An Individual Specific Electroencephalography Signal Pattern Verification Model Based on Machine Learning and Convolutional Neural Network

Meng-Hsiun Tsai, Chi-Yuan Hsia, Sheng K Wu, and Tzu-Ling Chen

***Abstract*—Under the development trend of artificial intelligence, biometrics has become a broadly applied popular technology in various situations, such as finance, non-profit organizations, and customs. However, traditional identification tools existed in the risks of being easily leaked out, stolen, or attack by hackers. Electroencephalography (EEG), a method for research on biometrics, collects electromagnetic waves on specific positions on the scalp and reflects individual brain activity. Much research proved that α band in EEG could distinguish individual differences, and the significance was proven in clinical neurophysiology. In EEG biometrics, complicated electrode channels were used in most research to cover the entire head for collecting brainwave records; however, such equipment could not satisfy the requirement for collectability in biometrics applications.**

This study develops an individual specific verification model with brainwaves through Convolutional Neural Network (CNN) for identity identification to protect biometric data of the athletes. Brainwave features are selected from 2 minutes static brainwave signals of participants collected by handy EEG through the Butterworth Low Pass Filter (BLPF) and Short-time Fourier Transform (STFT), and the verification evaluation model is developed by comparing several machine learning classifiers and the deep learning CNN model.

To solve the imbalance problem between personal data and general data, the Synthetic Minority Oversampling Technique (SMOTE) is adopted to achieve favorable effects in various model evaluation indicators. In the individual specific model, the selection of brainwave features at 2 second reveals the accuracy of 96.80%.

***Index Terms*—Electroencephalography, convolutional neural network, butterworth low pass filter, short-time fourier transform.**

I. Introduction

A. Research Background and Motivation

Under the development trend of artificial intelligence, biometrics has become a broadly applied popular technology in various situations, such as finance, non-profit organizations, and customs. Traditional identification tools (e.g. passwords, identification cards, and employee cards) existed in the risks of being easily leaked out and stolen. Hackers might attack targets through a combination of malicious emails, fictional personas, stolen passwords, and malware. Microsoft indicated that due to the hacking incident of the antidoping agency, some athletes' failed drug tests had been erased [1].

Electroencephalography (EEG), a method for biometrics research, collects electromagnetic waves on specific positions on the scalp and reflects individual brain activity [2]. From the aspect of biometrics, EEG satisfies the requirement for universality, as it is unique and could be applied to any person. Much research proved that α band in EEG could distinguish individual differences [3], and the significance was proven in clinical neurophysiology [4]. EEG not been exposed to the peripheral environment would not be intercepted long-distance; therefore, Individual EEG is more effective for anti-forgery than the face, iris, and fingerprint recognition. This biometric technology is revealed to be stronger than other technologies on an imposter's attack.

B. Research Objective and Contribution

To protect biometric data of the athletes, this study proposes an individual specific verification model for identity identification. This study utilizes a convenient electroencephalograph for the brainwaves collection to avoid wearing and discomfort problems from the subjects. Such EEG is combined with the machine learning algorithm to accurately distinguish each subject's identity with the least time to provide the innovative biometric technology in the real world. The contributions of this study are listed below.

- Convenient electroencephalograph application in past biometrics research needs a longer time to achieve high accuracy. In this study, EEG signals collected by the same convenient electroencephalograph achieve the high accuracy of brainwave identification within a shorter period.
- Autoregressive (AR) and Cosine Distance were respectively used in much past research for feature selection and the classified models. In this study, machine learning algorithm such as SVM, C4.5, and CART is proposed as the structure of EEG verification model. Furthermore, the deep learning algorithm Convolutional Neural Networks (CNN) is used as the major classified model of brainwave signals.
- Individual specific verification model structures are proposed in this study for different personal authentication and biometrics availability achievement.

II. Literature Review

A. Introduction of Biometrics

Biometrics has been applied to many systems for personal identification. The biological characteristics of a biometric

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system should conform to the characteristics of universality, uniqueness, permanence, and collectability. Practicable biometrics systems in the real world should fulfill the following requirements [5].

Universality: Each person should present specific biological characteristics.

Uniqueness: Any two persons should not present the same features.

Permanence: Biological characteristics should not change with time.

Collectability: The features should be easily collected by sensors and quantified.

