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Master's Degree Thesis

A Study on Design of AI Algorithms for Classification of Mental Stress Based on Electrocardiogram

Graduate School of Chosun University
Department of IT Fusion Technology
Mingu Kang

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정신적 스트레스 신호 분류를 위한 심전도 기반 **AI**
알고리즘 설계에 관한 연구

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This is to certify that the Master's Thesis of Mingu Kang

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Acronyms

ECG	Electrocardiogram
CNN	Convolutional Neural Networks
LSTM	Long Short Term Memory
SVM	Support Vector Machine
NB	Naive Bayes
OAA	One Against All
ROC Curve	Receiver Operating Characteristic Curve
PR Curve	Precision-Recall Curve
AUC	Area Under the Curve
AP	Average Precision

요 약

정신적 스트레스 신호 분류를 위한 심전도 기반 AI 알고리즘 설계에 관한 연구

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최근 경제 성장에 의한 생활환경의 개선으로 건강에 대한 관심이 높아지면서 신체적 건강관리뿐만 아니라 정신적 건강관리 또한 중요한 부분으로 인식되고 있다. 본 연구는 심전도 기반 Convolutional Neural Network (CNN) - Long Short Term Memory (LSTM), Support Vector Machine (SVM) - Naive Bayes (NB) 모델을 이용하여 정신적 스트레스 신호를 분류하는 앙상블 알고리즘을 제시했다. 스트레스를 받았거나 혹은 휴식 상태일 때의 심전도 신호로부터 R-S Peak, R-R Interval를 추출했다. 스트레스 신호 분류 알고리즘의 성능을 극대화하기 위하여 심전도 신호로부터 추출된 파라미터들을 SVM-NB, CNN-LSTM 모델에 적용하였고, 푸리에 변환을 응용한 Spectrogram을 통해 Training 데이터 개수를 증가시켜 스트레스 신호의 분류 모델에 대한 정확도를 향상시켰다. 그 후 Time-Frequency 영역에서 Epoch별 알고리즘의 성능을 나타내었고 스트레스 신호 분류 오차율을 계산했다. Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Precision-Recall (PR) Curve를 통해 스트레스 분류 알고리즘의 성능을 평가한 결과, 각각 98.3%, 98.12%, 97.6%의 정확도를 나타내었다. 이를 통해 정신적 스트레스에 시달리는 현대인들의 건강관리에 도움을 줄 수 있다.

I. Introduction

1.1. Research Background

1.1.1. Definition and type of stress

Recently, mental illnesses, such as depression, have emerged as social problems, and the desire to check the condition of one's mental health has increased. It is important to check one’s mental health status in advance and manage it periodically. Stress is a state of psychological and physical tension experienced in a particular environment. Excessive stress can result in a vicious cycle and cause chronic diseases, such as high blood pressure, heart disease, and even cancer. If serious, it can lead to death **[1,2].**

Stress is caused by several factors, and these include mental and physiological stresses. Mental stress can include concerns, economic anxiety, and various complaints about human relations in various places such as work or school. Physiological stress can include physical fatigue or hunger.

Previous studies have proposed classification of stress signals. Among them, a method commonly used to measure stress signals uses bio-signals. Bio-signals are generated inside the body via physiological principles such as nervous systems and blood vessels, and representative examples include electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), blood oxygen saturation, and pulse wave. Stress activates sympathetic nerves in the autonomic nervous system. The sympathetic nerve is an indicator that reflects whether a person is excited or nervous and can help determine a person’s level of stress.

1.1.2. Definition of ECG signal

Methods that measure stress using EEG, EMG, blood oxygen saturation, and pulse waves have different signal sizes depending on the location of the subject's electrode attachment. Moreover, these methods are complex as it includes high noise signal and many channels, and therefore it is difficult to extract accurate feature points **[3-5].**

To compensate for this, a typical method for measuring a stress signal uses an ECG signal. ECG is the most common and convenient method to indirectly check heart conditions noninvasively **[6].** ECG signals are useful for diagnosing arrhythmia and myocardial infarction and can be easily recorded repeatedly, making it easy to measure stress signals.

In addition, the activation state of the sympathetic and parasympathetic nerves of the autonomic nervous system can be identified, and through this, feature points for identifying the stress state can be extracted. When a stress signal is classified using an ECG signal, the feature extraction of a time domain and a frequency domain is mainly used. Feature values are extracted using the average value and standard deviation of the R-R interval in the time domain. Moreover, feature values are extracted using amplitude values of low frequency (LF) and high frequency (HF) bands representing power spectra in the frequency domain.

II. Classification of stress signals using bio-signals

2.1. Previous studies

2.1.1. The definition of deep learning

Deep learning is a method for classifying stress signals. Deep learning is a technique that sets basic parameters for data as a specific field of machine learning and trains computers to self-learn by recognizing patterns using multiple processing layers **[7]**. Representative examples of deep learning include convolutional neural networks (CNNs) and long short-term memory (LSTM). CNN is a type of deep learning and is mainly used to recognize images and extract features of data from input images, identify patterns, and classify images. LSTM is a special type of recurrent neural network (RNN) and is a neural network designed to remember and learn even if the distance between sequential input data is large. Machine learning can be divided into supervised and unsupervised learning according to the learning methods.

Supervised learning is a method of learning using data whose characteristics have already been determined and can be divided into regression analysis and classification according to the type. Representative examples include support vector machines (SVMs) and neural networks. Unlike supervised learning, unsupervised learning is a method of predicting the results of new data by grouping data without correct answer labels between similar features. K-mean clustering is an example of unsupervised learning.

Table 2.1 lists the methods for classifying stress signals using various bio-signals. As a result of classifying EEG into logistic regression (LR), SVM, and NB, the accuracy reached 94.6% **[8]**. However, this study took 2 h to measure stress signals using 128 channels, and the process of extracting feature points according to the number of channels was complicated, which made it difficult to accurately classify stress signals.

EEG signals were analyzed using SVM, multilayer perceptron (MLP), and NB to obtain 75% and 85.20% accuracy **[9,10]**. However, previous studies limited the number of training data to 15, which led to underfitting. Moreover, measuring stress signals using seven channels was complex and time-consuming. In another study that obtained 85% accuracy by analyzing EMG with SVM, it was difficult to extract accurate feature points as it had different amplitudes for the same motion owing to the fine movement of muscles and high noise signal **[11]**.

PPG was analyzed using CNN, linear regression, and SVM to obtain accuracies of 87.6%, 82%, and 86%, respectively **[12,13]**. However, in this study, it was difficult to classify stress signals as it detected noisy and incorrect peak values owing to the small difference in the calculation of the LF/HF ratio for the R-R interval and frequency domain.

EMG, galvanic skin response (GSR), and respiration signals were classified as SVM and K-nearest neighbors (KNN) to obtain the highest accuracy of 93.65% **[14].** However, in this study, it was difficult to accurately classify stress signals because the bio-signals contained noise, and the number of parameters was small. By classifying the ECG signal and the GSR signal into LDA and SVM, an accuracy of up to 92% was obtained **[15].** However, it was difficult to classify the stress signal because the distance between the classes was small.

Table 2.1. Classification of stress signals using bio-signals

Number	Title	Signal	Classifier	Accuracy
[8]	Machine learning framework for the detection of mental stress at multiple levels (2017)	EEG	LR, SVM, NB	94.6%
[9]	Classification of perceived human stress using physiological signals (2019)	EEG	NB, MLP	(avg). 59.21%
[10]	EEG based classification of long-term stress using psychological labeling (2020)	EEG	SVM	85.2%
[11]	EMG-based real time facial gesture recognition for stress monitoring (2018)	EMG	SVM	85%
[12]	Stress Classification Using Photoplethysmogram-Based Spatial and Frequency Domain Images (2020)	PPG	CNN	87.6%
[13]	Performance analysis of Machine Learning techniques for classification of stress levels using PPG signals (2020)	PPG	MLP, SVM	(avg). 84%
[14]	Physiological Signal Analysis and Classification of Stress from Virtual Reality Video Game(2020)	ECG	LDA, DT, SVM, GB, NB	(avg). 74%
[15]	Determination of stress in humans using data fusion of off-the-shelf wearable sensors data for electrocardiogram and galvanic sKin response(2018)	ECG, GSR, RESP	LDA. SVM	85%, 92%

2.1.2. Database of ECG signals

Table 2.2 shows the configuration of a database of electrocardiogram signals for classifying stress signals. WESAD data measures ECG signals in 15 subjects on wrist and chest wearing devices**[16]**. The average age of the experimenter is 27.5 ± 2.4, consisting of 12 men and 3 women. The dataset shows three emotional states (rest, stress, entertainment). In order to indicate the Without stress state, the ECG signal is measured after taking the operating state of rest and entertainment for each 5 minutes. Conversely, the ECG signal was measured after solving the questionnaire and Trier Social Stress Tests (TSST) for 10 minutes to indicate the Under stress state. TSST contains arithmetic and listening evaluations. In addition, the sampling frequency of this database is 360 Hz.

