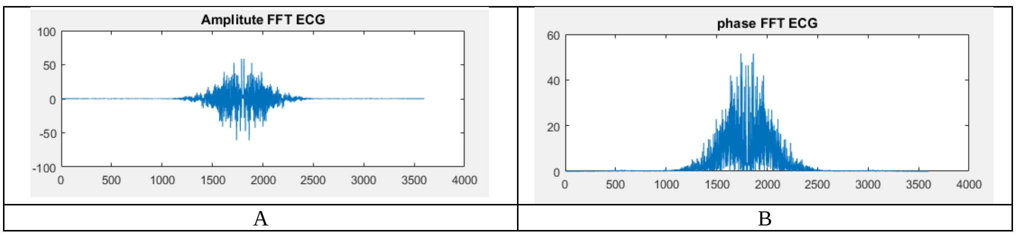


Figure 6 Fourier transform of the signal in two domains: domain (A) and phase (B).

4.4. Feature Reduction

PCA (Principal Component Analysis) is a transformation in vector space mainly used for reducing the dimensions of a dataset [20]. PCA was introduced by Karl Pearson in 1901 and involves the eigenvalue decomposition of the covariance matrix. PCA is a mathematical definition of an orthogonal linear transformation that brings the data into a new coordinate system, preserving the largest variance on the first coordinate axis, the second largest variance on the second coordinate axis, and so forth. PCA can be used to reduce the dimensions of data, preserving the components of the dataset that have the most impact on variance.

4. 5. Classification

Expert systems are useful for identifying actionable predictions. However, before presenting the method discussed in the network, the issue of data classification is raised to ensure that the data entered into the expert systems are effectively processed. In mathematics, a classifier is a function from X (feature space) to Y (labels). Classifiers can be either static or learner. Learner classifiers are those whose correspondence from X to Y improves with increased learning data. Learner classifiers are divided into supervised and unsupervised. There are various types of classifiers, some of which are used for classifying stress signals, including k-nearest neighbor, neural networks, support vector machines, hidden Markov models, and maximum similarity. The processor's goal is to extract features and generate a suitable feature vector for use in the classifier system. The classifier's goal is to recognize the desired arrhythmias. In this project, neural networks were used as the classifier system. Deep learning methods were employed to utilize the extracted data in the classical method. The following deep learning method was generated. As shown in ***Figure 7***, initially, the signal is acquired, and in the upper path, features are extracted and reduced using the classical method. In the lower path, the Cov a, b block is used, where a is equal to the size of the CNN1D kernel and b is the amount of pooling in Maxpooling. Finally, classical and deep learning features are combined to obtain a feature vector. Utilizing the softmax layer leads to data classification into one of the four classes with the highest probability.

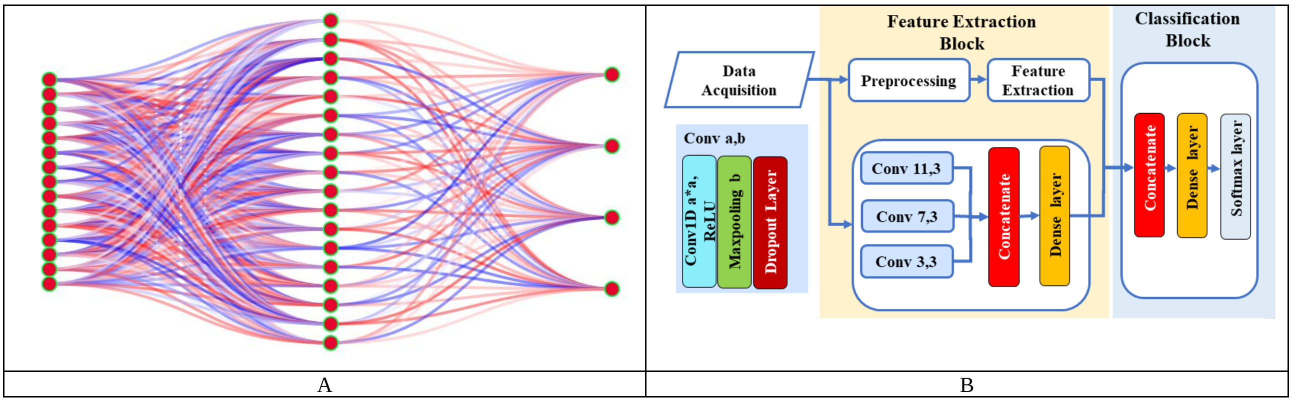


Figure 7: Block diagram of the proposed system for arrhythmia detection. Using neural network method (A), using deep learning method (B).