A biometric system is generally divided into verification systems and identification systems [6]. Verification systems refer to a user (e.g. Sam) being verified the identity with the personal features registered in the database. Such type of biometric system is a one-to-one comparison system, aiming to identify whether the person is Sam. Verification systems because of less time consuming are broadly applied to fast customs clearance, credit card withdrawal, and access control systems of a company. Identification systems are utilized for identifying a user's biological characteristics saved in the database in advance to find out who the person is. It is a one-to-more comparison system that is more time consuming and generally applied to criminal fingerprint recognition and DNA identification.

B. Electroencephalography (EEG)

EEG is the waveform signals measured by the micro voltage generated from the ion current of brain neurons by placing non-invasive electrodes on the cerebral cortex and amplified through an amplifier [7]. EEG is a primary physiological parameter broadly applied to medicine, e.g. sleep disorder diagnosis and epilepsy brainwave check. Furthermore, EGG is a fast and objective tool utilized in psychological research related to emotional analysis and pressure tests to simplify the traditional measurement process and human burden [8].

A lot of researchers regard that EEG could be the emerging technology for biometrics, as it presents the advantages of biometrics. Besides, brainwaves reveal uniqueness and anti-forgery (brain activities are sensitive to human pressure and emotion, and a criminal could not force a victim to recur the brainwave codes) [9].

According to the standards set by International Federation of Clinical Neurophysiology (IFCN), EEG frequency is divided into four subbands of Delta wave (δ, 0.5~4Hz), Theta wave (θ, 4~8Hz), Alpha wave (α, 8~13Hz), and Beta wave (β, 13~30Hz), shown in Fig. 1 [10]. The detailed descriptions are organized in Table I.

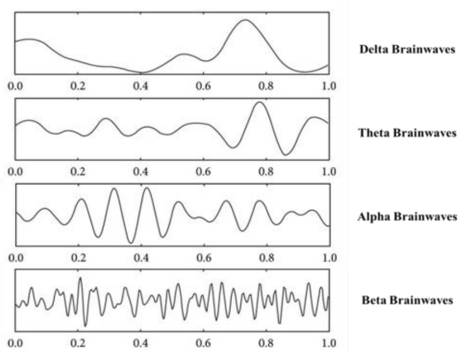


Fig. 1. Subband waveforms of brainwave.

TABLE I: DETAILED DESCRIPTIONS OF BRAINWAVE SUBBAND

Brainwave	**Frequency**	**Description**
δ wave	0.5~4Hz	"Unconscious level" waves It refers to unconscious state of deep sleep or coma.
θ wave	4~8Hz	"Subconscious level" waves It is a high-level spiritual state when a person appears conscious interruption for deeply physical relaxation [15].
α wave	8~13Hz	A bridge between "conscious and subconscious level" It is the periodic wave appearing on consciousness but physical relaxation. It is the bridge between consciousness and subconsciousness [16].
β wave	13~30Hz	"Conscious level" waves It is the brainwave fluctuation when a person is conscious or spiritually nervous and emotionally excited [17].

The frontal lobe on the head plays a critical role in brain activity as past research revealed a close relationship with personality, emotional response, concentration, rational thinking, and creative performance. When a person executes learning, emotional performance, and concentration, the neural network of the frontal lobe and parietal lobe is the major activity area [11], [12]. The electrode points are placed as in Fig. 2.

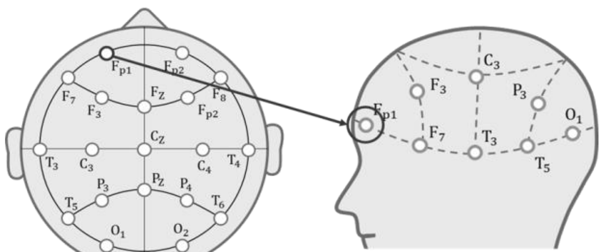


Fig. 2. Electrode points in the frontal lobe of the brain.

C. Data Imbalance

Data imbalance refers to the uneven distribution of predicted variables in a personal data set, where the proportion of a category in the data set is larger than the other category [13], [14]. In financial technology, the incidence of trading fraud cases and normal transaction cases also appears imbalance [15]. In the machine learning process, those imbalanced data would guide the prediction result to the side with more data. The accuracy is high but without any actual effectiveness. Oversampling balances major-category data sets by increasing the quantity of minor categories.

1) Random oversampling

A category with less proportion in the data set has randomly selected the subset. The category data in the subset are directly copied and added to the sample set [16]. This method tends to result in overfitting, as the adding data are copied directly from the data set into the training sample. Thus, lead to the bad classification of strange data.

