Abstract—Inrecent years, emotion recognition based on EEG
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Multi-scale Spatial-temporal Featu
^{Zhangfang} Hu, Haoze Wu, Lingxiao He
^{making} emotion analy
signals has received significant attention and research interest.
FEG signals have the advantages G Emotion Recognition
and Transformer for
oral Feature Extraction
wu, Lingxiao He
making emotion analysis crucial. In 1997, the concept of
Affective Computing (AC) was introduced by Professor Picard
from MIT, which expande G Emotion Recognition
and Transformer for
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Affective Computing (AC) was introduced by Professor Picard
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A Neural Network for EEG Emotion Recognition

that Combines CNN and Transformer for

Multi-scale Spatial-temporal Feature Extraction

Zhangfang Hu, Haoze Wu, Lingxiao He IAENG International Journal of Computer Science

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Ork for EEG Emotion Recognition

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atial-temporal Feature Extraction

Zhangfang Hu, Haoze Wu, Lingxiao He

making emotion analysis crucial. In 1997, the

EEG signals have the advantages of universality, spontaneity, and by the advantages of universality, spontaneity, and $\frac{EFG}{EFG}$ **is ginals have the advantages of universality, spontaneity, and** $\frac{EFG}{EFG}$ **is ginals have Multi-scale Spatial-temporal Feat**
 Abstract—In recent years, emotion recognition based on EEG and them capable based on the making emotion and
 difficulty in every step advantages of universality, spontaneity, and be **Multi-scale Spatial-temporal Feature**
 Zhangfang Hu, Haoze Wu, Lingxiao He
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signals has received significant attention and research interest.
 EEG signals have the advantages of universali **Example 18 CERT CONDUCT CONDUCT CONDUCT TREST**

Zhangfang Hu, Haoze Wu, Lingx

making emo

signals has received significant attention and research interest.

EGG isgnals have the advantages of universality, spontaneity, a **classification studies on the valence and arousal levels in the** Zhangfang Hu, Haoze Wu, Lingxiao He
 Mating emotion analysis
 Mating emotion analysis
 Dealing the alvantage of universality, spontaneity, and
 difficulty in deception, making them capable of accurately
 difficult Langrang FIU, Haoze WU, LIngxiao He
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 intrinsic emotion and the matrice of the computing
 intrinsic exceed significant attention and research interest. from MIT, which expec *Abstract***—In recent years, emotion recognition based on EEG** Affective Computing (
signals has received significant attention and research interest.

EEG signals have the advantages of universality, spontaneity, and beyo **COCOCYTER THE SET ALL CONDET ARREL CONDET SET ALL CONDITIONS ARE CONDITIONS (SURFACT COMPUTED)**
 CECC signals have the advantages of universality, spontaneity, and beyond traditional field

difficulty in deception, maki **based—In recent years, emotion recognition based on EEG** making emotion anal
signals has received significant attention and research interest.
EEG signals have the advantages of universality, spontaneity, and beyond tradi **Abstract—In recent years, emotion recognition based on EEG** Affective Computing (AC) signals has received significant attention and research interest. from MIT, which expande EEG signals have the advantages of universalit **EXEC Signals has received significant attention and research interest.** From MIT, which expansions has received significant attention and research interest. From MIT, which expanse be EEG signals have the advantages of un **ELG signals has received significant attention and research interest.** From M11, which expandes EEG signals have the advantages of universality, spontaneity, and byood traditional fields by
reflecting genuine emotional st Extra signals have the auxialized on the strategy and the constrained and the constrained beyond traditional field
 Relations and the valence and arousal levels in the more than the more of the particle of based on the v unceuty in tectorula, maxing them teams ability to classify humeturely and ternative and arousal levels in the conducted binary (high/low) and ternary (low/medium/high) classification studies on the valence and arousal lev Fenecting genuine emotional states. In this head, researchers have been and random forest in the conducted binary (high/low) and ternary (low/medium/high) and motions: sadness, intrinsic emotions, a clear definition of emo **Continuous the matter with the control in the spatial-temporal feature extraction. This model is employed for the four-class fiction in a set all arousal levels in the E. Kroupi et al. conduct DEAP dataset.
However, in or THEOREM STEAD TRANSMIGES ON THE VARIGE CALCT THEOREM AND THE CONDUCT THAT AN ANNEX CONDUCT THEOREM AND TRANSMIGHT CONDUCT THEOREM CONDUCT THEOREM CONDUCT THEOREM CONDUCT THEOREM CONDUCT THEOREM AND TRANSMIGHT CONDUCT THEO EXATE tracescentive of the other in the series the series of 91.26% on the four-class emotions.** Samester and average accurately placing emotion labels from the DEAP dataset within the based on the valence and arousal lev mitrinste emotions, a clear demition of emotions, a clear demition of emotionary particularly important. Therefore, this study ref Circumplex Model, which arranges emotions in a based on their valence and arousal levels. T Frempex Model, The arrange sensorion and actual manter mathematical

Index *Internals* and arousal levels. The study proposes in insclassification, while joint example in the DEAP dataset within the to recognize accurately based on their vancte and arousal reveal
placing emotion labels from the DEAP dataset within
two-dimensional emotional space of the circumplex me
Emotions are defined as four labels - Excited, Afraid, Sad,
Relaxed - based otional space of the circumplex model. Caussiant

1 as four labels - Excited, Afraid, Sad, and classificat

a hybrid deep learning model combining Gaussian

foremer is proposed for multi-scale

ure extraction. This model i d - based on a linear distribution of valence and arousal

ulterations with different kernel

urthermore, a hybrid deep learning model combining

and Transformer is proposed for multi-scale

temporal feature extraction. T CNN and Transformer is proposed for multi-scale

spatial-temporal feature extraction. This model is employed for

the classification of the four emotions. Finally, the model achieves

an average accuracy of 91.26% on the

spartal examples and transformer Strategiton. Instructed to the charming, the model scheme of 91.26% on the four-class emotion and random forest model for classification task. The experimental results show that ombining Example 15, 2013 ansformer, Emotion Classification

I. INTRODUCTION With the developm

T. MOTION is a psychological state and response of deep learning and applie

individuals to stimuli based on subjective experiences

 $\sum_{\text{invariant}}$ MOTION is a psychological state and response of deep learning and applicular context [1]. As a higher brain function, emotions particular context [1]. As a higher brain function, emotions in 2015, Zheng We pro I. INTRODUCTION With the developp

Fraction of the measurements have shifted

individuals to stimuli based on subjective experiences in a recognition, achieving a

particular context [1]. As a higher brain function, emoti I. INTRODUCTION

ITELES TO THE TECHNOLOGICAL SCIENCE Examples in the Ation of this content is a psychological state and response of deep learning and applied

individuals to stimuli based on subjective experiences in a

profoundly influence our learning, work, and daily liv MOTION is a psychological state and response of deep learning and interpret
particular context [1]. As a higher brain function, emotions In 2015, Zheng
profoundly influence our learning, work, and daily lives, five rhythms 2.017 jevideo of the Key Laboratory of Optical Information, emotion and intervention and the Tricular context [1]. As a higher brain function, emotions in 2015, Zheng from differences in a recognition, and daily lives, the **Example 3.1**
 Example 1.1 As a higher brain function, emotions In 2015, Zheng

profoundly influence our learning, work, and daily lives, five rhythms: δ , features from dif

Manuscript received on March 15, 2024; revi profoundly influence our learning,

Manuscript received on March 15, 2024; revork was supported in part by the Youth Fund F

Science Foundation of China (Grant No. 617

Science and Frontier Technology Rese:

Cstc2017jcyjAX Fractived on March 15, 2024; revised on June 18, 2024. This

classification r

revised on March Fund Program of the National Natural

ence Foundation of China (Grant No. 61703067), the Chongqing Basic

ence and Frontier Te Engineering, Chongqing Hipsering, Chongqing Hipsering, Chongqing Albinsering, The State Condensity of Posts and Technology Research Program of the S6.Cec2017jcyjAX0212), and the Science and Technology Research Program of S Manuscript received on March 15, 2024; revised on June 18, 2024. This classification
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Science Foundation of China (Grant No. 617030)
Science and Frontier Technology Research Cstc2017jcyjAX0212), and the Example 1.3652007151 met Your Count and Tregation of China (Grant No. 61703067), the Chongaing Basic (DBN). The ave are and Frontier Technology Research Program (Grant No. 686.08%, c2017jcyjAX0212), and the Science and Tec

Science and Frontier Technology Research Program (Grant No.

Cstc2017jcyjAX0212), and the Science and Technology Research Program (Grant No.

Chongqing Municipal Education Commission (KJ1704072).

2 Zhangfang Hu is a Profe Cstc2017jcyjAX0212), and the Science and Technology Research Program of Chongqing Municipal Education Commission (KJ1704072).

Zhangfang Hu is a Professor at the Key Laboratory of Optical Information

Sensing and Technolog

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Subsed on the strain and Transformer is proposed for multi-scale to and Transform is proposed a classification accuracy [5]. Add and Transform is proposed a classification method lawerage accuracy of 91.26% on the four-Example 10. Unity and Solution Computing CNA). The expect of Affective Computing (AC) was introduced by Professor Picard from MIT, which expanded the scope of emotion research beyond traditional fields by empowering comput Solution Mu, Lingxiao He

Solution analysis crucial. In 1997, the concept of

Affective Computing (AC) was introduced by Professor Picard

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beyond traditional fields b making emotion analysis crucial. In 1997, the concept of Affective Computing (AC) was introduced by Professor Picard from MIT, which expanded the scope of emotion research beyond traditional fields by empowering computers making emotion analysis crucial. In 1997, the concept of Affective Computing (AC) was introduced by Professor Picard from MIT, which expanded the scope of emotion research beyond traditional fields by empowering computers making emotion analysis crucial. In 1997, the concept of Affective Computing (AC) was introduced by Professor Picard from MIT, which expanded the scope of emotion research beyond traditional fields by empowering computers Affective Computing (AC) was introduced by Professor Picard
from MIT, which expanded the scope of emotion research
beyond traditional fields by empowering computers with the
ability to classify human emotions, thereby prom from MIT, which expanded the scope of emotion research
beyond traditional fields by empowering computers with the
ability to classify human emotions, thereby promoting more
natural human-computer interaction [2][3].
E. Kro beyond traditional fields by empowering computers with the ability to classify human emotions, thereby promoting more natural human-computer interaction [2][3].

E. Kroupi et al. conducted a classification study on three e ability to classify human emotions, thereby promoting more
natural human-computer interaction [2][3].
E. Kroupi et al. conducted a classification study on three
emotions: sadness, joy, and neutrality, using Linear
Discrimi natural human-computer interaction [2][3].

E. Kroupi et al. conducted a classification study on three

emotions: sadness, joy, and neutrality, using Linear

Discriminant Analysis (LDA). The experimental results

showed th E. Kroupi et al. conducted a classification study on three emotions: sadness, joy, and neutrality, using Linear Discriminant Analysis (LDA). The experimental results showed that neutral emotions were more prone to misclass emotions: sadness, joy, and neutrality, using Linear
Discriminant Analysis (LDA). The experimental results
showed that neutral emotions were more prone to
misclassification, while joy and sadness were relatively easier
to Discriminant Analysis (LDA). The experimental results
showed that neutral emotions were more prone to
misclassification, while joy and sadness were relatively easier
to recognize accurately [4]. Muhammad Zubair et al. empl showed that neutral emotions were more prone to
misclassification, while joy and sadness were relatively easier
to recognize accurately [4]. Muhammad Zubair et al. employed
Gaussian kernel support vector machines (SVM) for misclassification, while joy and sadness were relatively easier
to recognize accurately [4]. Muhammad Zubair et al. employed
Gaussian kernel support vector machines (SVM) for binary
classification of EEG-based emotions. Th to recognize accurately [4]. Muhammad Zubair et al. employed
Gaussian kernel support vector machines (SVM) for binary
classification of EEG-based emotions. They compared SVM
algorithms with different kernel functions and f uussian kernel support vector machines (SVM) for binary
ssisfication of EEG-based emotions. They compared SVM
gorithms with different kernel functions and found that the
uussian kernel SVM performed the best in terms of
ss classification of EEG-based emotions. They compared SVM
algorithms with different kernel functions and found that the
Gaussian kernel SVM performed the best in terms of
classification accuracy [5]. Additionally, Xie Qiao e algorithms with different kernel functions and found that the
Gaussian kernel SVM performed the best in terms of
classification accuracy [5]. Additionally, Xie Qiao et al.
proposed a classification method based on the XGB Gaussian kernel SVM performed the best in terms of classification accuracy [5]. Additionally, Xie Qiao et al.
proposed a classification method based on the XGBoost model
and random forest model for EEG-based emotion recog assification accuracy [5]. Additionally, Xie Qiao et al.
opposed a classification method based on the XGBoost model
d random forest model for EEG-based emotion recognition.
e experimental results showed that the average r proposed a classification method based on the XGBoost model
and random forest model for EEG-based emotion recognition.
The experimental results showed that the average recognition
rates of this classification model reach

particular context [1]. As a higher brain tunction, emotions In 2015, Zheng Wei
profoundly influence our learning, work, and daily lives, five rhythms: δ , θ ,
features from differe
Manuscript received on March 15, 20 and random forest model for EEG-based emotion recognition.
The experimental results showed that the average recognition
rates of this classification model reached 77.19% and 79.06%
for the arousal and valence dimensions, The experimental results showed that the average recognition
rates of this classification model reached 77.19% and 79.06%
for the arousal and valence dimensions, respectively. This
indicates that combining classifiers has rates of this classification model reached 77.19% and 79.06%
for the arousal and valence dimensions, respectively. This
indicates that combining classifiers has advantages over using a
single classifier in emotion classif for the arousal and valence dimensions, respectively. This
indicates that combining classifiers has advantages over using a
single classifier in emotion classification tasks [6].
With the development of deep learning tech indicates that combining classifiers has advantages over using a
single classifier in emotion classification tasks [6].
With the development of deep learning techniques,
researchers have shifted their focus from machine l single classifier in emotion classification tasks [6].