The MIT-BIH ST Change Database contains 28 ECG records, mostly data recording myocardial infarction symptoms caused by mental stress **[17]**. And to evaluate the mental stress of exercise, electrocardiogram signals for each topic (walking, running) are displayed. The last five records 323 to 327 are excerpts from the records of long term ECG signals and indicate ST rise. The sampling frequency of this database is 360 Hz. For this experiment, recording of 15 subject ECG signals was selected as a measure of the heart rate range for the same subject.

CLAS Database is data measuring 124 ECG signals according to 4 emotional states (Picture Test, Music Video, Stroop Test, and Math Test) from 62 subjects (45 males, 17 females) **[18].** Each ECG data consists of 31.

Table 2.2. Database of ECG signals to classify stress signals

MIT-BIH ST change Database				
Subject	Signal	Time	Data	Stressor
15(Man)	ECG	20 minutes	Under stress: 14 Without stress: 14	Exercise test (WalK, Run)
WESAD(Wearable stress and Affect Detection)				
Subject	Signal	Time	Data	Stressor
15(Man:12, Woman:3)	ECG	20 minutes	Under stress: 15 Without stress: 15	Rest, Funny video, TSST
CLAS Database				
Subject	Signal	Time	Data	Stressor
62(Man:45, Woman:17)	ECG	20 minutes	Under stress: 62 Without stress: 62	Picture Test, Music Video, Strop Test, Math Test

2.1.3. Removing noise and extracting feature points using ECG signals

The measurement of the ECG signal is a convenient way to indirectly check the state of the heart. When taking an ECG, noise is generated by several factors, which greatly reduces ECG classification accuracy. To solve this problem, we used a low-pass filter and confirmed that 90.89% of the noise was eliminated using a low-pass filter with a sampling frequency of 360 Hz and a cutoff frequency of 150 Hz. Figure 2.1 shows the extracted R-S Peak values from an ECG signal **[19].** R Peak and S Peak were extracted from ECG signals after setting a threshold. For R Peak, the highest point was extracted when the threshold was 0.2 mV or higher and the S Peak was extracted from the lowest point when the threshold was below -0.54 mV.

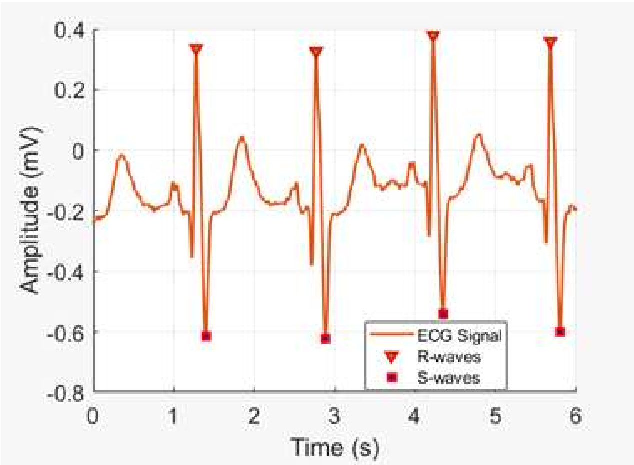

Figure 2.1. Feature point extraction by threshold

In the under stress state, the heart beats irregularly and quickly, the R-R interval of the ECG signal becomes narrow and the R-S Peak increases. On the other hand, in the without stress state, the heart is relatively stable, the R-R interval widens, and the R-S Peak decreases **[20]**. In each state, the average R-S Peak without stress state was found to be 1.47 mV and under stress it was 4.25 mV. Figure 2.2 shows the ECG signal in the Under Stress state and the ECG signal in the Without Stress state as spectrogram.

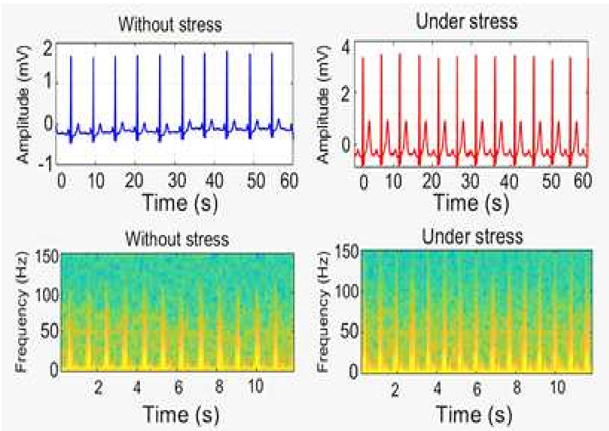

Figure 2.2. ECG signal as spectrogram

III. Classification of mental stress signals using AI algorithms

3.1. Classification of mental stress signals using CNN-LSTM

3.1.1. Add number of training data using spectrogram

In the case of algorithms that combine CNN-LSTM, there are a total of 58 existing ECG data. However, it is difficult to evaluate CNN-LSTM stress signal classification model with 58 ECG data. Therefore, the number of ECG data is added to improve the accuracy of the stress signal classification model. As shown in Figure 3.1, the Fast Fourier transform was applied to ECG Data and converted into Frequency Domain. Therefore, stress signals were classified using 58 Time Domain and 58 Frequency Domain of ECG Data.

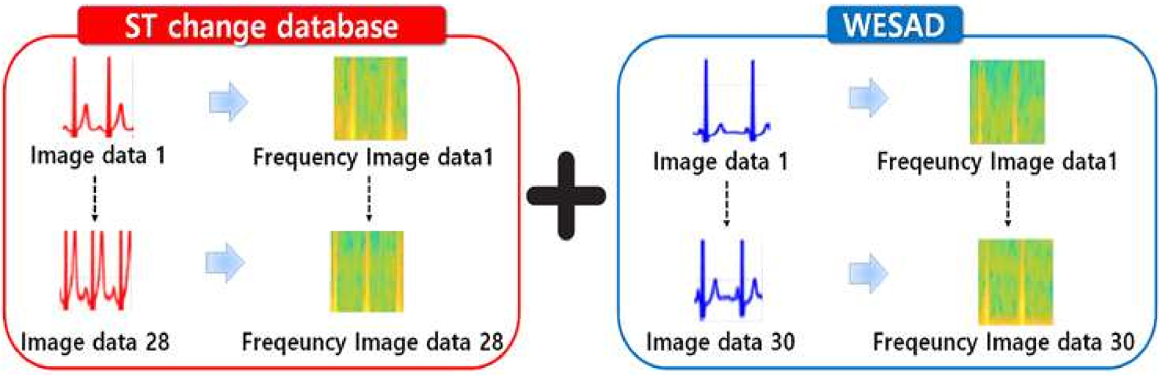

Figure 3.1. Adding the number of training data using a spectrogram

Figure 3.2 is a block diagram for classifying an ECG signal under stress state and an ECG signal in a without stress state using an AI algorithm that combines CNN-LSTM. It is divided into stages of removing noise from ECG data, extracting feature points of ECG signals using spectrogram, and classifying stress signals and evaluating performance using algorithms that combine CNN and LSTM.

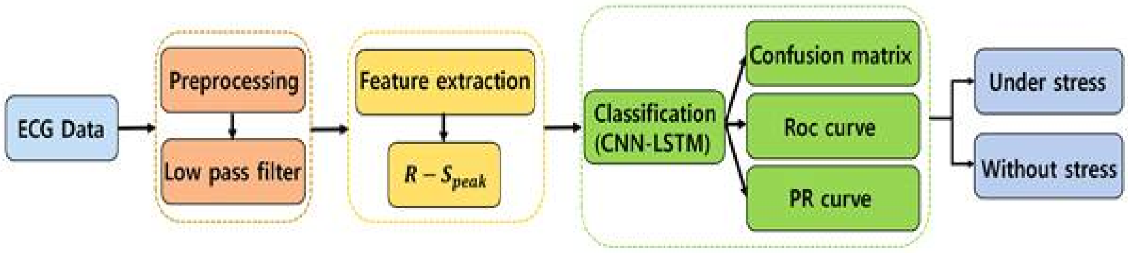

Figure 3.2. Classification block diagram of stress signals combined with CNN-LSTM

3.1.2. Design a mental stress classification algorithm using CNN-LSTM

Figure 3.3 shows the classification process of a stress signal using an algorithm that combines a CNN and LSTM. The classification composition was expressed in a total of 14 stages.