2) Synthetic minority over-sampling technique (SMOTE)

SMOTE, extended from random oversampling, randomly selects several samples from the data of a minor category and uses k-nearest neighbors as the basis for generating new samples. In this case, such new samples are located between originally minor-category sample sets and would not overlap with original samples. SMOTE could effectively improve overfitting resulted from random oversampling [17].

D. Introduction of Deep Learning

Deep Learning, as the latest branch on machine learning, simulates human neural thinking models, adjusts weights by calculating errors, and eventually generates the prediction model [18]. Deep learning could be considered as a bridge between traditional machine learning and artificial intelligence. Current deep learning structures contain Recurrent Neural Network (RNN), Deep Neural Networks (DNN), and CNN.

CNN is a feedforward neural network in deep learning. The network structure was first proposed by Fukushima *et al.* in 1982 [19], and the first model was applied to recognize handwriting mail codes by LeCun *et al.* in 1990 [20].

CNN has recently become popular research in the science field, particularly in constructing the classified models. As the source image can be directly inputted to the network, it is broadly applied to image recognition, video analysis, Natural Language Processing, and voice identification.

In this study, CNN is used as the major classified model of brainwave signals. Brainwave signals after transforming to spectrogram by Short-time Fourier Transform are placed in the CNN model structure (convolutional layer, pooling layer, fully connected layer), and identify personal identity accurately by the generated weight [21] (see Fig. 3).

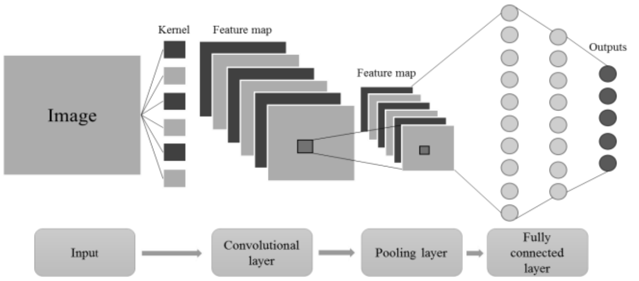


Fig. 3. CNN structure.

III. Research Method

A. Brief Description of Method

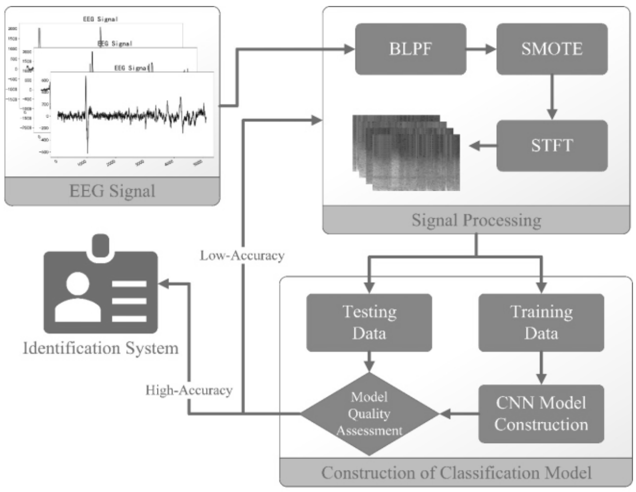


Fig. 4. Flowchart.

The brief description of the method in this chapter is shown in Fig. 4. The experiment of this study contains two main sections: identification and verification. An individual specified classification model is presented in the verification section. Due to lots of noise jamming in source brainwaves, several preprocessing steps are used for the processing and comparison. First, Butterworth Low Pass Filter (BLPF) is applied to filter high-frequency signals. Then, Short-Time Fourier Transform (STFT) is utilized for producing the spectrogram for the brainwave verification model. Compare to the general Fourier transform, STFT could better reflect the frequency change at different times.

B. Data Source

The data of this study were collected from 15 subjects, including 8 males and 7 females. All subjects age within 20-27 and are physically and mentally healthy without any medication. The experiment is executed in the meeting room no. 671 in Social Science and Management Building of National Chung Hsing University. During the experiment, the room is kept silent, and the subjects are requested to close their eyes and sit still for 120sec to collect the EEG data.

BrainLink electroencephalograph developed by Neurosky is applied for the experiment [22]. The EEG signals are collected from the electrode point FP1 on the prefrontal lobe [23] and transmit to the computer through Bluetooth. Compare to the medical electroencephalograph, the signals recorded by a similar sensor produced by the same manufacturer are proven up to 96% accuracy [24]. The specifications of BrainLink electroencephalograph are shown in Table II.

TABLE II: Specifications of BrainLink Electroencephalograph

Sampling frequency	512Hz
Transmission method	Bluethooth
Electrode position	FP1
Transmission range	<=10m
Weight	15g

C. Data Preprocessing

This section contains the description of two data preprocessing methods. These methods aim to decrease noise interference and increase the stability of the classification.