With the development of deep learning techniques,

researchers have shifted their focus from machine learning to

deep learning and applied it to the field of EEG-ba With the development of deep learning techniques,
researchers have shifted their focus from machine learning to
deep learning and applied it to the field of EEG-based emotion
recognition, achieving significant progress.
I researchers have shifted their focus from machine learning to
deep learning and applied it to the field of EEG-based emotion
recognition, achieving significant progress.
In 2015, Zheng Weilong et al. divided the EEG signa deep learning and applied it to the field of EEG-based emotion
recognition, achieving significant progress.
In 2015, Zheng Weilong et al. divided the EEG signals into
five rhythms: δ , θ , α , β and γ , and the recognition, achieving significant progress.

In 2015, Zheng Weilong et al. divided the EEG signals into

five rhythms: δ , θ , α , β and γ , and then extracted the DE

features from different frequency bands. In 2015, Zheng Weilong et al. divided the EEG signals into
five rhythms: δ , θ , α , β and γ , and then extracted the DE
features from different frequency bands. They conducted
classification research on three five rhythms: δ , θ , α , β and γ , and then extracted the DE
features from different frequency bands. They conducted
classification research on three emotional states: positive,
neutral, and negative, using SV features from different frequency bands. They conducted classification research on three emotional states: positive, neutral, and negative, using SVM and Deep Belief Networks (DBN). The average classification accuracy of D classification research on three emotional states: positive, neutral, and negative, using SVM and Deep Belief Networks (DBN). The average classification accuracy of DBN was found to be 86.08%, while SVM achieved an average neutral, and negative, using SVM and Deep Belief Networks
(DBN). The average classification accuracy of DBN was found
to be 86.08%, while SVM achieved an average accuracy of
83.99%. This indicates that DBN outperforms SVM

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they built a 5-layer CNN network to classify the three transitioning from traditional remotional states, achieving an average recognition rate of with CNN models making sig **IAENG International Journal of Computer Science**
they built a 5-layer CNN network to classify the three transitioning from traditional mace
motional states, achieving an average recognition rate of with CNN models making **IAENG International Journal of Computer Science**
they built a 5-layer CNN network to classify the three transitioning from traditional ma
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they built a 5-layer CNN network to classify the three transitioning from traditional nemotional states, achieving an average recognition rate of with CNN models making sig **IAENG International Journal of Computer**
they built a 5-layer CNN network to classify the three transitioning from trace
emotional states, achieving an average recognition rate of with CNN models made
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they built a 5-layer CNN network to classify the three transitioning fr

emotional states, achieving an average recognition rate of with CNN mod

88.2%. In the same year, Wen by built a 5-layer CNN network to classify the three transitioning from traditional machional states, achieving an average recognition rate of with CNN models making signifi .2%. In the same year, Wen Zhiyuan et al. direct they built a 5-layer CNN network to classify the three transitioning from traditional manumotional states, achieving an average recognition rate of with CNN models making signifies 88.2%. In the same year, Wen Zhiyuan et a they built a 5-layer CNN network to classify the three transitioning from traditiona
emotional states, achieving an average recognition rate of with CNN models making s
88.2%. In the same year, Wen Zhiyuan et al. directly emotional states, achieving an average recognition rate of with CNN models making sign

88.2%. In the same year, Wen Zhiyuan et al. directly used the CNNs have the advantage of

raw EEG signals from 32 channels as inputs f

88.2%. In the same year, Wen Zhiyuan et al. directly used the CNNs have the advantage of c
raw EEG signals from 32 channels as inputs for CNN-based information, they often ignore
emotion recognition. They rearranged the E raw EEG signals from 32 channels as inputs for CNN-based information, they ofter emotion recognition. They rearranged the EEG channels based limited ability to on Pearson correlation coefficients and found that the highes emotion recognition. They rearranged the EEG channels based imited ability to extract on Pearson correlation coefficients and found that the highest constraining their performance.

average recognition rate was achieved wh on Pearson correlation coefficients and found that the highest

a hybrid module that co

maximally adjacent arrangement. The average recognition rates

a hybrid module that co

maximally adjacent arrangement. The average r average recognition rate was achieved when using the a hybrid module that combin maximally adjacent arrangement. The average recognition rates leverage the advantages of percefore the valence and arousal dimensions in bina maximally adjacent arrangement. The average recognition rates
for the valence and arousal dimensions in binary classification created a parallel network
reached 77.98% and 72.98%, respectively [10].
In 2018, K. Yea-Hoon et for the valence and arousal dimensions in binary classification created a parallel networeached 77.98% and 72.98%, respectively [10].

In 2018, K. Yea-Hoon et al. utilized wavelet transform to features of EEG signal conver reached 77.98% and 72.98%, respectively [10]. multi-scale resolution featt

In 2018, K. Yea-Hoon et al. utilized wavelet transform to features of EEG signals.

convert EEG signals into color maps with a resolution of impro In 2018, K. Yea-Hoon et al. utilized wavelet transform to features of EEG signals.

convert EEG signals into color maps with a resolution of improved the training efficiency

42×200, and then used CNN to accurately extrac convert EEG signals into color maps with a resolution of improved the training ef 42×200 , and then used CNN to accurately extract and classify classification.
the features of EEG signals on these color maps. This The m 42×200, and then used CNN to accurately extract and classify classification.

the features of EEG signals on these color maps. This The main contributions of movative method resulted in an average recognition rate of 1.Th the features of EEG signals on these color maps. This The main contributions of this

imovative method resulted in an average recognition rate of 1.The reconstruction of emotion

73.4% for four emotional states, providing innovative method resulted in an average recognition rate of

73.4% for four emotional states, providing a new perspective

conding it to be used for a four-

for emotion recognition research [11]. In 2020, Du X et al.

27 73.4% for four emotional states, providing a new perspective enabling it to be used for emotion recognition research [11]. In 2020, Du X et al. 2. The proposal of a meposal of a meposal of a memochanism and LSTM, which eff for emotion recognition research [11]. In 2020, Du X et al. 2. The proposal of a m
proposed a hybrid model (ATDD-LSTM) based on attention Transformer, named (
mechanism and LSTM, which effectively characterized the combine proposed a hybrid model (ATDD-LSTM) based on attention Transformer, named C-T Blemcchanism and LSTM, which effectively characterized the combines CNN and Transformer sof functional relationships between EEG local perceptio mechanism and LSTM, which effectively characterized the combines CNN and Transformatial features of functional relationships between EEG local perception from CN signals at different electrodes and automatically selected T spatial features of functional relationships between EEG local perception from C
signals at different electrodes and automatically selected Transformer, thereby extra
utable EEG channels for emotion recognition [12]. In 20 signals at different electrodes and automatically selected Transformer, thereby extra
suitable EEG channels for emotion recognition [12]. In 2021, improving the accuracy and
n Y et al. introduced an emotion recognition mod suitable EEG channels for emotion recognition [12]. In 2021, improving the accuracy and eff
An Y et al. introduced an emotion recognition model that

combined spatioethery deconventional networks, leveraging features to ex An Y et al. introduced an emotion recognition model that 3.Th
combined spatiotemporal convolutional networks, leveraging feature
CNN to extract spatial features and using LSTM to capture incorpo
temporal features, effectiv mbined spatiotemporal convolutional networks, leveraging

features to capture differe

N to extract spatial features and using LSTM to capture incorporation of this mod

ontoin recognition [13]. Also in the same year, Gao CNN to extract spatial features and using LSTM to capture incorporation of this
temporal features, effectively improving the accuracy of spectral, and temperation recognition [13]. Also in the same year, Gao Z et al. achie temporal features, effectively improving the accuracy of spectral, and temperation recognition recognition model based on Multi-layer The structure of the convolutional Neural Network (MNCNN) and differential introduces re emotion recognition [13]. Also in the same year, Gao Z et al. achieving satisfactory results.

designed an emotion recognition model based on Multi-layer The structure of the paper

Convolutional Neural Network (MNCNN) and

designed an emotion recognition model based on Multi-layer The structure of the paper incorportional Neural Network (MNCNN) and differential introduces relevant research entropy, achieving a classification accuracy of 91.4 Convolutional Neural Network (MNCNN) and differential introduces relevant rest entropy, achieving a classification accuracy of 91.45% on the recognition. The second SEED dataset [14]. In 2022, Li Yang et al. proposed a mod entropy, achieving a classification accuracy of 91.45% on the recognition. The second part d
SEED dataset [14]. In 2022, Li Yang et al. proposed a model experiments, including preproce
clied Bidriectional Domain Adversaria SEED dataset [14]. In 2022, Li Yang et al. proposed a model
called Bidirectional Domain Adversarial Neural Network
(BiDANN), which enhanced the accuracy of emotion
classification by extracting asymmetrical features from th lled Bidirectional Domain Adversarial Neural Network calibrating emotion labels. The ti

iDANN), which enhanced the accuracy of emotion methods for experiments, includi

sistification by extracting asymmetrical features fr (BiDANN), which enhanced the accuracy of emotion methods for experiments, in
classification by extracting asymmetrical features from the left
and Transformer and a not
main particular and in 115].
In 2023, Yonghao Song et classification by extracting asymmetrical features from the left and Transformer and a novel

and right hemispheres of the brain [15].

Convolutional Transformer (EEGC) aimed at encapsulating models on the DEAP dataset. Th and right hemispheres of the brain [15]. fourth part presents the experim

In 2023, Yonghao Song et al. presented a compact detailed analysis and comparison

Convolutional Transformer (EEGC is amefficient in a unified EEG

In 2023, Yonghao Song et al. presented a compact detailed analysis and comparis

Convolutional Transformer (EEGC) aimed at encapsulating models on the DEAP dataset.

Iocal and global features within a unified EEG classific Convolutional Transformer (EEGC) aimed at encapsulating models on the DEAP dataset. T

local and global features within a unified EEG classification

framework. The EEGC is an efficient decoding method for

EEG data, comb local and global features within a unified EEG classification

framework. The EEGC is an efficient decoding method for

EEG data, combining the strengths of CNN and Transformer to

achieve significant performance improveme framework. The EEGC is an efficient decoding method for

EEG data, combining the strengths of CNN and Transformer to

achieve significant performance improvements across different

expected the conditions of the DEAP data EEG data, combining the strengths of CNN and Transformer to

achieve significant performance improvements across different

EEG datasets

ergresent global features [16]. Currently, most researchers have focused on binary o achieve significant performance improvements across different

EEG datasets, and visually demonstrating the model's ability to

Curent Mary University

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Curent Mary University EEG datasets, and visually demonstrating the model's ability to

represent global features [16].

Currently, most researchers have focused on binary or

termary classification of EGG emotion signals, with limited

explorat represent global features [16].