Figure 7 extracts classical features in the upper part and deep learning features in the lower path. In the deep learning path, three 1D CNN structures with dimensions of 3, 7, and 11 were used, and sample rate reduction was performed using Maxpooling with a size of 3. The Drop out layer was also used to identify and remove dead neurons. Finally, by combining classical and deep learning features in the fusion block, a feature vector is obtained. The utilization of the softmax layer leads to data classification into one of the four classes with the highest probability.

4.6. Classification Results Evaluation

In this project, a range of metrics are employed to assess simulation outcomes. Specifically, the system's efficacy in arrhythmia detection, quantified as the performance percentage, is evaluated using ***eq. (1)*** based on the network performance or accuracy metric. This metric signifies the percentage representing the overall accuracy or performance of the network.

$$A = 100\left(1 - \frac{Ne}{Nt}\right) \tag{1}$$

where Ne indicates the number of errors, and Nt represents the total number of test data. In the first part, a neural network is utilized for classifying extracted features. As observed, the combination of temporal and morphological features of ECG signals with features obtained from wavelet transform leads to an increase in the efficiency of the trained neural network. ***Figure 8*** displays the classification results using seven feature selection methods and neuron counts ranging from 1 to 90.

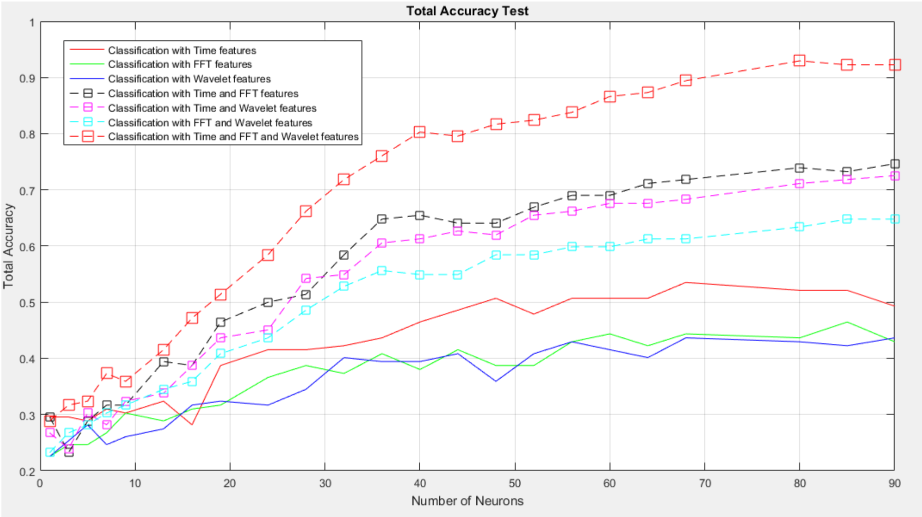
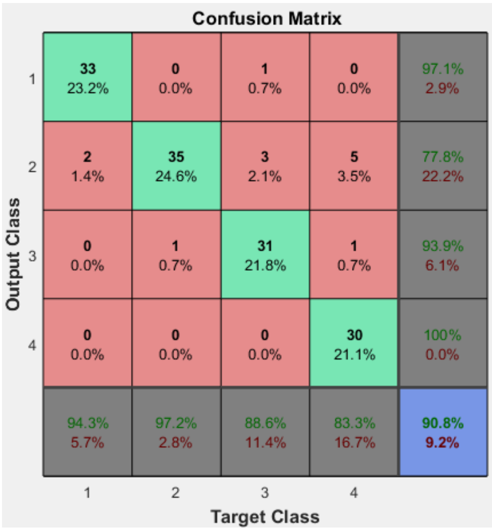


Figure 8 Accuracy classification results with various kind of features and neurons numbers.

The different lines represent the final classification accuracy for different datasets. The solid lines represent single temporal, frequency, and wavelet features, while the dashed lines represent pairwise combinations of them. The red square line represents the result of combining three temporal, frequency, and wavelet features, showing superior results. In ***Figure 9***, a confusion matrix is displayed for 90 neurons and three types of features.



	1	2	3	4	
1	33 23.2%	0 0.0%	1 0.7%	0 0.0%	97.1% 2.9%
2	2 1.4%	35 24.6%	3 2.1%	5 3.5%	77.8% 22.2%
3	0 0.0%	1 0.7%	31 21.8%	1 0.7%	93.9% 6.1%
4	0 0.0%	0 0.0%	0 0.0%	30 21.1%	100% 0.0%
	94.3% 5.7%	97.2% 2.8%	88.6% 11.4%	83.3% 16.7%	90.8% 9.2%

Figure 9: Confusion matrix for 90 neurons and three types of features.