1) Butterworth Low Pass Filter (BLPF)

During the signal processing, the signals affected by noise jamming, appearing on the collection environment or some factors; thus, result in signal distortion. For noise removal or specific frequency signals selection, a filter would be the best processing method.

Butterworth Filter, a common filter for signal processing, was proposed by Stephen Butterworth in 1930 [25]. The passband possesses the largest flat frequency response curve while the stop-band gradually decreased down to zero. In this study, the brainwave frequency band appears in the low frequency range; thus, the lowpass Butterworth Filter is utilized. The amplitude and frequency relationship are shown in (1).

$$G_n(\omega) = |H_n(j\omega)| = \frac{1}{\sqrt{1+(\omega/\omega_c)^{2n}}} \tag{1}$$

$G_n(\omega)$ is the frequency gain, $H_n(j\omega)$ denotes the transfer function, n is the filter order, ω is the angle frequency of signals, with radian/sec as the unit, and ω_c is the cutoff frequency when the amplitude reduces 3 decibel (dB). The filter contains highpass, bandpass, and lowpass patterns. Since brainwave signals appear on low frequency, lowpass Butterworth Filter is utilized in this study.

2) Synthetic Minority Oversampling Technique (SMOTE)

There is the basic assumption of even data distribution in classification algorithms; however, most data types are imbalanced. Undersampling and oversampling are utilized for dealing with those imbalanced data. As the numbers of individual brainwave data and total brainwave data are different in this study, oversampling is applied for improving the data imbalance problem without losing the source data.

SMOTE (Synthetic Minority Oversampling Technique) was proposed by Chawla *et al.* in 2002 [17], as the improvement of traditional random increment. Traditional random increment copies and trains data directly with few categories as the new samples, while SMOTE follows an algorithm based on few-category data to synthesize some new samples. The operation principle is shown as (2).

$$x_{new} = x_i + (x_j - x_i) \times \propto \tag{2}$$

x_i is a randomly selected few-category data. A sample x_j is randomly selected from several few-category samples nearest x_i with the distance $x_j - x_i$ between x_i and x_j. $\propto$ is a random number between 0 and 1. Taking x_i as the base and adding $\propto$ times of $x_j - x_i$, a new few-category sample point x_{new} is generated, Fig. 5.

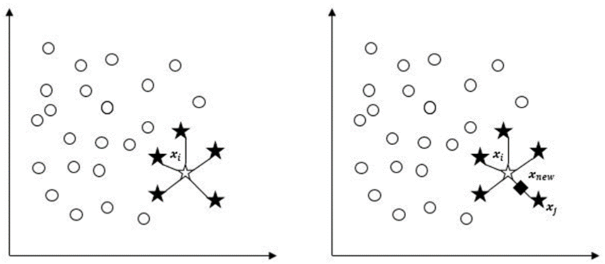


Fig. 5. SMOTE schematic diagram.

D. Signal Processing and Model Evaluation

The method of converting signals into spectrograms and the evaluation of model performance are described in this section.

1) Signal processing

Brainwave signals are 1D time-domain signals, recording the amplitude of 512 pieces per second. Nevertheless, observing the feature changes on each frequency of time-domain signals is difficult; thus, a lot of researchers transform time-domain signals into frequency domain signals for observation and analysis.

A spectrogram is a 3D image describing frequency changes at each time point. The vertical axis is the frequency; the horizontal axis the time. Colors distinguish the strength of the energy of frequency at each time point. A general spectrogram simply observes the relationship between amplitude and frequency; therefore, the time dimension is appended to the spectrogram to enhance better observation on the signal changes.

Signals are first divided into several discrete time points and transformed into the frequency domain from the time domain by Short-time Fourier Transform (STFT). The basic transformation equation is shown as (3).

$$X(t,f) = \int_{-\infty}^{\infty} x(\tau) w(t-\tau) e^{-j2\pi f\tau} d\tau \tag{3}$$

$X(t,f)$ is the time frequency matrix of $x(\tau)w(t-\tau)$ after Fourier Transform, $x(\tau)$ is the input signal for transformation and $w(t-\tau)$ is the window function. Generally utilized window function is Hamming Window for smoothing the discontinuous changes at cut-off to reduce energy leakage and better highlight the frequency component. In this case, better frequency responses could be acquired by multiplying signals with Hamming Window, as follows (4).

$$w(n) = 0.54 - 0.46 \cos\left(\frac{2n\pi}{M-1}\right), 0 \le n \le M-1 \tag{4}$$

where *M* is the length of the analysis window.