Currently, most researchers have focused on binary or

ternary clusters formula derivative of four-class emotion classification. Because the

exploration of four-class emotion classificatio Currently, most researchers have focused on binary
ternary classification of EEG emotion signals, with lim
exploration of four-class emotion classification. Because
training of quadruple classification requires a large num mary classification of EEG emotion signals, with limited

ploysiological signals for emotion

ploration of four-class emotion classification. Because the

implysiological signals for emotion

ta samples [17], and the commo

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transitioning from traditional machine learning to deep learning,

with CNN models making significant contributions [18]. While

CNNs have the advantage of capturing local receptive field

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CNNs have the advantage of capturing local receptive field

inform **ransitioning from traditional machine learning to deep learning,**
with CNN models making significant contributions [18]. While
CNNs have the advantage of capturing local receptive field
information, they often ignore glob **nal of Computer Science**

transitioning from traditional machine learning to deep learning,

with CNN models making significant contributions [18]. While

CNNs have the advantage of capturing local receptive field

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transitioning from traditional machine learning to deep learning,

with CNN models making significant contributions [18]. While

CNNs have the advantage of capturing local receptive field

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transitioning from traditional machine learning to deep learning,

with CNN models making significant contributions [18]. While

CNNs have the advantage of capturing local receptive field

li transitioning from traditional machine learning to deep learning,
with CNN models making significant contributions [18]. While
CNNs have the advantage of capturing local receptive field
information, they often ignore globa transitioning from traditional machine learning to deep learning,
with CNN models making significant contributions [18]. While
CNNs have the advantage of capturing local receptive field
information, they often ignore globa classification. th CNN models making significant contributions [18]. While
NNs have the advantage of capturing local receptive field
ormation, they often ignore global information and have
inted ability to extract temporal information, th NNs have the advantage of capturing local receptive field

formation, they often ignore global information and have

iited ability to extract temporal information, thus

instraining their performance. Therefore, this study information, they often ignore global information and have
limited ability to extract temporal information, thus
constraining their performance. Therefore, this study designed
a hybrid module that combines CNN and Transfor inted ability to extract temporal information, thus not network and the proposition module that combines CNN and Transformer to verage the advantages of perceiving global information, and areated a parallel network model c constraining their performance. Therefore, this study designed
a hybrid module that combines CNN and Transformer to
leverage the advantages of perceiving global information, and
created a parallel network model capable of a hybrid module that combines CNN and Transformer to
leverage the advantages of perceiving global information, and
created a parallel network model capable of extracting
multi-scale resolution features to better perceive d leverage the advantages of perceiving global information, and
created a parallel network model capable of extracting
multi-scale resolution features to better perceive deeper
features of EEG signals. This integration succe

created a parallel network model capable of extracting
multi-scale resolution features to better perceive deeper
features of EEG signals. This integration successfully
improved the training efficiency and accuracy of the f multi-scale resolution features to better perceive deeper
features of EEG signals. This integration successfully
improved the training efficiency and accuracy of the four-class
classification.
The main contributions of thi tures of EEG signals. This integration successfully
proved the training efficiency and accuracy of the four-class
ssisfication.
The main contributions of this paper are as follows:
1.The reconstruction of emotion labels in improved the training efficiency and accuracy of the four-class
classification.
The main contributions of this paper are as follows:
1. The reconstruction of emotion labels in the DEAP dataset,
enabling it to be used for a classification.

The main contributions of this paper are as follows:

1. The reconstruction of emotion labels in the DEAP dataset,

enabling it to be used for a four-class classification task.

2. The proposal of a multi-The main contributions of this paper are as follows:

1. The reconstruction of emotion labels in the DEAP dataset,

enabling it to be used for a four-class classification task.

2. The proposal of a multi-feature extractio 1. The reconstruction of emotion labels in the DEAP datase
enabling it to be used for a four-class classification task.

2. The proposal of a multi-feature extraction module based of
Transformer, named C-T Block. This mod abling it to be used for a four-class classification task.

2. The proposal of a multi-feature extraction module based on

ansformer, named C-T Block. This module effectively

mbines CNN and Transformer, utilizing the adva 2. The proposal of a multi-feature extraction module based on Transformer, named C-T Block. This module effectively combines CNN and Transformer, utilizing the advantages of local perception from CNN and global perception

Transformer, named C-T Block. This module effectively
combines CNN and Transformer, utilizing the advantages of
local perception from CNN and global perception from
Transformer, thereby extracting more feature information combines CNN and Transformer, utilizing the advantages of local perception from CNN and global perception from Transformer, thereby extracting more feature information and improving the accuracy and efficiency of emotion r local perception from CNN and global perception from
Transformer, thereby extracting more feature information and
improving the accuracy and efficiency of emotion recognition.
3. The introduction of a network model for ext Transformer, thereby extracting more feature information and
improving the accuracy and efficiency of emotion recognition.
3. The introduction of a network model for extracting deep
features to capture different depths of improving the accuracy and efficiency of emotion recognition.
3. The introduction of a network model for extracting deep
features to capture different depths of brainwave signals. The
incorporation of this model effectivel 3. The introduction of a network model for extracting deep
features to capture different depths of brainwave signals. The
incorporation of this model effectively enhances the spatial,
spectral, and temporal resolution of b features to capture different depths of brainwave signals. The
incorporation of this model effectively enhances the spatial,
spectral, and temporal resolution of brainwave signals,
achieving satisfactory results.
The struc incorporation of this model effectively enhances the spatial, spectral, and temporal resolution of brainwave signals, achieving satisfactory results. The structure of the paper is as follows: The first part introduces rele Exerce of the paper is as follows: The first part

evant research on EEG-based emotion

e second part describes the preparation for

cluding preprocessing the DEAP dataset and

tion labels. The third part presents the prop *A. DEAP database was developed in collaboration MEEG-based enforces in cognition.* The second part describes the preparation periments, including preprocessing the DEAP datasalibrating emotion labels. The third part prese ments, including peprocessing the DEAP dataset and
innents, including peprocessing the DEAP dataset and
rating emotion labels. The third part presents the proposed
ods for experiments, including the fusion module of CNN
Fr ealibrating emotion labels. The third part persents the proposed
calibrating emotion labels. The third part presents the proposed
methods for experiments, including the fusion module of CNN
and Transformer and a novel para

embrands consumed the membroles. The time part pressume proposed on a Transformer and a novel parallel network model. The fourth part presents the experimental results and provides a detailed analysis and comparison of the memos ior experiments, including the tastor inducte of CNTs
and Transformer and a novel parallel network model. The
fourth part presents the experimental results and provides a
detailed analysis and comparison of the propo and Transformer and a novel parafiel network model. The
fourth part presents the experimental results and provides a
detailed analysis and comparison of the proposed deep learning
models on the DEAP dataset. The fifth part From the presents the experimental results and provides a
detailed analysis and comparison of the proposed deep learning
models on the DEAP dataset. The fifth part is the conclusion.
II. EXPERIMENT PREPARATION
A. DEAP data detailed analysis and comparison of the proposed deep learning
models on the DEAP dataset. The fifth part is the conclusion.
I. EXPERIMENT PREPARATION
A. DEAP data set
The DEAP database was developed in collaboration by
Qu models on the DEAP dataset. The fifth part is the conclusion.

II. EXPERIMENT PREPARATION

A. DEAP data set

The DEAP database was developed in collaboration by

Queen Mary University of London, Trent University,

Universi II. EXPERIMENT PREPARATION

A. DEAP data set

The DEAP database was developed in collaboration by

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University of Geneva, and others, focusing on the study of

physiologic II. EXPERIMENT PREPARATION

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physiologic A. *DEAP* data set
The DEAP database was developed in collaboration by
Queen Mary University of London, Trent University,
University of Geneva, and others, focusing on the study of
physiological signals for emotion analysi From durate the DEAP database was developed in collaboration by
Queen Mary University of London, Trent University,
University of Geneva, and others, focusing on the study of
physiological signals for emotion analysis [19]. Ine DEAP database was developed in collaboration by
Queen Mary University of London, Trent University,
University of Geneva, and others, focusing on the study of
physiological signals for emotion analysis [19]. The databas Queen Mary University of London, Trent University, of Chiversity of Geneva, and others, focusing on the study of physiological signals for emotion analysis [19]. The database collected EEG data from 32 participants, who we University of Geneva, and others, focusing on the study of
physiological signals for emotion analysis [19]. The database
collected EEG data from 32 participants, who were asked to
watch 40 music videos to elicit different

THE EXPERIED DATA FOR:

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\hline\n\text{(b)} & \text{(d)} & \text{(e)} & \text{(f)} \\
\hline\n\text{(e)} & \text{(f)} & \text{(g)} & \text{(h)} \\
\hline\n\text{(h)} & \text{(i)} & \text{(i)} \\
\hline\n\text{(i)} & \text{(i)} & \text{(i)} \\
\hline\n\text{(ii)} & \text{(iii)} &$ Subsect Mumber of people
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 $\begin{array}{ccc}\n\bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet\n\end{array}$

Triggering condition

Fig. 1. 10-20 System channel

In Figure 1, the combination of letters and numbers

represents different Fig. 1. 10-20 System channel

Fig. 1. 10-20 System channel

Figure 1, the combination of letters and numbers

the experiments, the research team general data files for case of the 32 participants based on their respective (or) - \odot and a shape case of the sample rate of the sample in the combination of letters and numbers represents d Triggering condition

In Figure 1, the combination of letters and numbers

represents different electrode positions for EEG channels. After

the experiments, the research team generated data files for cash

of the 32 parti Fig. 1. 10-20 System channel

The main constitution of letters and numbers

Tepresents different electrode positions for EEG channels. After

the experiments, the research team generated data files for each

of the 32 part Fig. 1. 10-20 System channel

In Figure 1, the combination of letters and numbers

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the experiments, the research team generated data files for each

for the In Figure 1, the combination of letters and
represents different electrode positions for EEG chan
the experiments, the research team generated data fil
of the 32 participants based on their respective rating
further analys In Figure 1, the combination of letters and numbers
senst different electrode positions for EEG channels. After
separations the data preprocessing experiments, the research team generated data files for each in the data p represents attrent electrode positions for EEG cannels. Arter

are the experiments, the research team generated data files for each

the data preproces

of the 32 participants based on their respective ratings, enabling
 meet the represented as the sessented as a specific data structure: a man in the conduction of the 32 participants has the methanology of the inclusion of unrelated detailed records of various data during the experiment b or the 32 participants based on their respective ratings, enabling processing or ELSO signals particle and study. These data files not only provide the inclusion of unrelated decords of various data during the experiment

Interational since and since and music interation of the metallical records of various data during the experiment but also electrocoulogram). To adetailed records of various data during the experiment but also expect the m detailed records or various data during the experiment but also

secretocolongami). I

secret as rich resonance is research team downsampled the filtered signals.

original data by reducing the sampling frequency from the serve as rich ressources for subsequent research. To improve

data processing efficiency, the research team downsampled the filtered signals.

original data by reducing the sampling frequency from the filtered signals.

or data processing erricency, the research team downsampled the algorital data by reducing ind alta by reducing the sampling frequency from the algoritation original data by reducing the sampling prequency from the main char original data by reducing the sampling requency from the sample corresponding in the control of the main characteristies of the data while reducing the signal data is limited, resulting complexity of analysis. Table 1 pro original nigh requency to 128 Hz. Ints atownsampling retains

the main characteristics of the data while reducing the signal data is limited, result

the main characteristics of the duration of EEG signal collection meet

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placement, which provides strong support for related studies, as These labels serve as the basis
shown in Figure 1.
 $\begin{pmatrix} \overbrace{(\mathbf{F}\mathbf{p})}^{(\mathbf{r})} \\ \overbrace{(\mathbf{F}\mathbf{p})}^{(\mathbf{r})$ **nal of Computer Science**
These labels serve as the basis for researchers to evaluate
participants' emotional responses, enabling researchers to
understand the impact of different videos on participants'
emotions. Among th **nal of Computer Science**
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participants' emotional responses, enabling researchers to

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emotions. Amon The impact of different videos on participants'

mong the 40 channels, there are 32 EEG channels

hannels, including common signals like EOG and

s experiment, only the data from the 32 EEG

re used in the study.Table 1 pr Is serve as the basis for researchers to evaluate

" emotional responses, enabling researchers to

the impact of different videos on participants'

Nmong the 40 channels, there are 32 EEG channels

channels, including comm

Subject

Sample rate 128Hz

Sample rate 128Hz

Triggering condition 40 different movie clips

Data shape (40,32,8064)

B. Data preprocessing

In the data preprocessing stage, the analysis and

processing of EEG signals pos Number of people 32

Sample rate 128H:

Triggering condition 40 different me

Data shape (40,32,80

B. Data preprocessing

In the data preprocessing stage, the

processing of EEG signals posed significant c

the inclusion Sample rate 128Hz

Friggering condition 40 different movie clips

Data shape $(40,32,8064)$

Data preprocessing tage, the analysis and

Simple of EEG signals posed significant challenges due to

inclusion of unrelated sig Triggering condition 40 different movie clips

2014 And the metals and the data preprocessing stage, the analysis and

processing of EEG signals posed significant challenges due to

the inclusion of unrelated signals such

Data shape (40,32,8064)

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B. Data preprocessing

In the data preprocessing stage, the analysis and

processing of EEG signals posed significant challenges due to

the inclusion of unrelated signals Data snape $(40,52,8004)$
 B. Data preprocessing

In the data preprocessing stage, the analysis and

processing of EEG signals posed significant challenges due to

the inclusion of unrelated signals such as EOG

(electr B. Data preprocessing

In the data preprocessing stage, the analysis and

processing of EEG signals posed significant challenges due to

the inclusion of unrelated signals such as EOG

(electrooculogram). To address this B. Data preprocessing
In the data preprocessing stage, the analysis and
processing of EEG signals posed significant challenges due to
the inclusion of unrelated signals such as EOG
(electrooculogram). To address this chall 2. Eact preprocessing stage, the analysis and

In the data perpocessing stage, the analysis and

processing of EEG signals posed significant challenges due to

the inclusion of unrelated signals such as EOG

(electrooculog In the data preprocessing stage, the analysis and
processing of EEG signals posed significant challenges due to
the inclusion of unrelated signals such as EOG
(electrooculogram). To address this challenge, this study
emplo processing of EEG signals posed significant challenges due to
the inclusion of unrelated signals such as EOG
(electrooculogram). To address this challenge, this study
employed the ICA method to remove EEG artifacts from th the inclusion of unrelated signals such as EOG
(electrocoulogram). To address this challenge, this study
employed the ICA method to remove EEG artifacts from the
filtered signals.
As EEG data collection is difficult, time-(electrooculogram). To address this challenge, this study
employed the ICA method to remove EEG artifacts from the
filterd signals.
As EEG data collection is difficult, time-consuming, and
carries high ethical and safety r employed the ICA method to remove EEG artiracts from the
filtered signals.
As EEG data collection is difficult, time-consuming, and
carries high ethical and safety risks [21], the available EEG
signal data is limited, resu filtered signals.

As EEG data collection is difficult, time-consuming, and

As EEG data collection and safety risks [21], the available EEG

signal data is limited, resulting in a small database that does not

meet the re As EEG data conection is difficulted, time-consuming, and
carries high ethical and safety risks [21], the available EEG
signal data is limited, resulting in a small database that does not
meet the requirements for large-s carries mgn ethical and safety risks [21], the available EEG
signal data is limited, resulting in a small database that does not
meet the requirements for large-scale deep network analysis.
This presents a high risk of ov signal data is imited, resulting in a small database that does
meet the requirements for large-scale deep network analy
This presents a high risk of overfitting, making
augmentation necessary. This study utilized a slidin

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IAENG International Journal of Computer Science
After applying a sliding window to the EEG signals, this correlation between the valence
integrated the EEG data from 32 subjects, resulting in model and the subjects' phys
2 **IAENG International Journal of Computer Science**

After applying a sliding window to the EEG signals, this correlation between the valence a

study integrated the EEG data from 32 subjects, resulting in model and the subj 40×32×21 training data points. Here, 40 represents the signals **IAENG International Journal of Computer Science**
Collected from a sliding window to the EEG signals, this correlation between the valence
study integrated the EEG data from 32 subjects, resulting in model and the subjec **IAENG International Journal of Computer Science**

After applying a sliding window to the EEG signals, this correlation between the valence

study integrated the EEG data from 32 subjects, resulting in model and the subjec **IAENG International Journal of Comput**
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study integrated the EEG data from 32 subjects, resulting in model and the sta-

40×32×21 training dat **IAENG International Journal of Computer Scien**
After applying a sliding window to the EEG signals, this correlation between the vale
integrated the EEG data from 32 subjects, resulting in model and the subjects' pl
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After applying a sliding window to the EEG signals, this correlation between the valence

study integrated the EEG data from 32 subjects, resulting in model and the subjec

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After applying a sliding window to the EEG signals, this correlation between the val

study integrated the EEG data from 32 subjects, resulting in model and the subjects' 4 **IAENG International Journal of Computer Science**
 EXERC Accomplise After applying a sliding window to the EEG signals, this correlation between the valence study integrated the EEG data from 32 subjects, resulting in mo After applying a sliding window to the EEG signals, this correlation between the subjected from each subject of and 2 subjects, resulting in model and the subject of $40 \times 32 \times 21$ training data points. Here, 40 represent After applying a sliding window to the EEG signals, this correlation between the valued study integrated the EEG data from 32 subjects, resulting in model and the subjects' $40 \times 32 \times 21$ training data points. Here, 40 re After applying a sliding window to th
study integrated the EEG data from 32 su
40×32×21 training data points. Here, 40 rej
collected from each subject while watchi
represents the 32 subjects, and 21 is the expa
data. In t represents the 32 subjects, and 21 is the expansion factor for the circular model of data. In total, 26880 training data points were obtained.

After obtaining the integrated EEG data, this study further

applied the Sho data. In total, 26880 training data points were obtained. understand and classify the After obtaining the integrated EEG data, this study further and signal applied the Short-Time Fourier Transform (STFT) to these data. A After obtaining the integrated EEG data, this study further shown in Figure 4.

applied the Short-Time Fourier Transform (STFT) to these data. Arc

striven the sumerous advantages in processing EEG signals,

including hig applied the Short-Time Fourier Transform (STI
STFT has numerous advantages in processin
including high time-frequency resolution,
non-stationary signals, intuitive visualization, ε
for feature extraction and signal pr

non-stationary signals, intuitive visualization, and convenience
for feature extraction and signal processing. The STFT formula
is as follows:
 $STFT_z(t, \omega) = \int_{-\infty}^{\infty} \chi(\tau) \omega^* (\tau - t) e^{-j\omega \tau} d\tau$ (1)
In the equation: ω rep for feature extraction and signal processing. The STFT formula

is as follows:
 $STFT_x(t, \omega) = \int_{-\infty}^{\infty} \chi(\tau) \omega^* (\tau - t) e^{-j\omega \tau} d\tau$ (1)

In the equation: ω represents the angular frequency, $x(\tau)$

represents the value of is as follows:

STFT_x(t, ω)= $\int_{-\infty}^{\infty} \chi(\tau) \omega^* (\tau - t) e^{-j\omega \tau} d\tau$ (1)

In the equation: ω represents the angular frequency, $x(\tau)$

represents the value of the original signal in the time domain,
 $\omega(\tau-t)$ repre $SIFT_{\chi}(\mathbf{t}, \omega) = \int_{-\infty}^{\infty} \chi(\mathbf{r})\omega^* (\mathbf{r} - t) e^{-j\omega \tau} d\tau$ (1)

In the equation: ω represents the angular frequency, $x(t)$

represents the value of the original signal in the time domain,
 $\omega(\tau-t)$ represents the wi STFT_x(t, ω)= $\int_{-\infty}^{\infty} \chi(\tau) \omega^* (\tau - t) e^{-j\omega \tau} d\tau$ (1)

In the equals of the original signal in the time domain,

expresents the value of the original signal in the time domain,
 $\omega(\tau-t)$ represents the window funct In the equation: ω represents the angular frequency, $x(t)$ and $x(t)$ In the equation: ω represents the angula
represents the value of the original signal in
 $\omega(\tau-t)$ represents the window function sh
denotes conjugation.
Through STFT, this paper can effect
temporal and frequency features

Perspective for the study of emotions and the studied stress and the studied of emotions ($\frac{1}{2}$ and $\frac{1$ dimension measures the positive or negative tendency of extraction model of and the positive or states and the positive or negative tendency of extraction model of emotions, established on the dimensions of valence and ar Finany, stablished on the arousal score less than or equilibration of seconds

arousal score less than or equilibration of the seconds of the intensity of the intensity or
 C. Affective labeling Russell's circular model activation state of emotions and the state of emotions and the state of emotions ($\frac{23}{2}$. The ext describes the state of emotions, established on the dine a deep convoluning and the state of emotions of valence and ar are combined, they constitute a circular emotional space that ²

² ^a ⁸ Seconds(s)

Fig. 3. Time-frequency diagram

C. *Affective labeling*

Processing preprocessed EEG da

Russell's circular model of emotions, established on the

dimensions of valence and arousal, provides a Fig. 3. Time-frequency diagram

Fig. 3. Time-frequency diagram

The text describes a

processing preprocessed E

Russell's circular model of emotions, established on the

dimensions of valence and arousal, provides a uniqu Fig. 3. Time-frequency diagram

Fig. 3. Time-frequency diagram

The text describes a ne

dimensions of valence and arousal, provides a unique

dimensions of valence and arousal, provides a unique

dimension and accept of t The text describes a neum

Russell's circular model of emotions, established on the fed into a dependence and dimensions of valence and arousal, provides a unique where each layer passes the perspective for the study of em C. Affective labeling

Russell's circular model of emotions, established on the

dimensions of valence and arousal, provides a unique

extraction module. Up

perspective for the study of emotions [22]. The valence

extract

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correlation between the valence and arousal dimensions in the

model and the subjects' physiological data. For the DEAP

dataset, this discovery provides strong support for the

re-calibration of **nal of Computer Science**

correlation between the valence and arousal dimensions in the

model and the subjects' physiological data. For the DEAP

dataset, this discovery provides strong support for the

re-calibration of **nal of Computer Science**
correlation between the valence and arousal dimensions in the
model and the subjects' physiological data. For the DEAP
dataset, this discovery provides strong support for the
re-calibration of lab **read of Computer Science**
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model and the subjects' physiological data. For the DEAP
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model and the subjects' physiological data. For the DEAP

dataset, this discovery provides strong support for the

re-calibration o **nal of Computer Science**

correlation between the valence and arousal dimension

model and the subjects' physiological data. For the

dataset, this discovery provides strong support the

re-calibration of labels in this

9.0 Label

Label

Label

Label

definition: 2

definition: 3

Fig. 4. DEAP tags define Valence and arousal

In the rating matrix (40×4) of the DEAP dataset, each

video is scored by subjects on a continuous 9-point scal Label

Label

definition: 2

definition: 3

definition: 3

Fig. 4. DEAP tags define Valence and arousal

In the rating matrix (40×4) of the DEAP dataset, each

video is scored by subjects on a continuous 9-point scale Fig. 4. DEAP tags definition: 3

Fig. 4. DEAP tags define Valence and arousal

In the rating matrix (40×4) of the DEAP dataset, each

video is scored by subjects on a continuous 9-point scale for

valence, arousal, domina Fig. 4. DEAP tags define Valence and arousal
In the rating matrix (40×4) of the DEAP dataset, each
video is scored by subjects on a continuous 9-point scale for
valence, arousal, dominance, and likability [24]. This pa Fig. 4. DEAP tags define Valence and arousal
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video is scored by subjects on a continuous 9-point scale for
valence, arousal, dominance, and likability [24]. This paper
primarily focuses on the two dimensions video is scored by subjects on a continuous 9-point scale for
valence, arousal, dominance, and likability [24]. This paper
primarily focuses on the two dimensions of valence and arousal,
and integrates these labels into Ru valence, arousal, dominance, and likability [24]. This paper
primarily focuses on the two dimensions of valence and arousal,
and integrates these labels into Russell's circular model of
emotions. Specifically, based on the III, based on the original categorical labels
I encoding method, we define labels with a
er than 4.5 and an arousal score greater than
th a label of 0. Labels with a valence score
o 4.5 and an arousal score greater than 4. lence score greater than 4.5 and an arousal score greater than

is a "Excited" with a label of 0. Labels with a valence score

is than or equal to 4.5 and an arousal score greater than 4.5

e classified as "Afraid" with a 4.5 as "Excited" with a label of 0. Labels with a valence score
less than or equal to 4.5 and an arousal score greater than 4.5
are classified as "Afraid" with a label of 1. Labels with a
valence score less than or equal t less than or equal to 4.5 and an arousal score greater than 4.5
are classified as "Afraid" with a label of 1. Labels with a
valence score less than or equal to 4.5 and an arousal score less
than or equal to 4.5 are labeled

are classified as "Afraid" with a label of 1. Labels with a valence score less than or equal to 4.5 and an arousal score less than or equal to 4.5 are labeled as "Sad" with a label of 2. Finally, labels with a valence scor valence score less than or equal to 4.5 and an arousal score less
than or equal to 4.5 are labeled as "Sad" with a label of 2.
Finally, labels with a valence score greater than 4.5 and an
arousal score less than or equal t than or equal to 4.5 are labeled as "Sad" with a label of 2.