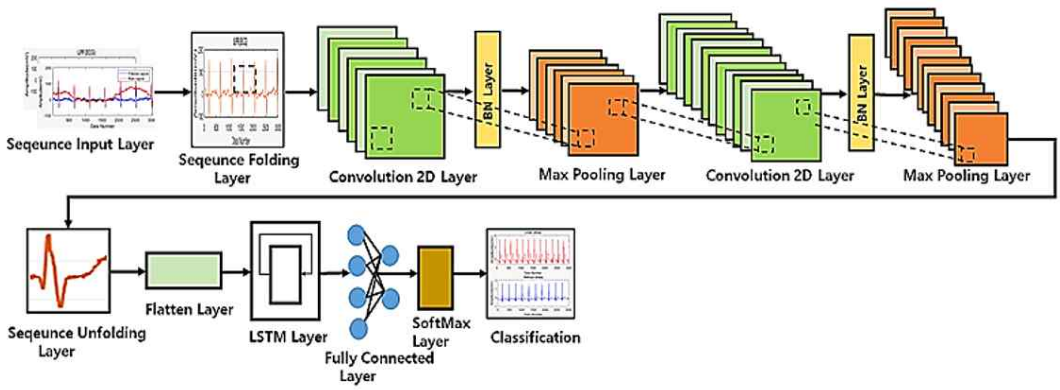

Figure 3.3. AI algorithm configuration diagram combining CNN-LSTM

In this study, as shown in Table 3.1, the hierarchical structure of the AI algorithm combining the CNN and LSTM is shown.

Table 3.1. Classification layers used to evaluate stress signals using CNN-LSTM

Number	Layer	Activations	Weights	Bias
1	Sequence Input Layer	124*124*3	-	-
2	Sequence Folding Layer	124*124*1	-	-
3	Convolution 2D Layer	124*124*6	5*5*3*6	1*1*6
4	Batch Normalization Layer	124*124*6	-	-
5	Max Pooling Layer	62*62*6	-	-
6	Convolution 2D Layer	62*62*12	3*3*6*12	1*1*12
7	Batch Normalization Layer	62*62*12	-	-
8	Max Pooling Layer	31*31*12	-	-
9	Sequence Unfolding Layer	31*31*12	-	-
10	Flatten Layer	11532	-	-
11	LSTM Layer	200	Input: 800*11532 Recurrent: 800*200	800*1
12	Fully Connected Layer	2	2*200	2*1
13	Softmax Layer	2	-	-
14	Classification	-	-	-

First, image sequence data of 124*124*3 is input to the Sequence Input Layer. After that, the data value is converted using the Sequence Folding Layer. The reason for using Sequence Folding Layer is that image sequence data can be converted into an array form, arranged and transferred to Convolution 2D Layer.

The first Convolution 2D layer contains six filters with a size of 5*5. As a result of calculating the Convolution Layer according to Equation (1) below, the size of the output value is 124*124*6. Equation (1) applies Padding and Stride as the calculation process of Convolution Layer and calculates the output value when input data and filter size are given. In this case, H, W represent the size of the input data, FH, and FW represent the size of the filter, S represents Stride, P represents Padding, OH, and OW represents the size of the output value.

$$(OH, OW) = (\frac{H+2P-FH}{S}+1, \frac{W+2P-FW}{S}+1) \tag{1}$$

Subsequently, the output data is connected to the Batch Normalization Layer. Normalize the size value of the data output from the Batch Normalization Layer to 124*124*6 and then connect to the Max Pooling Layer. As a result of applying Stride 2 as a 2*2 filter and calculating using Equation (2) below, the size of the output value is reduced to 62*62*6. Equation (2) represents the calculation process of the Max Pooling Layer. The output data size is the share of the size of the row and column divided by the pooling size.

$$(ORS, OCS) = (\frac{H}{P}, \frac{W}{P}) \tag{2}$$

The second Convolution Layer contains 12 filters with a size of 3*3. Subsequently, the output data is connected to the Batch Normalization Layer and the Max Pooling Layer. As a result, the output data size is reduced to 31*31*12. In order to transfer the output data size to the LSTM layer, a normalization operation is performed using the Sequence Unfolding Layer. Therefore, a feature vector is obtained using the Flatten Layer. The Flatten Layer has the advantage of not converting parameter values by converting the output value of the extracted feature map into one-dimensional array value and reconstructing it into input value of long short term memory **[21].** In the input layer, a weight value having a size of 800*11532 is applied to equations 7 to 11 below to extract a feature value.

$$i_t = \sigma(w_x x_t + w_h h_{t-1} + b_i) \tag{3}$$

$$g_t = \tanh(w_{xg} x_t + w_{hg} h_{t-1} + b_g) \tag{4}$$

$$f_t = \sigma(w_{xf} x_t + w_{hf} h_{t-1} + b_f) \tag{5}$$

$$o_t = \sigma(w_{xo} x_t + w_{ho} h_{t-1} + b_o) \tag{6}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ g_t \tag{7}$$

After that, the feature value calculated from the output gate is transferred to the output layer by applying Equation (8) below. Equation (8) represents a process of discarding unnecessary values from among several feature values calculated from the output gate and extracting necessary feature values. After extracting the feature values from -1 to 1 using the Tanh function, the feature values of the corresponding range calculated at the output gate are transferred to the output layer. The feature values extracted from the LSTM Layer are classified using a fully connected layer having a size of 2 and then the probability values of the images classified by the Softmax Layer are calculated.

$$h_t = o_t \circ \tanh(c_t) \tag{8}$$

Figure 3.4 shows the components of Convolution 2D Layer and LSTM Layer using Equations (1-7). Equations (1,2) represent a process of calculating Convolution 2D Layer among CNN models, and equations (3-7) represent a process of outputting a feature value using weight values of an input gate, a forget gate, and an output gate in the LSTM Layer.

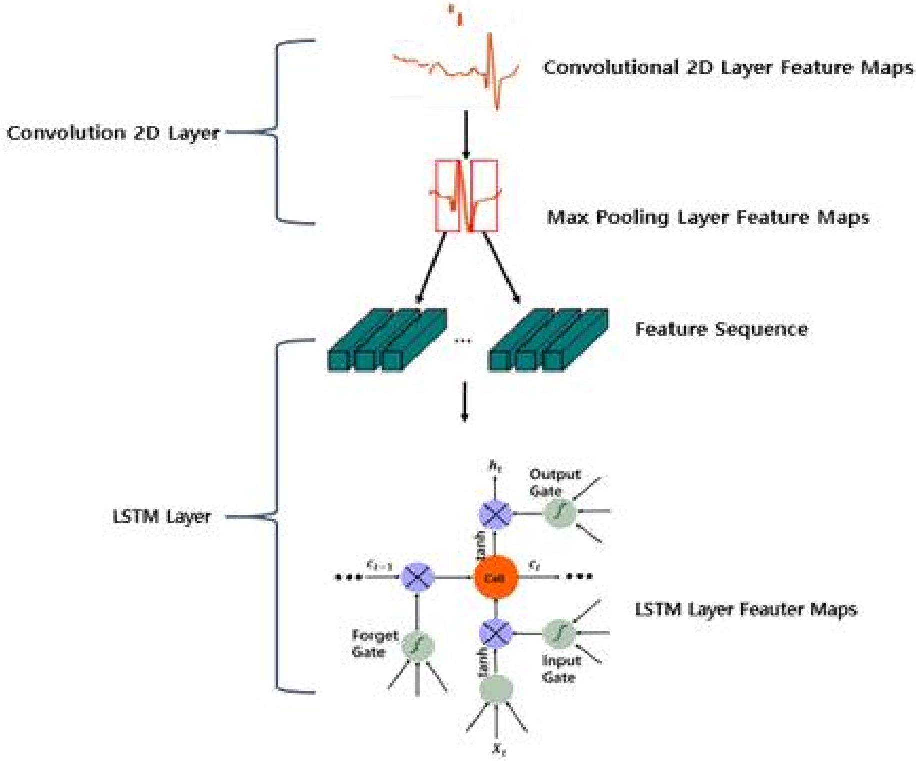

Figure 3.4. Components of Convolution 2D Layer and LSTM Layer

3.2. Classification of mental stress signals using SVM-NB

3.2.1. Data classification using SVM-NB

Figure 3.5 is a block diagram for classifying stress signals according to 4 emotional states using an AI algorithm that combines SVM-NB. It is divided into stages of removing noise from ECG data, extracting feature points of ECG signals using thresholds, presenting a classification process of stress signals using algorithms that combine SVM and NB and evaluating the classification performance of stress signals.