When substituting different time t for the window function moving along different time axes of signals, with windowing and Fourier transform, the absolute square $SP_x(t,f)$ after Short-time Fourier Transform could be acquired, as follows (5).

$$SP_x(t,f) = |X(t,f)|^2 = \left|\int_{-\infty}^{\infty} x(\tau) w(t-\tau) e^{-j2\pi f\tau} d\tau\right|^2 \tag{5}$$

2) Model evaluation

The evaluation of model performance plays an important role in the classification of deep learning, as it provides several objective standards to test the quality of the predictive model [26].

A confusion matrix is a visualization analysis table to evaluate classification models, listing the prediction categories of algorithms on each row and the type of source data on each line. The matrix is composed of values of True positive, True negative, False positive, and False negative [27].

Accuracy, a popular indicator for model evaluation, is calculated as the total percentage of all predicted samples being classified as correct in the classification model, as follows (6).

$$\frac{TP+TN}{Positive+Negative} = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

E. Deep Learning and Neural Network Structure

CNN, a transformation of neural networks, is broadly applied and developed in Computer Vision because it could precede layer-by-layer analysis and operation of 2D and 3D images [28], [29]. CNN is composed of an input layer, several hidden layers, and an output layer, generally including the convolutional layer, pooling layer, and fully connected layer.

Convolution, a special linear operation [30], inputs a 2D or 3D image (with color information) into the convolutional layer through n convolution kernels to convolute the feature map with n images. The operation of the convolutional layer is shown as (7), where $S(i,j)$ is the feature map of image and

I is the input image. 2D convolution kernels (or filters) are used for the convolution operation.

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n) \quad (7)$$

The pooling layer is preceded after the convolutional layer to solve the huge and easily appeared overfitting problem caused by the acquisition of the feature diagram through the convolutional layer for a classifier. A feature diagram in the pooling layer would generally be divided into several subregions, which are preceded by the aggregation statistics of the maximal value or the mean to reduce the feature space [31].

The fully Connected Layer, as the last stage of the convolution neural network, is similar to the traditional neural network (see Fig. 6). Several feature maps selected from the original image, through the processing of the convolutional layer and pooling layer, are input to the neuron for the operation. The fully connected layer is connected between input neuron and output neuron [32]. The operation process is shown as (8), where W is the weight vector, x is the input vector, and b is the bias vector.

$$Z = W^{\mathrm{T}} x + b \quad (8)$$

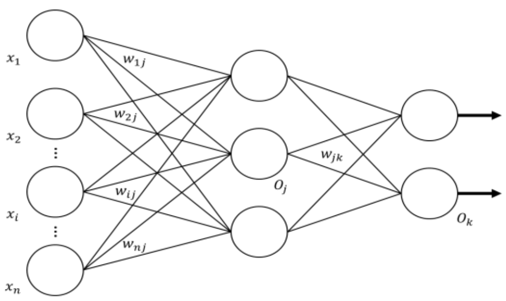


Fig. 6. Fully connected layer schematic diagram.

The value from the above network structure will be calculated by loss function to weight error between neural network prediction value and ground. The error is then transmitted to the convolution kernel and hidden layer through Backpropagation. The minimal error weight combination is then found out by shortening the difference between prediction and actual values. Cross entropy is used as the loss function in this study, as follows (9), where y_i is the true distribution value of data.

$$Loss = -\sum_m y_i \log(y'_i) \quad (9)$$

TABLE III: CNN-6L PARAMETER

Name	Output Number	Filter Size/ Stride
Conv1	16	3×3/1
Pool1	16	3×3/1
Conv2	16	3×3/1
Pool2	16	3×3/1
Fully connected1	128	
Fully connected2	128	

In this study, two CNN models (CNN-6L and CNN-12L) are structured. CNN-6L model contains two convolutional layers, two pooling layers, and two fully connected layers; CNN-12L model five convolutional layers, five pooling layers, and two fully connected layers. The parameters are shown in Table III and Table IV.