Finally, labels with a valence score greater than 4.5 and an

arousal score less than or equal to 4.5 are categorized as

"Relaxed" with a label of 3.

III. PRO Finally, labels with a valence score greater than 4.5 and an arousal score less than or equal to 4.5 are categorized as "Relaxed" with a label of 3.

III. PROPOSED METHOD

The text describes a neural network architecture f arousal score less than or equal to 4.5 are categorized as

"Relaxed" with a label of 3.

III. PROPOSED METHOD

The text describes a neural network architecture for

processing preprocessed EEG data of video stimuli. The d "Relaxed" with a label of 3.

III. PROPOSED METHOD

The text describes a neural network architecture for

processing preprocessed EEG data of video stimuli. The data is

fed into a deep convolutional module consisting of 5 III. PROPOSED METHOD
The text describes a neural network architecture for
processing preprocessed EEG data of video stimuli. The data is
fed into a deep convolutional module consisting of 5 layers,
where each layer passes III. PROPOSED METHOD
processing preprocessed EEG data of video stimuli. The data is
fed into a deep convolutional module consisting of 5 layers,
where each layer passes the convolved data to a feature
extraction module. Up III. PROPOSED METHOD
The text describes a neural network architecture for
processing preprocessed EEG data of video stimuli. The data is
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fed into a deep convolutional module consisting of 5 layers,
where each layer passes the convolved data to a feature
extraction module. Upon receiving the data

module in this study is inspired by the feature pyramid Exerces and the convolutional module of the three modules: deep convolutional module, feature extraction module, and convolution kernel of classification module. (attace extraction module, and convolution kernel of classi Below are detailed descriptions of the three modules: deep

convolutional module, feature extraction module, and convolution kernel of layer

classification module. Extraction module, and convolution kernel of layer

desi Eq. 5. Overall system tranework

Fig. 5. Overall system tranework

convolutional module, feature extraction module, and

convolution kernel of layer 1,

classification module. feature extraction module, and
 M is the fe Below are detailed descriptions of the three modules: deep In the equation: χ_i^{l-1} is the convolutional module, feature extraction module, and convolution kernel of layer I classification module.

1. *M* is the featur convolutional module, feature extraction module, and convolution kernel of layer 1
classification module. (and convolution kernel, b is the b
classification module. (and convolution fermel, b is the b
 \star is the previous classification module.
 I. M is the feature in a

convolution kernel in this study is inspired by multiple researchers. The deep convolutional max pooling layer with

module in this study is inspired by the feature pyra *A. Deep convolutional module*

and the convolution semel, b is the convolution

The effectiveness of multiscale EEG detection has been

^{Atter} the convolution operated by multiple researchers. The deep convolutional max *A. Deep convolutional module*

<sup>sourconvolution cernic, *b* is the convolution operation.

The effectiveness of multiscale EEG detection has been

After the convolution operation.

In act provided in this study is inspir</sup> half. The effectiveness of multiscale EEG detection has been

infirmed by multiple researchers. The deep convolutional max pooling layer with a kerne

odule in this study is inspired by the feature pyramid ext pooling layer, th confirmed by multiple researchers. The deep convolutional max pooling layer with a kernel
module in this study is inspired by the feature pyramid next pooling layer, the kernel
technique in image processing. It utilizes d module in this study is inspired by the feature pyramid next pooling layer, the kern
technique in image processing. It utilizes deep convolutional calculation for the pooling lay
layers and pooling layers to divide the in technique in image processing. It utilizes deep convolutional
algers and pooling layers to divide the input signal into multiple
scales with different resolutions. The designed deep
orvolutional module consists of five co layers and pooling layers to divide the input signal into multiple

scales with different resolutions. The designed deep

convolutional module consists of five consecutive layers

where each layer is designed based on the scales with different resolutions. The designed deep
convolutional module consists of five consecutive layers,
where each layer is designed based on the previous layer's
resolution being halved in order to capture feature From resolutions. The designed deep
 lule consists of five consecutive layers,

is designed based on the previous layer's In the equation: *down*

ived in order to capture features effectively. and χ_j^l is the output alle consists of five consecutive layers,
 s designed based on the previous layer's In the equation: *down*

ved in order to capture features effectively. and χ^j_i is the output feat

tically learns weights and extra odule, feature extraction module, and convolution kernel of layer 1, χ_1^f is the *j*-th feature in the that for the feature input map, ω is the weight manimum tend to the state in the state of a convolution of the descriptions of the three modules: deep In the equation: χ_1^{i-1} is the region corresponding to the *i*-th, feature extraction module, and convolution kernel of layer 1, χ_1^i is the j-th feature map of layer convo

and based on the volume layers,

find based on the previous layer's In the eorder to capture features effectively. and χ_j^l is

learns weights and extracts valuable Throu

el while downsampling the signal by half of

e

$$
x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * \omega_{ij}^l + b_j^l\right)
$$
 (2)

the anti-original size of 2x1. The equation: χ_i^{l-1} is the region corresponding to the *i*-th convolution kernel of layer 1, χ_i^l is the *j*-th feature map of layer 1, *M* is the feature input map, ω is the we id Sad Relaxed

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 community from framework

In the equation: χ_i^{l-1} is the region corresponding to the *i*-th

convolution kernel of layer 1, χ_i^l is the *j*-th feature map of layer

1, *M* is the feature input In the equation: χ_i is the view of layer 1, χ_i^L is the *y*-th feature map of layer 1, *M* is the feature input map, ω is the weight matrix of the convolution kernel, *b* is the bias, *f* is the activation functi

is the feature input map, ω is the weight matrix of the blution kernel, *b* is the bias, *f* is the weight matrix of the blution kernel, *b* is the bias, *f* is the activation function, and ne convolution operation.

t

$$
x_j^l = down_{\text{max}}(x_j^{l-1})
$$
 (3)

and χ_j^l is the output feature map of the pooling layer.
Through this operation, the data volume of layer x becomes

mvolution kernel, *b* is the bias, *f* is the activation function, and
s the convolution operation.
After the convolution operation, the output passes through a
ax pooling layer with a kernel size of 2×1. When entering th existed to convolution operation.

* is the convolution operation.

After the convolution operation.

there the convolution operation.

there the convolution operation, the output passes through a

max pooling layer with Extracts features with the convolution operation, the output passes through a
max pooling layer with a kernel size of 2×1. When entering the
next pooling layer, the kernel size is switched to 1×2. The
calculation for the max pooling layer with a kernel size of 2×1. When entering the
next pooling layer, the kernel size of 2×1. When entering the
next pooling layer, the kernel size is switched to 1×2. The
calculation for the pooling layer is mext pooling layer, the kernel size is switched to 1×2. The
next pooling layer, the kernel size is switched to 1×2. The
calculation for the pooling layer is as follows:
 $\chi_j^j = \frac{d}{\omega_{\text{max}}}\left(\chi_j^{l-1}\right)$ (3)
In the equatio Example 19 and the pooling layer, the Kerlier size is switched to 1-2. The calculation for the pooling layer is as follows:
 $x'_j = dOWn_{\text{max}}(x_j^{l-1})$ (3)

In the equation: $d_{\text{OW}}n_{\text{max}}$ represents the max pooling funct $x_j' = down_{\text{max}}(x_j^{t-1})$ (3)
the equation: $down_{\text{max}}$ represents the max pooling function,
d x_i^l is the output feature map of the pooling layer.
Through this operation, the data volume of layer x becomes
lif of layer x-1. the equation: *down_{max}* represents the max pooling function,
d χ_j^l is the output feature map of the pooling layer.
Through this operation, the data volume of layer x becomes
If of layer x-1. Each convolutional layer In the equation: $down_{max}$ represents the max pooling function,
and χ_1^1 is the output feature map of the pooling layer.
Through this operation, the data volume of layer x becomes
half of layer x-1. Each convolutional la and χ_1^1 is the output feature map of the pooling layer.

Through this operation, the data volume of layer x becomes

half of layer x-1. Each convolutional layer independently

extracts features without information ex

Most current researches use simple concatenation for feature
fusion, without considering the different impacts of various

IAENG International Journal of Computer Scie
interaction and fusion of information among different features, Self-Attention (MHSA) m
which leads to many networks not significantly improving the two layers of LayerNorm is **IAENG International Journal of Computer Science**
interaction and fusion of information among different features,
which leads to many networks not significantly improving the
robustness and accuracy of classification resul **TAENG International Journal of Computer Sci**
interaction and fusion of information among different features, Self-Attention (MHSA)
which leads to many networks not significantly improving the two layers of LayerNorm
robus **IAENG International Journal of Computer Science**
interaction and fusion of information among different features, Self-Attention (MHSA) module,
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interaction and fusion of information among different features,
which leads to many networks not significantly improving the
robustness and accuracy of classification results afte **TAENG International Journal of Computer Science**
interaction and fusion of information among different features, Self-Attention (MHSA) modula
which leads to many networks not significantly improving the two layers of Lay **IAENG International Journal of Computer Science**
interaction and fusion of information among different features, Self-Attention (MHSA) mod
which leads to many networks not significantly improving the two layers of LayerN **THENG International Journal of Computer Science**

interaction and fusion of information among different features,

which leads to many networks not significantly improving the

two layers of LayerNorm normal

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interaction and fusion of information among different features,

which leads to many networks not significantly improving the

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interaction and fusion of information among different features, Self-Attention (MHSA) modu

which leads to many networks not significantly improving** interaction and fusion of information among different features,
which leads to many networks not significantly improving the
robustness and accuracy of classification results after extracting
multiple features. This paper

Example 1.1 and a ReLU activation layer is primarily to potential layer conducts that a ReLU activation layer. Each convolutional layer is primarily and a ReLU activation of length $\frac{1}{280}$, $\frac{320}{320}$, $\frac{30}{30}$ Fig. 6. Design CNN-Transformer hybrid module

The module previous module

The constant of length 1280, which is then into of length 1280, which is then into of length 1280, 30, 80, and 4 respectively

The CNN part consist **Layer Complimation**
 Layer Complimation
 Layer Convolution Complete the extraction of length 1280, 320, 80, and 4 respective the LogSoftmax layer. Log

Fig. 6. Design CNN-Transformer hybrid module

The CNN part consi Feature Combination
 $\begin{array}{c}\n\vdots \\
\downarrow\n\end{array}$ Feature Combination
 $\begin{array}{c}\n\vdots \\
\downarrow\n\end{array}$ To length 1280, which is the
 $\begin{array}{c}\n\vdots \\
\downarrow\n\end{array}$ The CNN part consists of three convolutional layers with a

Fig. 6. Design CN Fig. 6. Design CNN-Transformer hybrid module

Fig. 6. Design CNN-Transformer hybrid module

the profolmax layer Log

the negoform at a respect to the predicted probability for

Fig. 6. Design CNN-Transformer hybrid module **Performance and generalization ability.** The normalization formula is as follows:
 $\mu_{\beta} = \frac{1}{m} \sum_{i=1}^{m} x_i$ (4) A. Experimentals were the the strengthend probable the predicted probable descent calculation,

The CNN Fig. 6. Design CNN-Transformer hybrid module
The CNN part consists of three convolutional lay
kernel size of 3x3, a stride of 1, and padding of 1.
each convolutional layer is a Batch Normalization
and a ReLU activation la

$$
\mu_{\beta} = \frac{1}{m} \sum_{i=1}^{m} x_i
$$
\n(4) A. Experimental setup
\nThe article was deployed on an NVIDIA RTX 2080 GPU

$$
y = \frac{x_i - \mu_\beta}{\sqrt{\frac{1}{m} \sum_{i=1}^m (x_i - \mu_\beta)}^2} \ast \gamma + \beta
$$
\n
$$
\
$$

In the equation: *x* represents the batch input data, *m*

In the equation: *x*_{*i*} represents the neural network, improve the model's

IF formance and generalization ability. The normalization

The article was deployed process of the neural network, improve the model's

performance and generalization ability. The normalization

formula is as follows:
 $\mu_{\beta} = \frac{1}{m} \sum_{i=1}^{m} x_i$ (4) *A. Experimental setup*

The article was deployed

se and generalization ability. The normalization
formula is as follows:
 $\mu_{\beta} = \frac{1}{m} \sum_{i=1}^{m} x_i$ (4) *A. Experiment*
The article wa
 $y = \frac{x_i - \mu_{\beta}}{\sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_{\beta})^2 + \varepsilon}} * \gamma + \beta$ server and the more framewor Formula is as follows:
 $\mu_{\beta} = \frac{1}{m} \sum_{i=1}^{m} x_i$ (4) *A. Experimental setup*

The article was deployed of
 $y = \frac{x_i - \mu_{\beta}}{\sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_{\beta})} + \varepsilon} * \gamma + \beta$ (5) a learning rate of 0.0001, and

training with 5 parameter. $\mu_{\beta} = \frac{1}{m} \sum_{i=1}^{m} x_i$ (4) A. Experimental set.