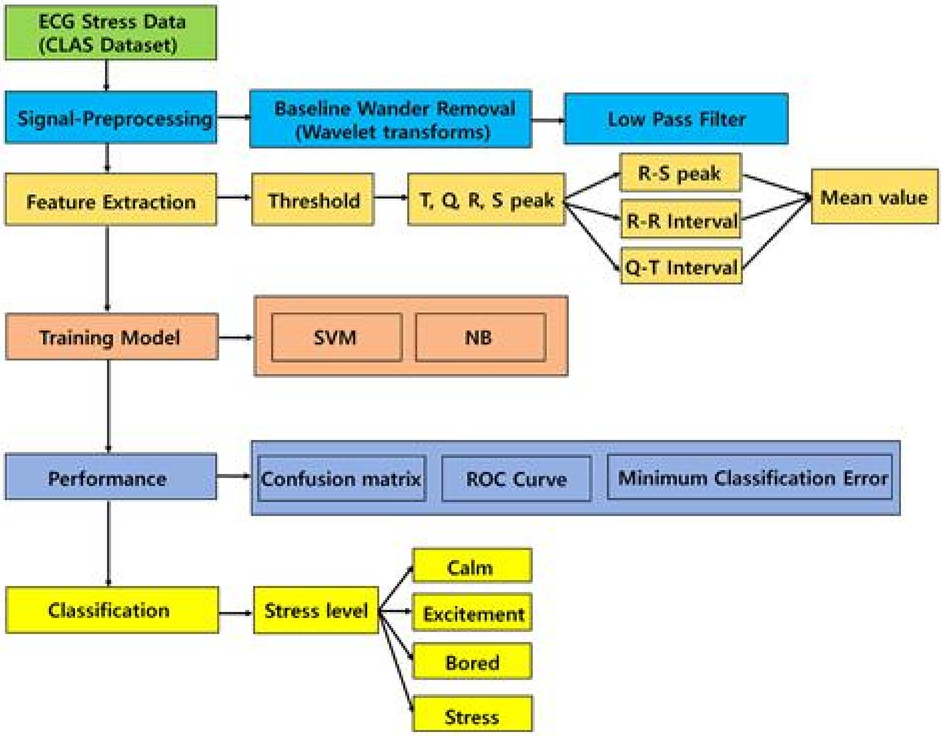

Figure 3.5. Classification block of stress signals combined with SVM-NB

Figure 3.6 classified the CLAS Database into 4 emotional states according to stress levels using a stress classification model that combines SVM and NB. Stress levels 1 and 2 are Calm and Excitement, and among the 4 emotional states, Picture Test and Music Video's ECG Data are included. Stress levels 3 and 4 are Bored and Stress, and among the 4 emotional states, ECG Data from the Stroop Test and Math Test are included. Therefore, stress levels 1 and 2 correspond to Without Stress, and stress levels 3 and 4 correspond to Under Stress.

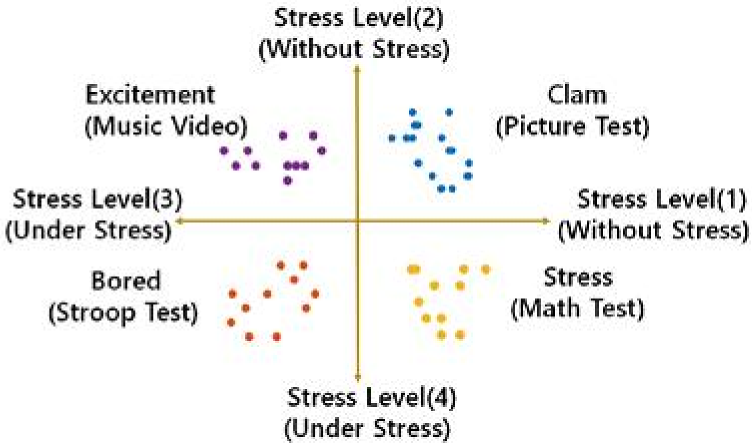

Figure 3.6. Classification of ECG Data using CLAS Database

SVM is a method of classifying classes using optimal decision boundaries to classify non-linear data in various dimensions **[22,23]**. SVM increases classification accuracy for new data by maximizing Margin, rather than simply finding a classification plane or minimizing sample errors. The stress classification model using the existing SVM by CLAS Database analysis used the Sequential Minimal Optimization (SMO) algorithm. SMO is used to perform binary classification of training data **[24]**. However, if there is a lot of data, the parameter value must be adjusted to find the decision boundary between the 2 data. However, due to the large amount of computation and complexity in adjusting parameter values, Overfitting occurs and classification accuracy for several classes is lowered.

To address these problems, classes were classified by applying the one-against-all (OAA) technique to SVM **[25]**. The OAA technique is used to classify multiple classes. Given K classes, the label of data in class i is set to +1 and the label of data in the remaining classes is set to -1 and binary classification is performed by the number of classes. Figure 3.7 is a graph that represents the classification process of ECG data for four emotional states using the OAA technique of SVM.

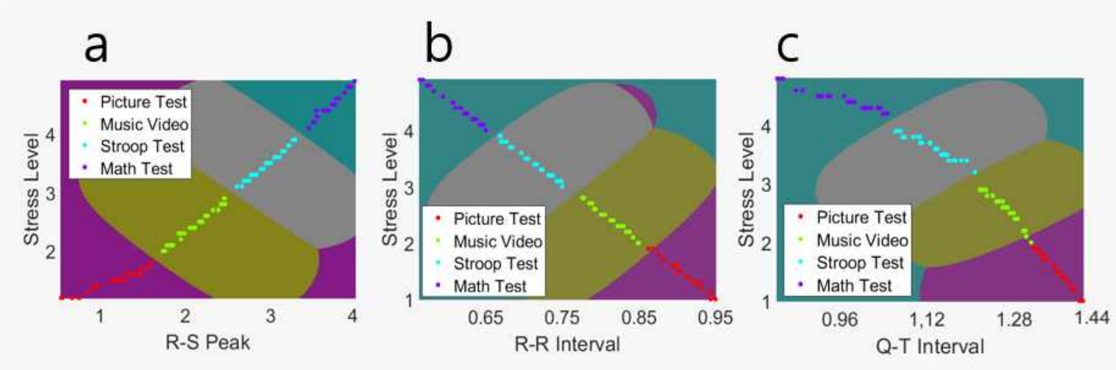

Figure 3.7. Stress classification using SVM

The data for R-S peak, R-R interval, and Q-T interval were classified according to stress levels after determining the margin for the decision boundary between the classes of four emotional states using Equation(9-10). In this case, I represents the number of classes, X represents a decision boundary, W represents a vector perpendicular to the decision boundary, B represents a bias and Min represents margin.

$$w \cdot x_1 + B = \pm 1,\ I = 1 \ldots N \tag{9}$$

$$Min \frac{1}{2} \parallel W \parallel ^2 \tag{10}$$

NB is a conditional probability based statistical classification method that calculates the feature probability that data belongs to each class **[26].** Naïve means that all variables are equal and Bayes means the probability that a variable belongs to a specific class. NB calculates the probability that the variable belongs to a specific class using Equation (11) which represents a data classification method using Bayes Theorem **[27].** P(A) represents the probability determined before the result appears, and P(B | A) represents the probability that B occurs under the condition that A occurs.

$$P(A \mid B) = (p(B \mid A)P(A))/(P(B)) \tag{11}$$

Figure 3.8 is a graph showing the classification process of ECG data for four emotional states using contours according to Naïve Bayes (NB).