TABLE IV: CNN-12L PARAMETER

Name	Output Number	Filter Size/ Stride
Conv1	16	3×3/1
Pool1	16	3×3/1
Conv2	32	3×3/1
Pool2	32	3×3/1
Conv3	64	3×3/1
Pool3	64	3×3/1
Conv4	64	3×3/1
Pool4	64	3×3/1
Conv5	64	3×3/1
Pool5	64	3×3/1
Fully connected1	128	
Fully connected2	128	

F. Verification Model Architecture

According to Algorithm 1, the individual specific models are divide into brainwaves of a single person and others (i.e. A and non-A) in the frequency domain signal processing. SMOTE is used for increasing the brainwave data of a single person to reach the equivalent of the number of others' brainwave data. The data are further split into testing and training sets for model construction and evaluation to authenticate the person (matching the brainwave data of A or not).

Algorithm 1 Individual specific model training

Input:
SMOTE, Synthetic Minority Oversampling Technique;
k, The number of minor brainwave segments;
j, The number of training sets;
M, Learning scheme(Convolutional neural network);
Output:
Classifiers, *M*;
1: **for** $i = 1$ to k **do**
2: Use SMOTE to increase minor category samples;
3: Set 13 times of SMOTE multiple;
4: **end for**
5: **for** $a = 1$ to j **do**
6: Training CNN classifiers using *j*-th training sets;
7: **end for**
8: **return** *M*;

IV. EXPERIMENT AND RESULT

A. Experiment Process and Experiment Environment

The experiment process contains the following steps. First, filter the source data of brainwave, then select features through frequency domain signals, and finally input the selected features to the classifier for model construction and evaluation.

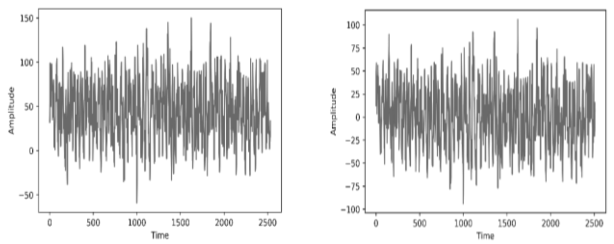
TensorFlow is an open-source frame for machine learning and deep learning offered by Google. In this study, the kits in TensorFlow are utilized for constructing CNN and a computer matched with GPU (Graphics Processing Unit) is applied to enhance the speed on the training model. In terms of file splitting and spectrogram making, Python and the provided kits (Scipy, Numpy, Pandas, Matplotlib) are used for the processing.

B. Signal Conversion and Processing

The source data in this study are the CSV format. Since EEG is an easily-disturbed signal, the segments of front and last 10 seconds are cut out of each EEG data, and the remaining 100 seconds are divided into 2, 5, 10, and 20 segments for different experiments.

Although the noise generated in the environment is reduced in the collecting process, there is still some noise interference in the source brainwave signals. Therefore, the Butterworth filter is adopted for processing noise before converting EEG into spectra.

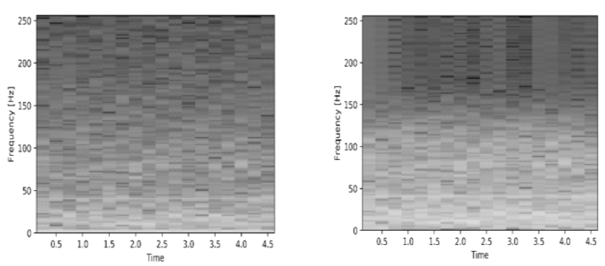
This study adopts Low pass in the Butterworth filter for allowing the pass of signals with low frequency and gradually decreasing the pass of signals with high frequency. Fig. 7 is the time-domain comparison before and after EEG passing BLPF, which shows the overall amplitude variation is more concentrated.



(a) Time domain before using a filter (b) Time domain after using a filter

Fig. 7. Comparison of EEG time domain with BLPF.

A spectrogram could compare the effect through BLPF. From Fig. 8, the energy in spectrogram (b) concentrates on low frequency, and the high frequency is comparatively weaker than it in spectrogram (a), especially above 150Hz.



(a) Spectrogram before using a filter (b) Spectrogram after using a filter

Fig. 8. Comparison of EEG spectrogram with BLPF.

C. Experimental Result of Deep Learning and Machine Learning

Besides training the CNN model, three traditional machine learning algorithms of C4.5, CART, and SVM are utilized in the model construction in this study. The three classifiers are used for comparing whether the individual specific model of CNN outperforms than traditional machine learning classifiers. First, the data set is split into the training set and testing set with the proportion of 8:2. Indicators of Accuracy, Specificity, Sensitivity, and the F1 Score are eventually adopted for model evaluation.