The article was deply
 $y = \frac{x_i - \mu_{\beta}}{\sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_{\beta})^2 + \varepsilon}} * \gamma + \beta$ server and the model w

framework. During trait

In the equation: x represents the b

nal of Computer Science
Self-Attention (MHSA) module, a feed-forward module, and
two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
after the feed-forwar **nal of Computer Science**
Self-Attention (MHSA) module, a feed-forward module, and
two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
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Self-Attention (MHSA) module, a feed-forward module, and
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Self-Attention (MHSA) module, a feed-forward module, and
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Self-Attention (MHSA) module, a feed-forward module, and
two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
after the feed-forwa **n (MHSA)** module, a feed-forward module, and

t LayerNorm normalization modules[25]. The two

n layers are placed before the MHSA module and

1-forward module. The calculation method for the

chanism is as follows:
 $(Q_{ij$ Forward module, and

podules^[25]. The two

MHSA module and

tion method for the
 $\frac{\partial u^k}{\partial t^k}$
 $\frac{\partial u^k}{\partial t^k}$ (6)

the query vector, key *itf itf its its* Forward module, and

modules^[25]. The two

ine MHSA module and

ulation method for the
 $Q_{if} K_{if}^T$
 $\sqrt{d_k}$ (6)

the query vector, key

ne attention module,

ion, and d_k represents **Attention (MHSA)** module, a feed-forward module, and
 Attention (MHSA) module, a feed-forward module, and
 Attention layers are placed before the MHSA module and
 Attention layers are placed before the MHSA module Self-Attention (MHSA) module, a feed-forward module, and
two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
after the feed-forward module. The calculation Self-Attention (MHSA) module, a feed-forward module, and
two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
after the feed-forward module. The calculation Self-Attention (MHSA) module, a feed-forward module, and
two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
after the feed-forward module. The calculation

$$
Attention(Q_{_{itf}}, K_{_{itf}}, V_{_{its}}) = Soft \max(\frac{Q_{itf}}{V_{itf}} K_{itf}^T) V_{_{its}} \qquad (6)
$$

two layers of LayerNorm normalization modules[25]. The two
normalization layers are placed before the MHSA module and
after the feed-forward module. The calculation method for the
attention mechanism is as follows:
 $\frac{H}{$ atter the feed-forward module. The calculation method for the attention mechanism is as follows:
 $\frac{Q_{if}K_{if}^T}{d_k}$ (6)
 $\frac{d}{d_k}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt}$ $\frac{d}{dt$ attention mechanism is as follows:

Attention($Q_{ijf}, K_{ijf}, V_{its}$)=Soft max($\frac{Q_{ijf} K_{ijf}^T}{\sqrt{d_k}}$) V_{its} (6)

In the equation: Q_{ijf}, K_{ijf} , and V_{ijf} represent the query vector, key

vector, and value vector inputs in t Attention($Q_{ijf}, K_{ijf}, V_{its}$)=Soft max($\frac{Q_{ijf}K_{ijf}^T}{\sqrt{d_k}}$ (6)

In the equation: Q_{ijf}, K_{ijf} , and V_{ijf} represent the query vector, key

vector, and value vector inputs in the attention module,
 Softmax() represen Attention(Q_{ij} , K_{ij} , V_{lis})=Soft max($\frac{Q_{ij}K_{ij}'}{\sqrt{d_k}}$) V_{lis} (6)
In the equation: Q_{ij} , K_{iij} , and V_{ij} represent the query vector, key
vector, and value vector inputs in the attention module,
Softmax() rep Attention(Q_{ijf} , K_{ijf} , V_{lis})=Soft max($\frac{Q_{ijf}}{\sqrt{d_k}}$ (6)

In the equation: Q_{ijf} , K_{iif} , and V_{ijf} represent the query vector, key

vector, and value vector inputs in the attention module,
 Softmax() repr $\sqrt{u_k}$
In the equation: $Q_{ufs} K_{ufs}$ and V_{ufs} represent the query vector, key
vector, and value vector inputs in the attention module,
Softmax(.) represents the Softmax function, and d_k represents
the dimension of In the equation: Q_{itf} , K_{itf} , and V_{itf} represent the q
vector, and value vector inputs in the att
Softmax() represents the Softmax function, at
the dimension of K_{itf} .
In the feature extraction module, this pape *oftmax(-)* represents the Softmax function, and d_k represents the Softmax function, and d_k represe dimension of K_{ij} . In the feature extraction module, this paper utilizes 5 odules. Since the input data size of eac Frametary of the flattens and combines the 5 sets of data length 1280, which is the module first and combine flattens and combine flattens.
The first flattens are the input data size of each module is different, the modul In the feature extraction module, this paper utilizes 5 C-T
modules. Since the input data size of each module is different,
each module will be adjusted internally based on the input data
size. The output data size will a modules. Since the input data size of each module is different,
each module will be adjusted internally based on the input data
size. The output data size will also change according to the
input data. Therefore, an average

C. Classification Module

The module first flattens and combined

The module first flattens and combined

output by the previous module to form a

of length 1280, 320, 80, and 4 respectively. Finall

the product is then i C. *Classification Module*

The module first flattens and

orleaght 1280, which is then into

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bination
 $\frac{1}{2}$ intervals of four FC (fully ex
 $\frac{1}{2}$ intervals of four FC (fully ex
 $\frac{1}{2}$ int Some the model first flatence on the model for the model in the model of the state in the state of the state in the state of the s meath module will be adjusted internally based on the input data
size. The output data size will also change according to the
input data. Therefore, an average pooling module is added after
the C-T modules to unify the out size. The output data size will also change according to the
input data. Therefore, an average pooling module is added after
the C-T modules to unify the output data size of the 5 layers of
C-T modules, resulting in featur mput data. Therefore, an average pooling module is added after
the C-T modules to unify the output data size of the 5 layers of
C-T modules, resulting in feature data with an output size of
 $(256, 1, 1)$.
C. Classificatio the C-T modules to unify the output data size of the 5 layers of
C-T modules, resulting in feature data with an output size of
C-T modules, resulting in feature data with an output size of
(256, 1, 1).
C. Classification M descent calculation, LogSoftmax heavily penalizes highly
incorrelate calculation, C. Classification Module
The module first flattens and combines the 5 sets of data
of length 1280, which is then input to the fully connect (256, 1, 1).

C. Classification Module

The module first flattens and combines the 5 sets of data

output by the previous module to form a one-dimensional data

of length 1280, which is then input to the fully connected l *C. Classification Module*
The module first flattens and combines the 5 sets of data
output by the previous module to form a one-dimensional data
of length 1280, which is then input to the fully connected layer.
It consis explored to the steading and the steading of the steady
stration module, this paper utilizes 5 C-T
input data size of each module is different,
that size of each module is different,
that stars will also change according *()* represents the Softmax function, and d_k represents
raison of K_{ijk} .
raision of K_{ijk}
reading that is reading the function module, this paper utilizes 5 C-T
. Since the input data size of each module is different, Experience the equation: *x_i* represents the *i*-th element of the input vectors is of flength 1280, which is then input to the fully connected layer.
It consists of four FC (fully connected) layers with sizes of 1280,

$$
LogSoft \max(x_i) = log(\frac{\exp(x_i)}{\sum_j \exp(x_i)})
$$
 (7)

x.

IV. EXPERIMENT

utilized. For the DEAP dataset, a batch size of 16 was selected
for training with 50 iterations. To prevent overfitting, a dropout server and the model was trained and tested using the PyTorch a learning rate of 0.0001, and cross-entropy loss function was Experimental setupped and NVIDIA RTX 2080
 A. Experimental setupped and the model was tellulation is as follows:
 A. Experimental setup
 A. Experimental setup

The article was deployed on an NVIDIA RTX 2080 of
 A. the correct classes, further optimizing training time. The formula

LogSoftmax calculation is as follows:
 $LogSoft \, \text{max}(x_i) = log(\frac{\exp(x_i)}{\sum_j \exp(x_i)})$ (7)

the equation: x_i represents the *i*-th element of the input vector

IV. EXP set the model was trained and tested the model was trained the model was trained and tested using the model was trained and tested using the PyTorch model was trained and tested using the PyTorch framework. During trainin *LogSoft* max(x_i) = log($\frac{\exp(x_i)}{\sum_j \exp(x_i)}$ (7)
In the equation: x_i represents the *i*-th element of the input vector
x.
IV. EXPERIMENT
A. Experimental setup
The article was deployed on an NVIDIA RTX 2080 GPU
server and LogSoft max(x_i) = $\log(\frac{1}{\sum_{j} exp(x_i)})$ (7)

In the equation: x_i represents the *i*-th element of the input vector

x.

IV. EXPERIMENT

A. Experimental setup

The article was deployed on an NVIDIA RTX 2080 GPU

server an $\sum_j \exp(x_i)$
In the equation: x_i represents the *i*-th element of the input vector x .
IV. EXPERIMENT
A. Experimental setup
The article was deployed on an NVIDIA RTX 2080 GPU
server and the model was trained and tested u In the equation: x_i represents the *i*-th element of the input vector x .

IV. EXPERIMENT

A. Experimental setup

The article was deployed on an NVIDIA RTX 2080 GPU

server and the model was trained and tested using th IV. EXPERIMENT
IV. EXPERIMENT
A. Experimental setup
The article was deployed on an NVIDIA RTX 20
server and the model was trained and tested using the
framework. During training, Adam optimizer was cheader
a learning rate IV. EXPERIMENT
I. *Experimental setup*
The article was deployed on an NVIDIA RTX 2080 GPU
ver and the model was trained and tested using the PyTorch
mework. During training, Adam optimizer was chosen with
earning rate of 0 IV. EXPERIMENT

A. Experimental setup

The article was deployed on an NVIDIA RTX 2080 GPU

server and the model was trained and tested using the PyTorch

framework. During training, Adam optimizer was chosen with

a learni IV. EXPERIMENT

A. Experimental setup

The article was deployed on an NVIDIA RTX 2080 GPU

server and the model was trained and tested using the PyTorch

framework. During training, Adam optimizer was chosen with

a learni A. *Experimental setup*
The article was deployed on an NVIDIA RTX 2080 GPU
server and the model was trained and tested using the PyTorch
framework. During training, Adam optimizer was chosen with
a learning rate of 0.0001, A. *Experimental setup*
The article was deployed on an NVIDIA RTX 2080 GPU
server and the model was trained and tested using the PyTorch
framework. During training, Adam optimizer was chosen with
a learning rate of 0.0001,

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function is:

$$
L = -\frac{1}{N} \sum_{i} \sum_{c=1}^{M} y_{ic} \log(p_{ic})
$$
 (8) 2) D_{i}^{i}

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performs set to 5.
 $\sum_{i}^{M} y_{ic} \log(p_{ic})$ (8) 2) Differ

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the number of categories of the major rol

the probability of th **IAENG International Journal of Computer Science**

function is:
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In the equation:*M* represents the number of categories of the major role. To determin **IAENG International Journal of Computer Science**
function is:
 $L = -\frac{1}{N} \sum_{i} \sum_{c=1}^{M} y_{ic} \log(p_{ic})$ (8) 2) Different feature extraction
In the equation:*M* represents the number of categories of the major role. To determ **EXECUTE:** INDENG International Journal of Computer Science

function is:
 $L = -\frac{1}{N} \sum_{i=1}^{M} y_i \log(p_i)$ (8) $2)$ Different feature extraction

In the equation. *I* represents the number of categories of the major role. T **EXECUTE:** International Journal of Computer Scien

function is:
 $L = -\frac{1}{N} \sum_{i=1}^{M} y_{ic} \log(p_{ic})$ (8) $\frac{2}{D}$ *Different feature extract*

In the equation: *M* represents the number of categories of the major role. To **IAENG Internatio**

function is:
 $L = -\frac{1}{N} \sum_{i} \sum_{c=1}^{M} y_{ic} \log(p_{ic})$

In the equation:*M* represents the number of categories

classification, *i* represents the number of categories

classification, y_{ic} represents *B.* $L = -\frac{1}{N} \sum_{i}^{M} \sum_{c=1}^{M} y_{ic} \log(p_{ic})$
 B. A. the equation:*M* represents the number of categorial assification, *i* represents the number of categorial assification, *y_{ic}* represents the probability of the cla function is:
 $L = -\frac{1}{N} \sum_{i}^{M} y_{ic} \log(p_{ic})$ (8) $\frac{2}{N}$

In the equation:*M* represents the number of categories of the major

classification, *i* represents the number of categories of the convolutions, *y_{ic}* repres

 $L = -\frac{1}{N} \sum_{i} \sum_{c=1} y_{ic} \log(p_{ic})$ (8) 2) Different feature extraction

In the equation:*M* represents the number of categories of the major role. To determine

classification, *i* represents the number of categories of t In the equation:*N* represents the number of categories of the major role. To determine the classification, *i* represents the probability of the class i convolutional kernel and the investigated by the model.