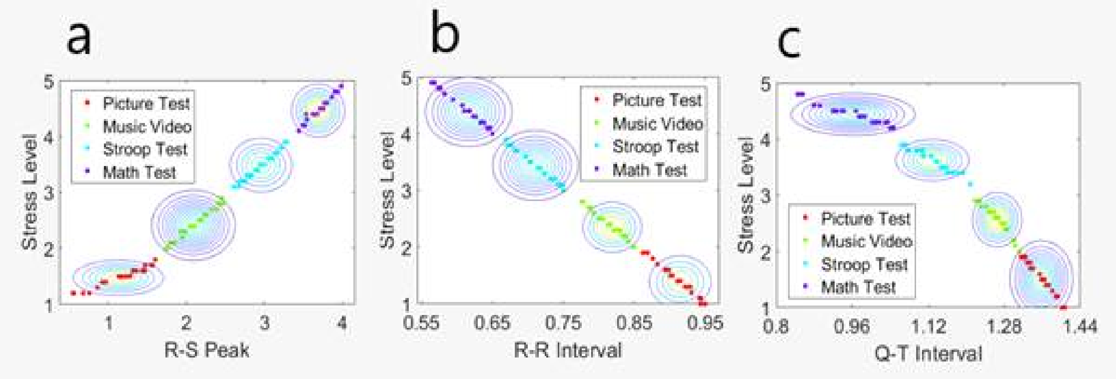

Figure 3.8. Stress classification using NB

The graph in Figure 3.9 represents the stress classification process according to the four emotional states using a stress classification model that combines SVM and NB. Using the OAA technique of SVM, labels are set on the class corresponding to each state and the ECG data range is indicated using the decision boundary point. Subsequently, the probability that the parameter belongs to the corresponding class is calculated using the contour line according to Naïve Bayes (NB) theorem.

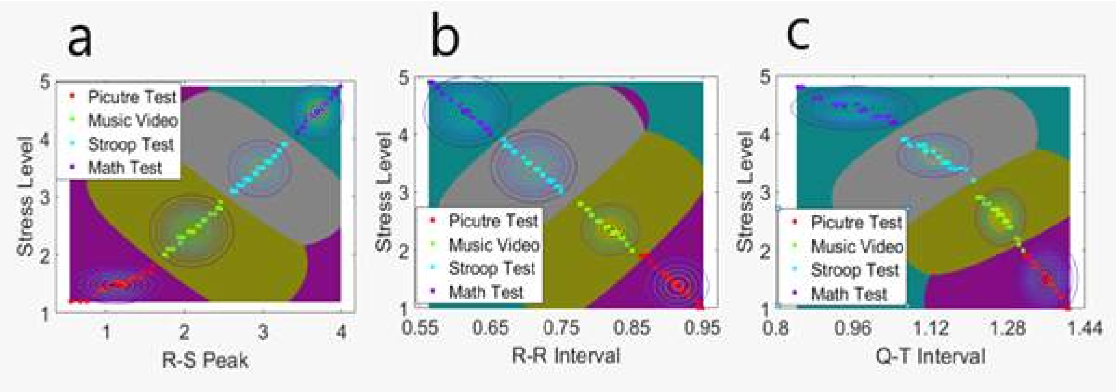

Figure 3.9. Stress classification using SVM and NB

Figure 3.9.1 shows the cross-validation process used to evaluate the performance of the SVM-NB model. K-fold cross-validation divides the data into k groups, extracts one of the groups, uses it as a test set, and uses the remaining K-1 groups as a training set. Repeating K times, each test yields one classification accuracy and then an average K to obtain the final performance of the classification.

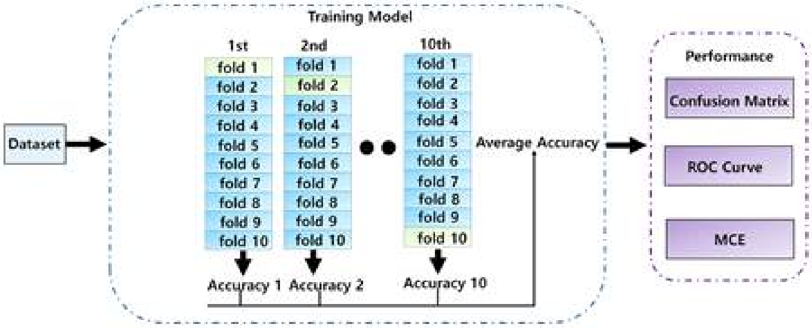

Figure 3.9.1 Stress classification using cross-validation

As shown in Figure 3.9.2 the performance of the stress classification model combining SVM and NB was demonstrated using 10-fold cross-validation. Owing to the classification, overfitting can be prevented by achieving accuracies of 98.9%, 98.7%, and 98.4% using 7 fold cross-validation.

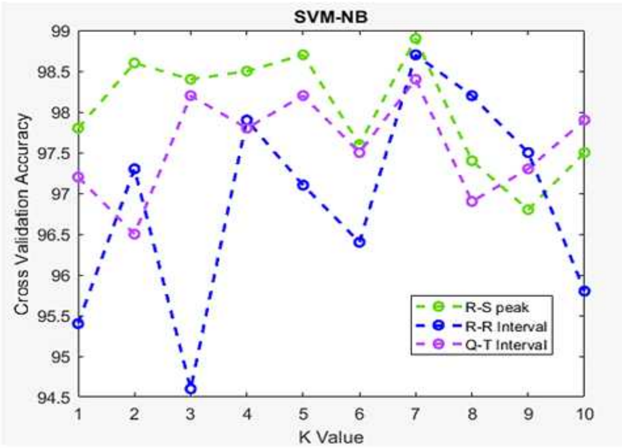

Figure 3.9.2 Stress classification using 10-fold cross-validation

IV. Experiment result

4.1. Stress classification performance evaluation using CNN-LSTM

In this study, the Confusion Matrix, ROC Curve, and PR Curve were used to evaluate the performance of the CNN-LSTM model's classification of stress signals **[28].** Confusion Matrix is an indicator used to evaluate the performance of a model. It represents a matrix that shows how accurately the predicted values predicted the actual observations. Table 4.1 shows the values of accuracy, sensitivity, specificity, precision, and negative predictive value for the classification model performance of stress signals using Equations (18-22).

Table 4.1. Evaluation of Classification Performance of Stress Signals for Time Domain and Frequency Domain

Time Domain					
Stress	Precision	Sensitivity	Specificity	Negative Predictive Value	Accuracy
Performance (%)	93.1%	96.4%	93.3%	96.6%	94.8%
Error (%)	6.9%	3.6%	6.7%	3.4%	5.2%
Frequency Domain					
Stress	Precision	Sensitivity	Specificity	Negative Predictive Value	Accuracy
Performance (%)	96.6%	100%	96.7%	100%	98.3%
Error (%)	3.4%	0.0%	3.3%	0.0%	1.7%

Equation (12) means accuracy and is the probability of correctly classifying the ECG signal under stress and the ECG signal in the without stress. The classification accuracy of stress signals in the time domain and frequency domain of ECG data was 94.8% and 98.3%, respectively. The sensitivity to the classification of stress signals in the time domain and frequency domain of ECG data was 96.4% and 100%, respectively

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

$$Sensitivity = \frac{TP}{FN+TP} \tag{13}$$

Equation (14) means specificity and is the probability that the algorithm correctly classified the ECG signal of without stress among the ECG data of without stress. The specificity for the classification of stress signals in the time domain and frequency domain of ECG data was 93.3% and 96.7%, respectively. Equation (15) means precision and is the probability that the algorithm correctly classifies the ECG signal in the under stress among the ECG data in the under stress. The accuracy of the classification of stress signals in the time domain and frequency domain of ECG data was 93.1% and 96.6%, respectively.

$$Specificity = \frac{TN}{TN+FP} \tag{14}$$

$$\mathrm{P}recision = \frac{TP}{TP+FP} \tag{15}$$

Equation (16) means the Negative predictive value and is the probability that the algorithm correctly classifies the ECG signal in the under stress when the result is the ECG data in the under stress.

$$Native\,\mathrm{P}redictive\ Value = \frac{TN}{TN+FN} \tag{16}$$

Figure 4.1 shows the performance of the stress signal classification model using the Confusion Matrix. Figure 4.1(a) shows the confusion matrix for the time domain of ECG data, and Figure 4.1(b) shows the confusion matrix for the frequency domain of the ECG data. The stress classification accuracy of the CNN-LSTM algorithm was 98.3%. The accuracy of the existing stress signal classification algorithm was 83.6% **[29].** These results improved the accuracy by 14.7% compared to the existing stress signal classification algorithm.