To enhance classical method performance, deep learning is utilized along with extracted features. Figure 10 displays a confusion matrix using deep learning classification. Improvement of the classical method with the inclusion of deep learning networks along with extracted features has been employed. ***Figure 10*** illustrates the confusion matrix using deep learning classification.

Figure 10 Confusion matrix using deep learning classification.

Table 2 provides a comparative overview of various simulation results. These results show lower accuracy compared to deep learning methods but with significantly less computational complexity. Using 10-fold cross-validation, the table is calculated ten times, and based on it, the accuracy and precision of each class can be computed. ***Figure 11*** shows an overview of accuracy and precision in data classification using deep learning, with the mean and variance calculated for each class.

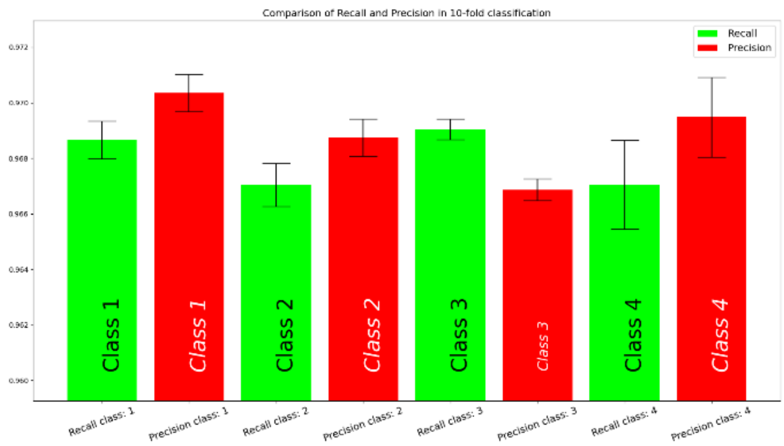


Figure 11 Mean and variance of 4 groups in the 10-fold method using deep learning classification.

Finally, for comparison, the results are compared with other articles in ***Table 2***. In this table, ECG data classification with the aid of deep learning is provided. The classification accuracy in these results is very high and suitable, but the number of parameters used in this study is much lower due to the incorporation of injected features.

Table 2. Overview of Identification Results

Authors	Years	Solution method	Accuracy Result (%)	Number of Parameters in the Model (NP)
Golany, Tomer et al [21]	2020	Incorporating ODE-based simulator into GAN for ECG synthesis	95.3	3M<NP <5M
Zhu, Jiaojiao et al. [22]	2021	Deep Representation Learning	89.4	15M
Shen, et al. [23]	2021	RR in Traconv3	90	3M<NP <5M
Rahman et al. [24]	2022	AlexNet, SqueezeNet, and ResNet50	93.8	62M
Weimann Kuba et al.[25]	2022	Transfer learning	94.5	50M
A.A. Ahmed et al. [26]	2023	1D-CNN	99.0	60M
H. Narotamo et al. [27]	2024	LSTM+GRU+1D and 2D CNN	79.67%	10M<NP <50M
Our Team	2024	Neural Network	90.8 ±0.8	10K
Our Team	2024	Deep learning	96.3±0.6	32K

The extracted features using MATLAB 2020 were classified in a classical environment. Then, in the next stage, the extracted features were utilized in Python environment. This was done due to the diverse capabilities of these two environments and the possibility of continuing the process in the Python environment. It is worth mentioning that these operations were performed using a system with the following hardware specifications: CPU Core i7 processors, GPU GeForce GTX 1080 graphics card, Windows 8.1 operating system with 32 gigabytes of RAM. The execution time for neural network and deep learning tests is approximately 0.5 and 1.2 seconds, respectively. These pieces of information demonstrate the execution speed of the model in the specified environment, which may vary in other environments with different hardware and settings.

5. Conclusion

In this study, in the initial stage, signals were divided into four groups and features were extracted from them. In the classical method, an accuracy of 90.8% was achieved. In the next stage, using deep learning networks, the simulation accuracy increased to 96.3% with 10-fold cross-validation. Although the classical method achieves faster results, the identification accuracy in deep learning is significantly higher. The proposed deep learning method, utilizing feature extraction from data, provides adequate training, and effectively reduces these features using PCA. The combined use of useful features and raw data in the input of the deep learning network complements the features. Therefore, in the training process using deep learning, a combination of classical data and deep learning is introduced to the network, leading to increased accuracy in classification. Additionally, due to the low number of parameters in the network, this product can be executed on embedded devices such as Raspberry Pi.

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