Even the p In the equation:*M* represents the number of categories of the classification, *i* represents the number of categories of the classification and the ideasification, y_e represents the probability of the class *i* of the Examples the model of the classification, *i* represents the number of categories of the classification task, this real label, and p_k represents the probability of the class *i* of the classification task, this real lab **Example 10**

classification, y_e represents the probability of the class *i* of the classification by modifying the

real label, and p_e represents the probability of the class *i* verification by modifying the

predic convolution. Example 2 presents the probability of the state of the state and a 3x3 convolutional

2. Ablation experiment

2. Ablation experiment

2. Different depth convolution modules

2. Transformer and a 1x1 control of Transformer and with a 3x3 convolutional k
 B. Ablation experiment
 I) Different depth convolution modules
 IV Transformer and a 1x1 convolution
 This study primarily utilizes a deep convolutional module as

Table 3 presents t and 8 illustrate the training curves of accuracy and loss inclusion of Transformer and a 1x1 complement and the external framework, which *B. Ablation experiment* of Transformer and a 1x1 conv

1) Different depth convolution modules

This study primarily utilizes a deep convolutional module as Table 3 resents the average

the overall framework, which derive *I) Different depth convolution modules*

This study primarily utilizes a deep convolutional module as

the overall framework, which derives five parallel channels

from the dep convolutional module. The study investigat This study primarily utilizes a deep con
the overall framework, which derives fi
from the deep convolutional module. The s
impact of varying depths of convolutio
emotion classification tasks. Specifically
conducted with th e overall framework, which derives five parallel channels

walues for different feature ex

mom the deep convolutional module. The study investigates the

10 display the training accura

pototion classification tasks. Spec

from the deep convolutional module. The study investigates the 10 display the training
impact of varying depths of convolutional layers on EEG feature extraction mo
emotion classification tasks. Specifically, experiments

conducted with three, four, five, and six layers of deep set curve.

When Transformer is not u

Table 2 presents the average accuracy and average loss

values under different deep convolutional modules. Figures 7 the train Convolution. When Transforme

Table 2 presents the average accuracy and average loss

and 8 illustrate the training curves of accuracy and loss for each

and 8 illustrate the training curves of accuracy and loss for each
 Table 2 presents the average accuracy and average loss

under different deep convolutional modules. Figures 7 the training accuracy and loss

and 8 illustrate the training curves of accuracy and loss for each

the average values under different deep convolutional modules. Figures 7 the training accuracy and
and 8 illustrate the training curves of accuracy and loss for each The average accuracy is
deep convolutional module. The dashed lines and 8 illustrate the training curves of accuracy and loss for each

that of a 3x3 convolutional kerne

training set curves, while the solid lines represent the that of a 3x3 convolutional kerne

training set curves, while deep convolutional module. The dashed lines represent the that of a 3x3 convolutional
training set curves, while the solid lines represent the validation higher by 0.127. However,
set curves.
When the depth of convolutiona training set curves, while the solid lines represent the validation

to a noticeable improvement

when the depth of convolutional layers is five (The lines

to a noticeable improvement

when the depth of convolutional lay set curves.

to a noticeable improvement, po

when the depth of convolutional layers is five (The lines

mearked with circular dots in Figures 7 and 8), the performance improvement achieved with mearked significantly outp When the depth of convolutional layers is five (The lines features from the global context marked with circular dots in Figures 7 and 8), the performance improvement achieved with the significantly outer from so ther laye marked with circular dots in Figures 7 and 8), the performance improvement achieved wisgnificantly outperforms other layer configurations. The results are poorest when the average accuracy is 3.27 percentage points higher significantly outperforms other layer configurations. The results are poorest when using a average accuracy is 3.27 percentage points higher than that of lines marked with star-shaped po

three-layer convolution, and the a average accuracy is 3.27 percentage points higher than that of lines marked w
three-layer convolution, and the average loss is reduced by may be due to
0.067 compared to four-layer and six-layer convolutional reduces the r EVERT FRINGTH THE SURVE TON THE SURVERT THE SURVENTIES THE STONGHING INTENDENT THE UNIVERSITY THE INTERNATE TH 0.067 compared to four-layer and six-layer convolutional reduces the receptive field. A

models. The effect of three-layer (The lines marked with deeper network to compensa

downward triangle points in Figures 7 and 8) an

set to 5 . **nal of Computer Science**

performs best when the number of deep convolutional layers is

set to 5.

2) Different feature extraction modules

In the feature extraction module, the C-T module plays a

major role. To determi

NG International Journal of Computer Science

performs best when the number of deep convolutional

set to 5.

log(p_i) (8) 2) Different feature extraction modules

In the feature extraction module, the C-T module

ber **ENG International Journal of Computer**

performs best when tl

set to 5.
 ic $log(p_{ic})$ (8) 2) Different feature

In the feature extr

umber of categories of the major role. To deter

noher of categories of the classifica **IAENG International Journal of Computer Science**

performs best when the number of deep convolutional layers is
 $L = -\frac{1}{N} \sum_{i=1}^{M} y_{ie} \log(p_{ie})$ (8) 2) Different feature extraction modules
 L represents the number of $L = -\frac{1}{N} \sum_{i=1}^{M} y_i \log(p_i)$ set to 5.

In the equation.*M* represents the number of categories of the major role. To determine the sassification, *i* represents the number of categories of the calculation are relative e **nal of Computer Science**
performs best when the number of deep conv
set to 5.
2) Different feature extraction modules
In the feature extraction module, the C-
major role. To determine the impact of
convolutional kernel an **2)**
2) Different feature extraction modules

2) Different feature extraction modules

2) Different feature extraction modules

In the feature extraction module, the C-T module plays a

major role. To determine the impac **If of Computer Science**

In the number of deep convolutional layers is

to 5.
 Different feature extraction modules

In the feature extraction module, the C-T module plays a

pior role. To determine the impact of the sc mal of Computer Science
performs best when the number of deep convolutional layers is
set to 5.
2) Different feature extraction modules
In the feature extraction module, the C-T module plays a
major role. To determine the **nal of Computer Science**

performs best when the number of deep convolutional layers is

set to 5.

2) Different feature extraction modules

In the feature extraction module, the C-T module plays a

major role. To determi **nal of Computer Science**
performs best when the number of deep convolutional layers is
set to 5.
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In the feature extraction module, the C-T module plays a
major role. To determine th **nal of Computer Science**
performs best when the number of deep convolutional layers is
set to 5.
2) Different feature extraction modules
In the feature extraction module, the C-T module plays a
major role. To determine th **nal of Computer Science**

performs best when the number of deep convolutional layers is

set to 5.

2) Different feature extraction modules

In the feature extraction module, the C-T module plays a

major role. To determi **Example 18x3**
performs best when the number of deep convolutional layers is
set to 5.
2) Different feature extraction modules
in the feature extraction module, the C-T module plays a
major role. To determine the impact of performs best when the number of deep convolutional layers is
set to 5.
2) Different feature extraction modules
In the feature extraction module, the C-T module plays a
major role. To determine the impact of the scale of t performs best when the number of deep convolutional layers is
set to 5.
2) Different feature extraction modules
In the feature extraction modules, the C-T module plays a
major role. To determine the impact of the Scale of performs best when the number of deep convolutional layers is
set to 5.
2) Different feature extraction modules
In the feature extraction modules
In the feature extraction module, the C-T module plays a
major role. To dete to 5.

Different feature extraction modules

In the feature extraction module, the C-T module plays a

yior role. To determine the impact of the scale of the

mvolutional kernel and the inclusion of the Transformer on

exl 2) Different feature extraction modules
In the feature extraction module, the C-T module plays a
major role. To determine the impact of the scale of the
convolutional kernel and the inclusion of the Transformer on
the clas In the feature extraction module, the C-T module plays a
major role. To determine the impact of the scale of the
convolutional kernel and the inclusion of the Transformer on
the classification task, this study conducted an major role. To determine the impact of the scale of the convolutional kernel and the inclusion of the Transformer on the classification task, this study conducted analysis and verification by modifying the C-T module. The convolutional kernel and the inclusion of the Transformer on
the classification task, this study conducted analysis and
verification by modifying the C-T module. The experimental
settings are as follows: without the inclus the classification task, this study converification by modifying the C-T modu
settings are as follows: without the inclu
and with a 3x3 convolutional kernel, w
Transformer and a 3x3 convolutional kern
of Transformer and a rification by modifying the C-T module. The experimental
tings are as follows: without the inclusion of Transformer
d with a 3x3 convolutional kernel, with the inclusion of
ansformer and a 3x3 convolutional kernel, with th

settings are as follows: without the inclusion of Transformer
and with a 3x3 convolutional kernel, with the inclusion of
Transformer and a 3x3 convolutional kernel, with the inclusion
of Transformer and a 1x1 convolutional

impact of varying depths of convolutional layers on EEG feature extraction modules. Termotion classification tasks. Specifically, experiments were training set curve, while the solution conducted with three, four, five, an emotion classification tasks. Specifically, experiments were training set curve, while the solic
conducted with three, four, five, and six layers of deep set curve.
Table 2 presents the average accuracy and average loss do and with a 3x3 convolutional kernel, with the inclusion of Transformer and a 3x3 convolutional kernel, with the inclusion of Transformer and a 1x1 convolutional kernel, and with the inclusion of Transformer and a 5x5 convo Transformer and a 3x3 convolutional kernel, with the inclusion
of Transformer and a 1x1 convolutional kernel, and with the
inclusion of Transformer and a 5x5 convolutional kernel.
Table 3 presents the average accuracy and of Transformer and a 1x1 convolutional kernel, and with the
inclusion of Transformer and a 5x5 convolutional kernel.
Table 3 presents the average accuracy and average loss
values for different feature extraction modules. F inclusion of Transformer and a 5x5 convolutional kernel.

Table 3 presents the average accuracy and average loss

values for different feature extraction modules. Figures 9 and

10 display the training accuracy and loss cu Table 3 presents the average accuracy and average loss
values for different feature extraction modules. Figures 9 and
10 display the training accuracy and loss curves for different
feature extraction modules. The dashed li values for different feature extraction modules. Figures 9 and
10 display the training accuracy and loss curves for different
feature extraction modules. The dashed line represents the
training set curve, while the solid l 10 display the training accuracy and loss curves for different feature extraction modules. The dashed line represents the varianing set curve, while the solid line represents the validation set curve.

When Transformer is feature extraction modules. The dashed line represents the training set curve, while the solid line represents the validation set curve.