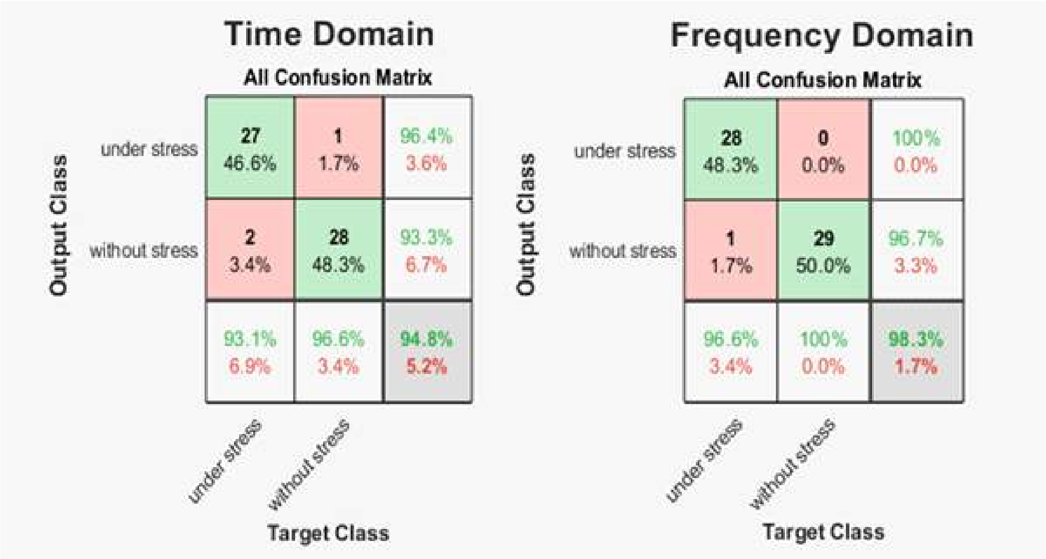

Figure 4.1. Evaluation of classification performance of stress signals using Confusion Matrix

Figure 4.2 shows a graph of the number of epochs required to achieve classification performance validation of stress signals and mean square error rate (MSE). In Figure 4.2(a), the classification error rate of the stress signal was the smallest in Epoch 219 and the classification performance of the stress signal was excellent. In Figure 4.2(b), the classification error rate of the stress signal was the smallest in Epoch 223 and the classification performance of the stress signal was excellent.

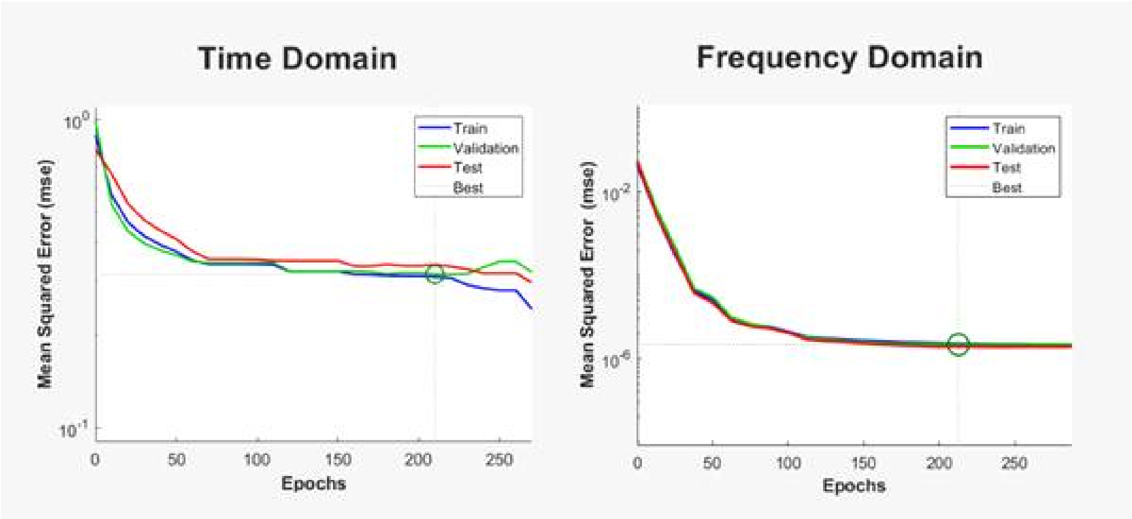

Figure 4.2. Classifier performance evaluation according to epoch

Figure 4.3 shows the ROC Curve according to the epoch values of the Time Domain and Frequency Domain of ECG Data. The Receiver Operating Characteristic (ROC) Curve is a performance evaluation technique of the Binary Classifier System, and is an analysis method to determine the presence or absence of diseases such as stress **[30].** Area under the Curve (AUC) is an index that evaluates the classification performance of stress signals.

When the AUC range is 0.9 or more and less than 1.0, the classification performance of the stress signal is excellent, whereas when the AUC range is 0.8 or more and less than 0.9, the classification performance of the stress signal is low. AUC of ROC Curve in Time Domain was 94.67% and AUC of Frequency Domain was 98.12%. The AUC of the stress signal using the existing ROC Curve was 85.7% **[31].** Therefore, the AUC of the ROC curve was improved by 12.42% compared to the existing stress signal classification algorithm. In addition, the AUC value of the frequency domain is 3.45% higher than the AUC value of the time domain, indicating that the classification performance of the stress signal is better.

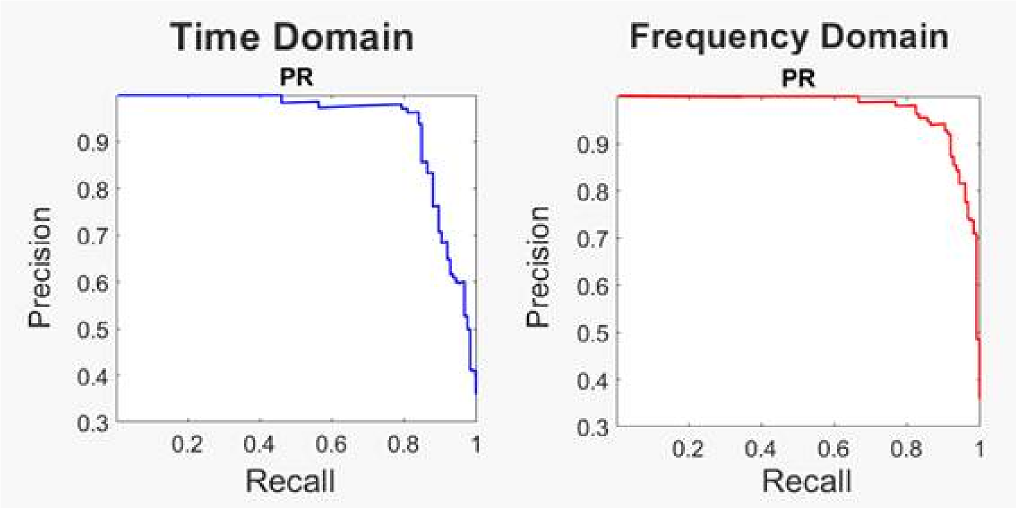

Figure 4.3. Stress classification performance evaluation using ROC Curves

Figure 4.4 shows the Precision-Recall (PR) Curve according to the epoch values of the Time Domain and Frequency Domain of ECG Data. The ROC curve has a lot of difficulty in evaluating the classification performance of stress signals because the shape of the curve is biased to one side when the data set is very unstable **[32].** The PR curve is used to overcome the shortcomings of the ROC curve and shows the relationship between precision and recall. Average Precision (AP) of the PR curve is an index to evaluate the classification performance of stress signals **[32].** The X axis represents Recall (Sensitivity) and the Y axis represents Precision. In the PR Curve, the larger the AP, the better the classification performance of the stress signal.

PR Curve AP of Time Domain was 93.8% and PR Curve AP of Frequency Domain was 97.6%. The AP of the stress signal using the existing PR Curve was 84.2% **[33].** Therefore, compared to the classification algorithm of the existing stress signal, the AP of the PR curve was improved by 13.4%. In addition, the frequency domain AP value is 3.8% higher than the time domain AP value, indicating that the stress classification performance is better.