1) CNN authentication result with individual specific model

Table V lists the number of pictures used at different seconds in the individual-specific models of CNN-6L and CNN-12L, and the data are split into the training set and testing set with the proportion of 80/20. To improve the data imbalance between the personal category and total category, SMOTE is adopted for increasing the data in the personal category and set the multiple to 13 times to reach the equivalent number of the other person categories. Furthermore, the hyper parameters of the model at different seconds are set consistent, Max Step 2000 steps, batch size 16 pieces of the electroencephalogram, and learning rate 0.0001.

TABLE V: NUMBER OF PICTURES INPUT TO CNN INDIVIDUAL SPECIFIC MODEL AT DIFFERENT SECONDS

Second	Number of picture
2s	1400
5s	560
10s	280
20s	140

TABLE VI: ACCURACY COMPARISON OF INDIVIDUAL SPECIFIC MODEL AT 2 SECOND BETWEEN CNN-6L AND CNN-12L

Person	CNN-6L	CNN-12L	Person	CNN-6L	CNN-12L
1	95.70%	97.85%	9	96.09%	96.09%
2	97.51%	97.51%	10	95.36%	95.36%
3	97.85%	98.19%	11	94.63%	94.63%
4	96.09%	96.44%	12	95.02%	96.78%
5	97.12%	97.12%	13	97.85%	97.85%
6	96.44%	98.58%	14	98.19%	98.19%
7	92.48%	94.63%	15	95.70%	95.70%
8	96.09%	97.12%	Average	96.15%	96.80%

TABLE VII: ACCURACY COMPARISON OF INDIVIDUAL SPECIFIC MODEL AT 5 SECOND BETWEEN CNN-6L AND CNN-12L

Person	CNN -6L	CNN -12L	Person	CNN -6L	CNN -12L
1	100%	99.12%	9	97.31%	97.31%
2	92.87%	93.75%	10	93.75%	93.75%
3	96.44%	98.19%	11	92.87%	91.94%
4	95.56%	96.44%	12	94.63%	94.63%
5	97.31%	97.31%	13	97.31%	97.31%
6	97.31%	97.31%	14	95.56%	96.44%
7	94.63%	94.63%	15	95.56%	96.44%
8	96.44%	96.44%	Average	95.87%	96.07%

TABLE VIII: ACCURACY COMPARISON OF INDIVIDUAL SPECIFIC MODEL AT 10 SECOND BETWEEN CNN-6L AND CNN-12L

Person	CNN -6L	CNN -12L	Person	CNN -6L	CNN -12L
1	96.44%	98.19%	9	98.19%	94.63%
2	98.19%	96.44%	10	96.44%	96.44%
3	98.19%	98.19%	11	92.87%	94.63%
4	98.19%	98.19%	12	98.19%	98.19%
5	94.63%	94.63%	13	94.63%	96.44%
6	98.19%	96.44%	14	98.19%	98.19%
7	98.19%	98.19%	15	92.87%	98.19%
8	92.87%	92.87%	Average	96.40%	96.66%

TABLE IX: ACCURACY COMPARISON OF INDIVIDUAL SPECIFIC MODEL AT 20 SECOND BETWEEN CNN-6L AND CNN-12L

Person	CNN -6L	CNN -12L	Person	CNN -6L	CNN -12L
1	100%	100%	9	92.87%	96.44%
2	96.44%	96.44%	10	96.44%	92.87%
3	100%	100%	11	96.44%	96.44%
4	96.44%	96.44%	12	100%	100%
5	92.87%	92.87%	13	89.31%	89.31%
6	96.44%	96.44%	14	96.44%	100%
7	92.87%	85.69%	15	89.31%	89.31%
8	96.44%	96.44%	Average	95.47%	95.27%

Fig. 9 integrates the average accuracy of CNN-6L and CNN-12L at various seconds. The highest accuracy 96.8% appears on the using of CNN-12L at 2 seconds, followed by the accuracy of 96.66% of CNN-12L at 10 seconds.

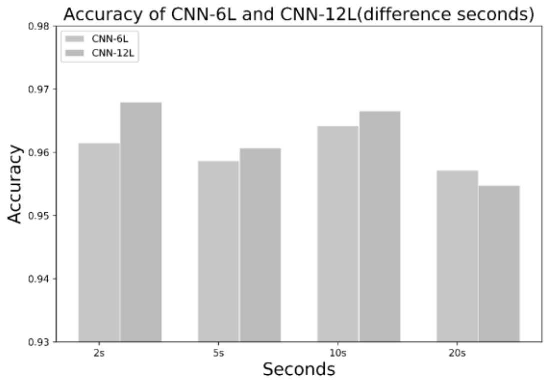


Fig. 9. Average accuracy of individual specific model at various seconds between CNN-6L and CNN-12L.