When Transformer is not used (The lines marked with downward triangle points in Figu training set curve, while the solid line represents the validation
set curve.
When Transformer is not used (The lines marked with
downward triangle points in Figures 9 and 10), it is evident that
the training accuracy and set curve.
When Transformer is not used (The lines marked with
downward triangle points in Figures 9 and 10), it is evident that
the training accuracy and loss curves are significantly affected.
The average accuracy is 14. When Transformer is not used (The lines marked with
downward triangle points in Figures 9 and 10), it is evident that
the training accuracy and loss curves are significantly affected.
The average accuracy is 14.08 percent downward triangle points in Figures 9 and 10), it is evident that
the training accuracy and loss curves are significantly affected.
The average accuracy is 14.08 percentage points lower than
that of a 3x3 convolutional ker the training accuracy and loss curves are significantly affected.
The average accuracy is 14.08 percentage points lower than
that of a 3x3 convolutional kernel, and the average loss value is
higher by 0.127. However, the i The average accuracy is 14.08 percentage points lower than
that of a 3x3 convolutional kernel, and the average loss value is
higher by 0.127. However, the inclusion of Transformer leads
to a noticeable improvement, possib that of a 3x3 convolutional kernel, and the average loss value is
higher by 0.127. However, the inclusion of Transformer leads
to a noticeable improvement, possibly because it captures more
features from the global context higher by 0.127. However, the inclusion of Transformer leads
to a noticeable improvement, possibly because it captures more
features from the global context of the time slices. Despite the
improvement achieved with the in to a noticeable improvement, possibly because it captures more
features from the global context of the time slices. Despite the
improvement achieved with the inclusion of Transformer, the
results are poorest when using a 1 features from the global context of the time slices. Despite the
improvement achieved with the inclusion of Transformer, the
results are poorest when using a 1x1 convolutional kernel (The
lines marked with star-shaped poin improvement achieved with the inclusion of Transformer, the
results are poorest when using a 1x1 convolutional kernel (The
lines marked with star-shaped points in Figures 9 and 10). This
may be due to the small size of th results are poorest when using a 1x1 convolutional kernel (The
lines marked with star-shaped points in Figures 9 and 10). This
may be due to the small size of the convolutional kernel, which
reduces the receptive field. A lines marked with star-shaped points in Figures 9 and 10). T
may be due to the small size of the convolutional kernel, w
reduces the receptive field. A smaller receptive field requir-
deeper network to compensate, but the in suy be due to the small size of the convolutional kernel, which
duces the receptive field. A smaller receptive field requires a
eper network to compensate, but the convolutional network
the C-T module consists of only t reduces the receptive field. A smaller receptive field requires a deeper network to compensate, but the convolutional network in the C-T module consists of only three layers, resulting in poor performance. The use of a 3x3 deeper network to compensate, but the convolutional network
in the C-T module consists of only three layers, resulting in
poor performance. The use of a 3x3 convolutional kernel (The
lines marked with circular dots in Figu outperforms a 5x5 kernel (The live in Figures 9 and 10) by 3.23
he accuracy and a decrease of 0.12
convolutional kernel performs s
of 5x5 kernel requires a larger con
overall computation burden.
a In summary, in this stud

accuracy and a decrease of 0.121 in average loss value. A $3x3$	convolutional kernel performs significantly better, and using a 5x5 kernel requires a larger computational cost, increasing the overall computation burden. In summary, in this study's model, the inclusion of Transformer performs better than without it, and a 3x3 convolutional kernel performs better than a 1x1 or 5x5 kernel.		s marked with square points in Figures ℓ and δ), the nce is much worse than that of the five-layer onal model, likely due to the excessive number of ding to learning redundancy and overfitting. mary, in the model proposed in this paper, after a experiments and comparative analysis, the model
		TABLE II	VALUES OF AVERAGE ACCURACY AND AVERAGE LOSS FUNCTION UNDER DIFFERENT DEPTH CONVOLUTIONAL MODULES
Average Loss	Average Acc	The deepest data size	Depth umber of convolution layers
0.408	87.99%	(32, 10, 32)	3 floors
0.588	86.36%	(32,10,16)	4 floors
0.332	91.26%	(32,5,16)	5 floors
0.592	86.86%	(32,5,8)	6 floors

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TABLE Ⅲ

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^{0.0}

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 Experimental results and analysis
 D Experimental result

As shown in Figure 11 and Figure 12, are the accuracy and

loss function values of the training set and validation set during

the traini

Volume 51, Issue 8, August 2024, Pages 1094-1104

 $\begin{array}{|c|c|c|c|c|}\n \hline \text{9.05} & \text{than traditional CNN information in a step-by-
0.25} & \text{than traditional CNN information in a step-by-
to information in a step-by-
to information in a step-by-
to information decay or 1
not effectively capture
Transformers. Therefore, considered superior to Sir
CPs. The effect is not used to be a single-
transformers. Therefore, considered superior to Sir
CPs. The effect is not used to be a single-
this study. The compared methods include Support Vector
Machine (SVM) [5], a CNN-based approach that integrates
multimodal data [26], a 3DCNN design using single-variable
convolutional layers and multi-variable convolutional layers
(CPL)$ 0.50

0.25

0.25

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0 10 20

10 30 40 50

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10 considered superior

10 considered superior

10 con Convolutional and the information convolutional layers and multi-variable convolutional layers and the set of the considered superior to Singh Fig. 12. Training loss function eurove of neural network results indicate that 0.25

0.00 0 10 20 30 40 50

Fransformers. Therefore, the

Epoch number

Fig. 12. Training loss function curve of neural network

2) *Experimental analysis*

To evaluate the effectiveness of the proposed method, a

compar (Bi-LSTM) [29]. The aim was to demonstrate the differences

(GRU) and a scheen of the proposed method, a

experimental analysis

(Considered superior to Singh et

Fig. 12. Training loss function curve of neural network

t combines CNN and Bidirectional Long Short-Term Memory Fig. 12. Training loss function curve of neural network

2) *Experimental analysis*

To evaluate the effectiveness of the proposed method, a

comparison was made with existing state-of-the-art methods in

this study. The c 2) Experimental analysis

To evaluate the effectiveness of the proposed method, a

comparison was made with existing state-of-the-art methods in

this study. The compared methods include Support Vector

Machine (SVM) [5], Experimental analysis

To evaluate the effectiveness of the proposed method, a

s study. The compared methods include Support Vector

s tudy. The compared methods include Support Vector

achine (SVM) [5], a CNN-based appro To evaluate the effectiveness of the proposed method, a
comparison was made with existing state-of-the-art methods in
this study. The compared methods include Support Vector
this study, ISM and CM and the integrates multim comparison was made with existing state-of-the-art methods in W. COM

this study. The compared methods include Support Vector

Machine (SVM) [5], a CNN-based approach that integrates

multimodal data [26], a 3DCNN design u this study. The compared methods include Support Vector

Machine (SVM) [5], a CNN-based approach that integrates

multimodal data [26], a 3DCNN design using single-variable

convolutional layers and multi-variable convolut

multimodal data [26], a 3DCNN design using single-variable

corvolutional layers

corvolutional layers and multi-variable convolutional layers

(GRU) with solel that incorporates Gated Recurrent Units

(GRU) with solel tha convolutional layers and multi-variable convolutional layers

[27], an RNN model that incorporates Gated Recurrent Units

(GRU) with skip comeonsines (28], and a hybrid model that

combines CNN and Bidirectional Long Short method. COMPARISON WITH OTHER METHODS

Note of the street of the street of the control of the differences

STM) [29]. The aim was to demonstrate the differences

e proposed model was evaluated on the DEAP dataset in

the tour-clas

nal of Computer Science
the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of C **nal of Computer Science**
the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of C **nal of Computer Science**
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deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
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the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
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 the traditional SVM method was slightly inferior compared to
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capability of CNN did not **nal of Computer Science**
the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
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the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of C **nal of Computer Science**
the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of C **nal of Computer Science**
the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of **Transform is a study in the proposed method in the traditional SVM method was slightly inferior compared to deep learning methods. Additionally, while Kwon and Chao improved upon traditional CNN, the singular feature ext** the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of CNN did not fully leverage the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of CNN did not fully leverage the traditional SVM method was slightly inferior compared to
deep learning methods. Additionally, while Kwon and Chao
improved upon traditional CNN, the singular feature extraction
capability of CNN did not fully leverage al.'s hybrid model of CNN and Bi-LS1M performed better

in traditional CNN; however, Bi-LSTM processes

formation in a step-by-step iterative manner, which may lead

information decay or loss over multiple time steps and m than traditional CNN; however, B1-LSTM processes
information in a step-by-step iterative manner, which may lead
to information decay or loss over multiple time steps and may
not effectively capture long-range dependencies, information in a step-by-step iterative manner, which may lead
to information decay or loss over multiple time steps and may
not effectively capture long-range dependencies, unlike
Transformers. Therefore, the proposed me

V. CONCLUSION

Machine (SVM) [5], a CNN-based approach that integrates

of the DEAP dataset is propose

emultimodal data [26], a 3DCNN design using single-variable

convolutional layers

corrections and multi-variable convolutional layer four-classification of emotion in EEG signals.
Transformers. Therefore, the proposed method in this study is
considered superior to Singh *et al.*'s approach. The comparative
results indicate that the proposed method in th not effectively capture long-range dependencies, unlike

Transformers. Therefore, the proposed method in this study is

results indicate that the proposed method in this study shows

results indicate that the proposed meth Transformers. Therefore, the proposed method in this study is
considered superior to Singh *et al.*'s approach. The comparative
results indicate that the proposed method in this study shows
better performance in EEG-based considered superior to Singh *et al.*'s approach. The comparative
results indicate that the proposed method in this study shows
better performance in EEG-based emotion recognition tasks.
 $V.$ CONCLUSION
In this paper, a m results indicate that the proposed method in this study shows
better performance in EEG-based emotion recognition tasks.

V. CONCLUSION

In this paper, a method for restructuring the emotional labels

of the DEAP dataset i better performance in EEG-based emotion recognition tasks.

V. CONCLUSION

In this paper, a method for restructuring the emotional labels

of the DEAP dataset is proposed, along with a C-T module for

extracting deep featu V. CONCLUSION
In this paper, a method for restructuring the emotional labels
of the DEAP dataset is proposed, along with a C-T module for
textracting deep features and a deep learning model for the
four-classification of e V. CONCLUSION

U. CONCLUSION

U. CONCLUSION

Of the DEAP dataset is proposed, along with a C-T module for

extracting deep features and a deep learning model for the

four-classification of emotion recognition in EEG signa V. CONCLUSION

In this paper, a method for restructuring the emotional labels

of the DEAP dataset is proposed, along with a C-T module for

extracting deep features and a deep learning model for the

four-classification o In this paper, a method for restructuring the emotional labels
of the DEAP dataset is proposed, along with a C-T module for
extracting deep features and a deep learning model for the
four-classification of emotion recognit of the DEAP dataset is proposed, along with a C-T module for extracting deep features and a deep learning model for the four-classification of emotion recognition in EEG signals. Firstly, the preprocessed EEG signals are s extracting deep features and a deep learning model for the
four-classification of emotion recognition in EEG signals.
Firstly, the preprocessed EEG signals are subjected to
windowing, resulting in a fourfold increase in th four-classification of emotion recognition in EEG signals.
Firstly, the preprocessed EEG signals are subjected to
windowing, resulting in a fourfold increase in the training data.
Subsequently, the EEG signals are transfor rstly, the preprocessed EEG signals are subjected to
ndowing, resulting in a fourfold increase in the training data.
bsequently, the EEG signals are transformed into
ne-frequency maps using short-time Fourier transform and windowing, resulting in a fourfold increase in the training data.
Subsequently, the EEG signals are transformed into
time-frequency maps using short-time Fourier transform and
input into the deep convolutional module. The Subsequently, the EEG signals are transformed into
time-frequency maps using short-time Fourier transform and
input into the deep convolutional module. The deep
convolutional module extracts feature information at differen time-frequency maps using short-time Fourier transform and
input into the deep convolutional module. The deep
convolutional module extracts feature information at different
depths from the EEG signals, which is then input input into the deep convolutional module. The deep
convolutional module extracts feature information at different
depths from the EEG signals, which is then input into the
feature extraction module. In the feature extracti

TABLE IV Comparing with current state-of-the-art methods, the
proposed method in this paper demonstrates a higher apply this deep learning network model to more datasets to comprehensively evaluate its effectiveness and robustness, as well as to further explore its performance potential. convolutional module extracts feature information at different
depths from the EEG signals, which is then input into the
feature extraction module. In the feature extraction module, the
use of the C-T module effectively en depths from the EEG signals, which is then input into the feature extraction module. In the feature extraction module, the use of the C-T module effectively enhances the capability to extract global and local information f Comparing with current state-or-the-art inctitudes, the
proposed method in this paper demonstrates a higher
classification accuracy, providing full validation of the
effectiveness of the algorithm. In future work, the plan osed method in this paper demonstrates a higher
ification accuracy, providing full validation of the
titveness of the algorithm. In future work, the plan is to
y this deep learning network model to more datasets to
prehens is fication accuracy, providing full validation of the
tiveness of the algorithm. In future work, the plan is to
y this deep learning network model to more datasets to
prehensively evaluate its effectiveness and robustness effectiveness of the algorithm. In future work, the plan is to
apply this deep learning network model to more datasets to
comprehensively evaluate its effectiveness and robustness, as
well as to further explore its perform Street Start and The digit and the Multimedial of the Human-Computer is effectiveness and robustness, as
as to further explore its performance potential.
 EXECUTE:
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 EXECUT apply this deep learning network model to more datasets to
comprehensively evaluate its effectiveness and robustness, as
well as to further explore its performance potential.

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- prehensively evaluate its effectiveness and robustness, as

as to further explore its performance potential.

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