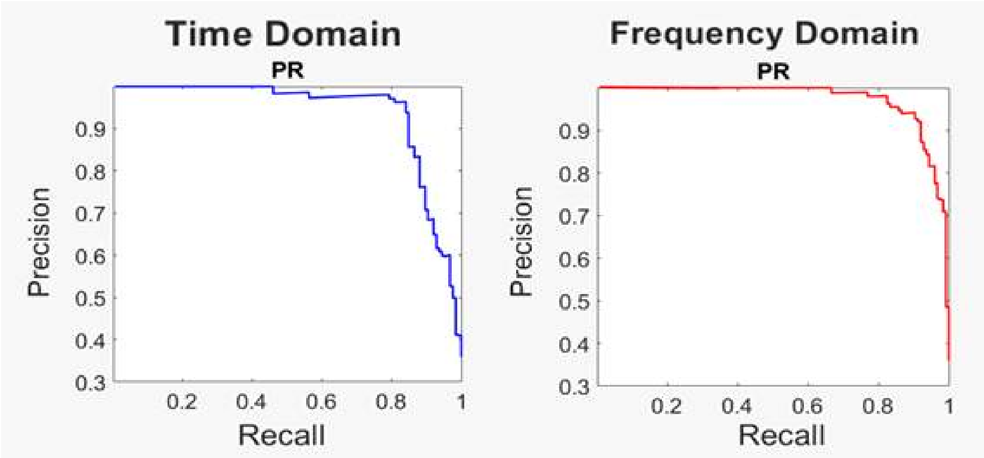

Figure 4.4. Evaluation of the classification performance using PR Curve

The existing stress signal classification algorithm using the time domain and frequency domain of ECG Data was set to Epoch=10 and Batch Size=64. As a result, the time domain and frequency domain accuracies of the existing stress signal classification algorithm were 83.6% and 74.5% **[34].** However, this structure may cause overfitting in the process of classifying stress signals.

Figure 4.5 shows the classification accuracy of stress signals using CNN-LSTM. After setting Epoch=20 and Batch Size=64, the classification accuracy of stress signals in the time domain and frequency domain of ECG data was measured. As a result of classification, the Elapsed Time of Time Domain was 7min 48sec, and the verification accuracy was 94.13%. Frequency Domain's Elapsed Time was 7min 31sec, and the verification accuracy was 98.26%. Therefore, it showed 10.53% and 23.76% higher accuracy than the existing time domain and frequency domain classification algorithms for stress signals.

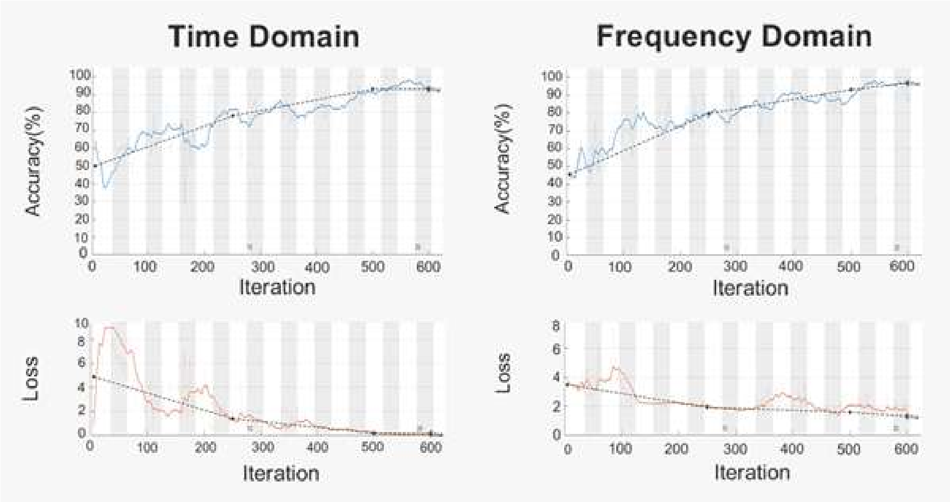

Figure 4.5. Time-Frequency Domain stress signal classification

In this study, we evaluated the stress classification performance of CNN, LSTM, and CNN-LSTM models. First, we classified stress signals using CNN. After inputting the time series data values of the ECG database into the Image Input Layer, the feature map is extracted using the Convolutional Layer, Batch Normalization, and Max Pooling Layer. After performing the stress classification process using the Fully Connected Layer and Softmax Layer, the final stage, the classification stage, was classified into Under stress and Without stress. The classification accuracy of stress signals using CNN was 88.35%.

Then, the stress signals were classified using LSTM. LSTM is a type of Recurrent Neural Network, an artificial neural network that recognizes patterns in data in the form of sequences such as text and gene signal analysis. After inputting the sequence data values of the ECG database to the Sequence Input Layer, the output values were calculated using the LSTM Layer and ReLU. After performing the stress classification process using the Fully Connected Layer, the final stage, the classification stage, was classified into Under Stress and Without Stress. The classification accuracy of stress signals using LSTM was 86.25%.

Table 4.2 compares the stress classification accuracy of CNN, LSTM, and CNN-LSTM models. After setting Epoch=20, Batch Size=64, Elapsed Time and Accuracy are shown. As a result, the CNN-LSTM model has an elapsed time 1 minute faster than the CNN and LSTM models, and the accuracy is improved by 9.91% and 12.01%.

Table 4.2. Comparison of classification accuracy of stress signals using CNN, LSTM and CNN-LSTM

	CNN-LSTM	CNN	LSTM
Elapsed Time	7min 31sec	9min 32sec	9min 45sec
Accuracy	98.26%	88.35%	86.25%

Figure 4.6 shows AUC and AP of CNN, LSTM, and CNN-LSTM models using ROC Curve and PR Curve. The AUC of CNN-LSTM was 98.12%. The AUC of CNN and LSTM were 87.5% and 84.3%. Therefore, the CNN-LSTM model has 10.62% and 13.82% higher AUC values than the CNN and LSTM models, indicating that the classification performance of stress signals is better. The AP of CNN-LSTM was 97.6%, and the AP of CNN and LSTM was 88.2% and 86.02%. Therefore, the CNN-LSTM model has 9.4% and 11.58% higher AP values than the CNN and LSTM models, indicating that the classification performance of stress signals is better.

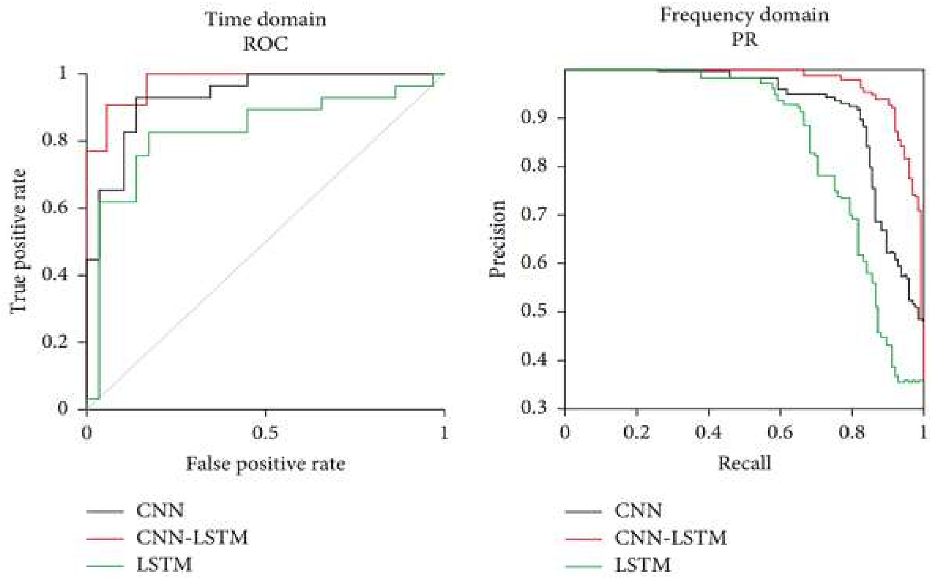

Figure 4.6. Evaluation of classification performance of stress signals using ROC and PR Curves

4.2. Stress classification performance evaluation using SVM-NB

Equation (17) is used to determine the accuracy and it is the probability of accurately classifying four emotional states. The average accuracy according to R-S peak, R-R interval, and Q-T interval was 97.6% using a stress classification model that combines SVM and NB.

$$Accuracy = \frac{TP + TN}{Total\,Dataset} \tag{17}$$

Equation (18) is used to determine the precision. For example, it is the probability that the algorithm is accurately classified as a Picture Test during the Picture Test. After calculating the precision for the four emotional states using the similar method, the average precision was shown. Using a stress classification model that combines SVM and NB, the average precision according to R-S peak, R-R interval, and Q-T interval was 97.5%.

$$\mathrm{P}recision = \frac{TP}{TP + FP} \tag{18}$$

Equation (10) is used to calculate the recall. Among the data predicted by the Picture Test, it is the probability that the algorithm is accurately classified as Picture Test. After calculating the recall for the four emotional states in a similar way, the average recall was shown. Using a stress classification model that combines SVM and NB, the average recall according to R-S peak, R-R interval and Q-T interval was 97.4%.

$$Recall = \frac{TP}{TP + FN} \tag{19}$$

Figure 4.7 shows the performance of a stress classification model that combines SVM and NB using confusion matrix**.** The accuracy of the stress classification model using the existing SVM was 88.9%. In this study, the average accuracy of the stress classification model using SVM was 96.3%. In addition, the performance of the stress classification model was evaluated by combining the NB model with the SVM. Therefore, the average accuracy of the stress classification model combining SVM and NB was 97.6%. These results demonstrate that the accuracy was improved by 8.7% compared with that of the existing stress classification model using CLAS dataset. Additionally, stress classification using four levels can accurately classify emotional status than that of stress classification using two levels.