2) Individual specific model authentication with traditional classifier

Traditional classifiers (C4.5, CART, SVM) in traditional machine learning algorithms are used in this study for comparisons. Time signals processed by Butterworth filter are transformed into frequency domain signals through Fourier Transform.

The frequency through Fourier Transform is organized as δ wave, θ wave, and low/medium/high frequency α wave and β wave in this study. Furthermore, the mean energy, maximum energy, and the standard deviation of energy in various wavebands are organized as 24 features for classification in the traditional machine learning classifiers.

For improving data imbalance between the personal category and general category, SMOTE is further utilized in the experiment for increasing the data in the personal category and set the multiple to 13 times to reach the equivalent number of the other person categories. Table. 10. lists the number of data used at different seconds, which are split into the training set and testing set with the proportion of 80/20.

TABLE X: NUMBER OF DATA INPUT OF INDIVIDUAL SPECIFIC MODEL WITH TRADITIONAL CLASSIFIER AT VARIOUS SECONDS

Second	Number of data
2s	1204
5s	471
10s	233
20s	104

TABLE XI: COMPARISON OF ACCURACY OF INDIVIDUAL SPECIFIC MODEL WITH DIFFERENT TRADITIONAL CLASSIFIERS

	C4.5	CART	SVM
2 Second	91.19%	89.67%	89.44%
5 Second	91.55%	88.38%	91.58%
10 Second	93.62%	92.91%	92.72%
20 Second	95.45%	94.18%	93.39%

3) Comprehensive comparison of model result

The average accuracy, average sensitivity, and average F1-score of all classifiers at different seconds are integrated into the following figures. It is noticed that the individual specific CNN model could be adopted for authentication in a shorter period and receives favorable results in evaluation among all the items. In the long-period analysis, the individual specific CNN model does not appear an obvious difference from traditional classifiers on the authentication, possibly due to fewer training pictures.

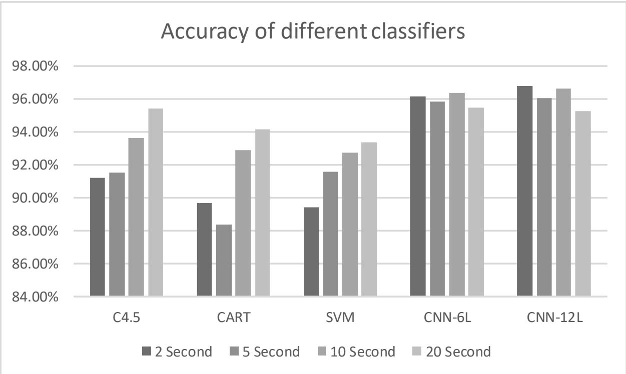


Fig. 10. Comparison of average accuracy of model with different classifiers at various seconds.

V. Conclusion

This study mainly develops the CNN brainwave verification model to protect athletes' biometric data. The individual-specific verification model is limited to the brainwave data collection of 15 people around 20-27 ages. In the future, more data of different age groups will be collected to fit reality situation. Brainwave features are selected from 2 minutes static brainwave signals of participants through the Butterworth Low Pass Filter and Short-time Fourier Transform, and the verification evaluation model is developed by comparing several machine learning classifiers and the deep learning CNN model.

There is much research on the application of brainwave on authentication; however, the practicability in real life is still examined. Past research showed that select 90 seconds of brainwave features collected from handy electroencephalographs could achieve maximal accuracy, which is restricted for application in real life [33]. The model proposed by this study requires the selection of fewer than 90 seconds (2-20sec); thus, it conforms better to the real-life application.

Category imbalance has been a classical problem in many data sets (e.g. medical data, information security data). The imbalance sample proportion in the data sets would result in bad classification. SMOTE is used in this study to solve the imbalance problem between personal data and general data and reach favorable effects in various model evaluation indicators.

This study proposes the individual specific models where the selection of brainwave features at 2 seconds achieves the accuracy of 96.80%. It presents a certain potential for authentication. The effect of short-period brainwave selection is better than past relevant studies; thus, it could be a real-time verification indicator and apply for fast and secure verification measures.

Conflict of Interest

The authors declare that they have no conflict of interest

Author Contributions

All authors contributed extensively to the work presented in this paper. M.H.T. and S.K.W. conceived the study; M.H.T. developed the concept, improved the manuscript, and supervised the work; C.Y.H. conducted the research, analyzed the data, and wrote the paper; T.L.C. revised this paper. All authors had approved the final version.

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