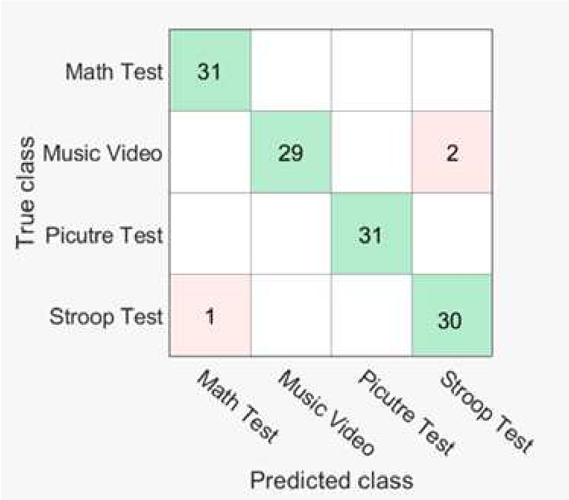

Figure 4.7. Stress classification performance evaluation using the confusion matrix

Figure 4.8 shows the ROC Curve according to the R-S peak, R-R interval, and Q-T interval of four emotional states using a stress classification model that combines SVM and NB. ROC curve analysis is a curve drawn with the Y-axis as true positive rate and the X-axis as false positive rate of the tested values**.** The performance of the stress classification model was evaluated using the area under the curve (AUC) in the graph of the ROC curve. According to the AUC value, it can be classified into low accuracy (AUC≤0.7), medium (0.7<AUC≤0.9) and high accuracy (0.9<AUC<1)**.**

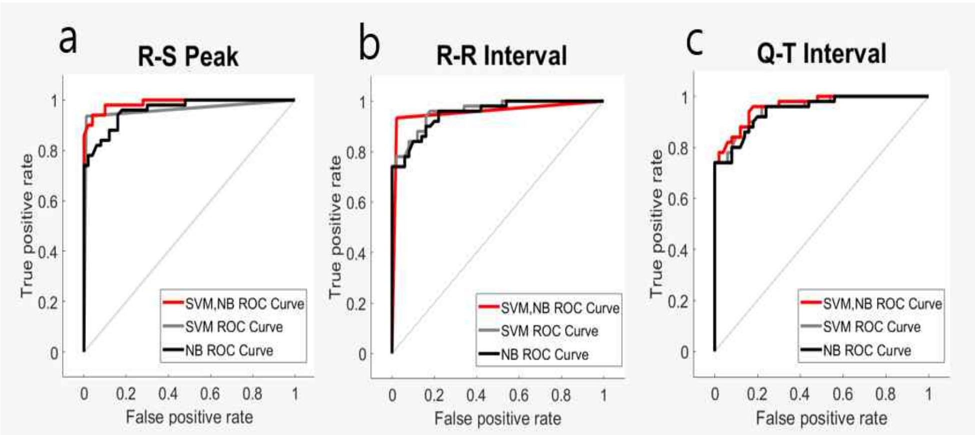

Figure 4.8. Evaluation of stress classification performance using ROC curve

Table 4.3 compares the performance with the existing stress classification model using the AUC value of the ROC curve **[35-37].** The average AUC according to the stress classification model combining SVM and NB was 97.9%. The AUC of the best stress classification model using the existing ROC curve was 87%. Therefore, the AUC of the ROC curve improved by up to 10.9% compared with that of the conventional stress classification model **[35].** In addition, models that combine SVM and NB had 1.1% and 2.5% higher AUC values than that of SVM and NB models, respectively.

Table 4.3. Stress classification performance comparison using the AUC value of the ROC Curve

Previous Study		This Study	
Model	AUC (ROC Curve)	Model	AUC (ROC Curve)
SVM and NB	87%	SVM and NB	97.9%

V. Conclusion

In this study, we proposed a method for classifying mental stress signals using an AI algorithm, SVM-NB, and CNN-LSTM. The stress classification method using SVM-NB calculated the average values of the R-S peak, R-R interval, and Q-T interval after extracting the Q, R, S, and T peak values of the ECG signal to confirm the four stress states according to the stress level. Notably, the classification accuracy improved. The accuracy of the proposed stress classification model that combined the SVM and NB was 97.6%. These results showed an 8.7% improvement in accuracy compared to the existing stress classification models.

The AI algorithm combined with CNN-LSTM classified the ECG signals in the time and frequency domains separately to prevent overfitting and improve the accuracy of the stress signal classification model. The stress classification accuracy of the proposed CNN-LSTM algorithm was 98.3%. These results showed that the accuracy was improved by 14.7% compared with the existing methods that classify under stress and without stress.

However, to improve the stress classification accuracy it is necessary to remove the microscopic noise of bio-signals. The AI algorithm structure using SVM-NB and CNN-LSTM, such as designing a wearable transform filter to remove the baseline fluctuation using the Fourier transform and the sleep sound. Further research to improve the stress classification model is expected to contribute to mental health management by indexing the stress experienced by modern people. Periodic stress management is also expected to contribute to the prevention of various diseases, such as depression, high blood pressure, and diabetes.

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2) **Min Gu Kang**, Si Ho Shin, Gengjia Zhang, Jaehyo Jung and Youn Tae Kim, “Mental Stress Classification Based on Support Vector Machine and Naïve Bayes Using Electrocardiogram Signal ”, Sensors 2021, 1-15 (2021)

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1) **<u>Min Gu Kang</u>**, Si Ho Shin, Gengjia Zhang, Jaehyo Jung, Meina Li and Youn Tae Kim, "Mental Stress Detection with Ensemble Model and Random Cropping using Electrocardiogram ", 2021 International Conference on Computational Science and Computational Intelligence (CSCI). IEEE, Dec. 2021.

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Abstract

A Study on Design of AI Algorithms for Classification of Mental stress Based on Electrocardiogram

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Recently, owing to the improvement of the living environment and economic growth, interest in health has increased. Moreover, both physical and mental health management is recognized as an important part of health. In this study, an AI algorithm for classifying mental stress signals using electrocardiogram-based convolutional neural network (CNN)-long short-term memory (LSTM) and support vector machine (SVM)-naive Bayes (NB) models was presented. The R-S peak and R-R interval were extracted from the ECG signals during stress or resting state. To maximize the performance of the stress signal classification algorithm, parameters extracted from ECG signals were applied to the SVM-NB and CNN-LSTM models, and the accuracy of the stress signal classification model was improved by increasing the number of training data through a spectrogram applied with Fourier transform. Subsequently, the performance of the algorithm for each epoch was illustrated in the time-frequency domain and the stress signal classification error. The results of the stress classification algorithm showed that the accuracies of the confusion matrix, receiver operating characteristic (ROC) curve, and precision-recall (PR) curve were 98.3%, 98.12%, and 97.6%, respectively. Therefore, the proposed algorithm can help in the health management of modern people who suffer from mental stress.

감사의 글

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연구 주제에 대한 조언과 문제점 해결을 위해 지도해 주신 정재효 교수님께 감사드립니다. 연구를 진행하면서 낙심하던 순간들도 있었지만 매번 다시 시작할 수 있도록 따뜻하게 이끌어 주신 점 가슴 깊이 감사드립니다,

2년이 넘는 세월 동안 같은 연구실에서 가족처럼 생활한 인공지능 헬스케어 연구실 구성원들께 감사드립니다. 여러모로 서툰 저를 인내로 가르쳐주신 신시호, 박지원 선배님, 그리고 자기 연구처럼 함께 고민해 주고 토론해 준 다은 후배에게 고마운 마음을 전하고 싶습니다.

마지막으로 제가 부족함 없이 공부에만 전념할 수 있게 모든 지원을 아끼지 않으셨고 저를 위해 멀리서 항상 기도해 주신 부모님께 감사드리며, 이 작은 결실을 바칩니다.

2021년 12월

강민구 올림