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Research Article

Emotional Expression and Analysis in Music Performance Based on Edge Computing

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The expression of emotion in music performance is the soul of music, and the emotion revealed by the performer during the performance can bring emotional resonance to the audience. The emotions expressed by music such as joy, anger, and sadness are the meaning of music's existence. Music without emotion will be dead. However, the music itself has no emotion at all; it is just a regular sound, so the emotional reading of music performance is very important. Music performance is an interpretation of music, and it is the most important emotional information and communication medium for human beings. Through the appreciation of the works to express the author's emotions, the different performance forms of musical instruments, dance, and singing bring emotional resonance to the audience. Edge computing is the core technology and edge node of the Internet of everything in the new era, and it is constantly innovating with the rapid development of computers and the great changes brought about by them. Nowadays, people's demand for emotional information processing of music performances has also increased. The research attention to music performance and the attention to its application technology have also received unprecedented development, so the requirements for the ability of human and machine interaction are getting higher and higher. With the increasing maturity of multimedia and communication technologies, there is an increasing expectation of using computers to express human thoughts and emotions. By combining the two, Dongfeng's expression and analysis of music emotions through edge computing have also ushered in new developments. For example, people upload or share music and dance videos to their friends through WeChat, QQ, Douyin, etc., which greatly enriches people's emotional world. The analysis and judgment of music emotion are the main subject of the joint development of both musicology and psychological research. With the help of computer science technology and artificial intelligence and other tools, the purpose of music emotional research can also be achieved. Particularly with the advancement of science and technology and the vigorous development of computer application technology, people's needs for emotional expression and analysis of music can now be carried out with the help of computers. However, the amount of data generated is extremely large, and using edge servers for data processing can improve the efficiency of analysis and processing to meet people's needs.

1. Introduction

The essence of music is to express people's emotions and yearning for beautiful things. In ancient times, the way of singing emotional expression in music expressed people's emotions through the performance of poetry, pipa, erhu, flute, qin, and other musical instruments, or by reciting verses or lyrics through the voice, but the scope of singing was generally small. The way of communication is through people-to-people communication, and in today's era with the development of the Internet, the way to express emotions to music through the Internet has become more diverse, and its speed of dissemination is faster and the scope is more global [1, 2]. In the field of multimedia, many achievements have been made today; for example, the digital storage, compression, and encoding technology of music signals are improving day by day. The increasing development of its multimedia application technology and the gradual closeness of people's lives in the fields of mobile devices, radio music, teaching applications, digital economy, etc., show extraordinary prospects [3]. The use of edge computing for music performance should be used for intelligence and the expression of human emotions to music; it involves a wide range of disciplines, such as information processing, artificial computers to simulate human creativity in music performance, music knowledge, dance, and human psychology, and intelligent identification technology; the difficulty of development can be imagined. However, the research work on the expression, recognition, and application of music performance and emotion is still in the budding stage of all things, and the intellectualization and digitization of music emotion is very meaningful and promising for the reform and development of applied technology [4–6]. It will provide an effective way for the development of the field of intelligence, the guidance of emotions, and the creative improvement of art. Regarding the development of music and performance identification technology development research and the development of storage technology research, I believe that the achievements in the near future will be extraordinary. Finally, music is a way for humans to express emotions, and computer networks are an important tool to facilitate people. Combining the two will surely promote the development of the interaction between human emotional expression and edge computing to a new height.

2. Introduction to Models of Affective Computing

With the continuous development of the mobile Internet, the convenience brought to people by new applications such as webcasting, online education, and telephone video has been continuously improved [7, 8]. In order to meet the user's data requirements for a smooth network, it is a feasible solution to use the edge server to perform emotional computing data tasks, because the user can effectively receive the data processed by the computer server and the browsing requirements of information in real time, thereby reducing excessive cumbersomeness. The process causes network congestion, so as to improve the quality of service to users. Today, most scholars do not combine remote computing resources in the resource optimization problem of edge computing [9–11]. What we need to do is to optimize the combination of sentiment extraction analysis and edge computing to achieve a better user service experience. For example, in order to enhance the atmosphere in the live broadcast of Douyin, we need to play appropriate music in the live broadcast room in time to bring the rhythm. To set off the role of the atmosphere, it requires the timely response of the system. However, if the atmosphere of the live broadcast room is not played in time, playing inappropriate music will cause adverse effects, so it is extremely important to play music with the corresponding atmosphere in time. However, there are always times when the network or system is stuck and the response is not timely. Therefore, combined with the above problems, this chapter proposes a solution that combines edge data computing and data compression processing to improve delay processing of the system for better emotional expression analysis tasks. The advantages of this model are reflected in the fast analysis and processing speed and the high integrity of the analysis data; when the model is stuck or delayed in network operation, the use of edge computing for data compression can effectively solve the above problems. The established emotional computing model is used to analyze emotional data to optimize the delay or network freeze generated by the system, and the optimized music emotional analysis results will be more complete and faster.

2.1. Network Model of Emotion Processing. The model is divided into three layers: the cloud control center layer; the edge node layer; and the user layer [12–14]. In the cloud control center layer, all music emotional data are uploaded to cloud computing for data storage and information emotional computing classification, so as to analyze and record the emotions expressed by music, such as joy and sadness. In the edge layer, after the data are collected, the information data are divided into two parts. One is that the edge server processes and calculates by itself, and the other is that it is sent back to the cloud center layer for processing and calculation. In the user layer, the user's mobile device data are compressed and uploaded to the associated small base station for processing and calculation requirements. The corresponding music is set in various mobile devices and the music is processed emotionally, so as to bring a better pleasant experience to the user [15]. In this model, the emotional data calculation is performed by uploading the compressed data to the nearby small base station on the user side, that is, the edge layer for initial calculation; in the edge node, the data are first divided into two parts, and part of the edge is carried out by itself calculation, part of which is uploaded to the cloud server. This three-layer operation can not only ensure the speed of data processing, but also ensure the accuracy of the data. The network model application is shown in Figure 1.

2.2. Affective Computing Processing Delay Research

2.2.1. EN Time Delay Model. It is assumed that each emotional computing task data can be split arbitrarily; that is, when all emotional data that need to be calculated are uploaded to the edge computing node, the edge computing server will divide each emotional computing data task. Among them, the edge computing task can only be performed when the edge server completes the division task, and another part of the computing is completed by the cloud server [16–18]. Therefore, the data transmission time delay of the jth mobile device related to the kth SBS (small base station) is as follows:

$$t_{k,j}^{\text{comp},e} = \frac{\eta_{k,j} D_{k,j} z_{k,j}}{\int_{k,j}^{\text{comp},e}}. \quad (1)$$

Among them, $\eta_{k,j} \in [0,1]$ represents the proportion occupied by the calculation task division of the jth mobile device related to the SBS in the range of 0–1, and the emotion of the jth mobile device related to the Kth SBS is represented in $f_{k,j}^{\text{comp},e}$, the total amount of computing resources. These two functions greatly facilitate the calculation of emotional

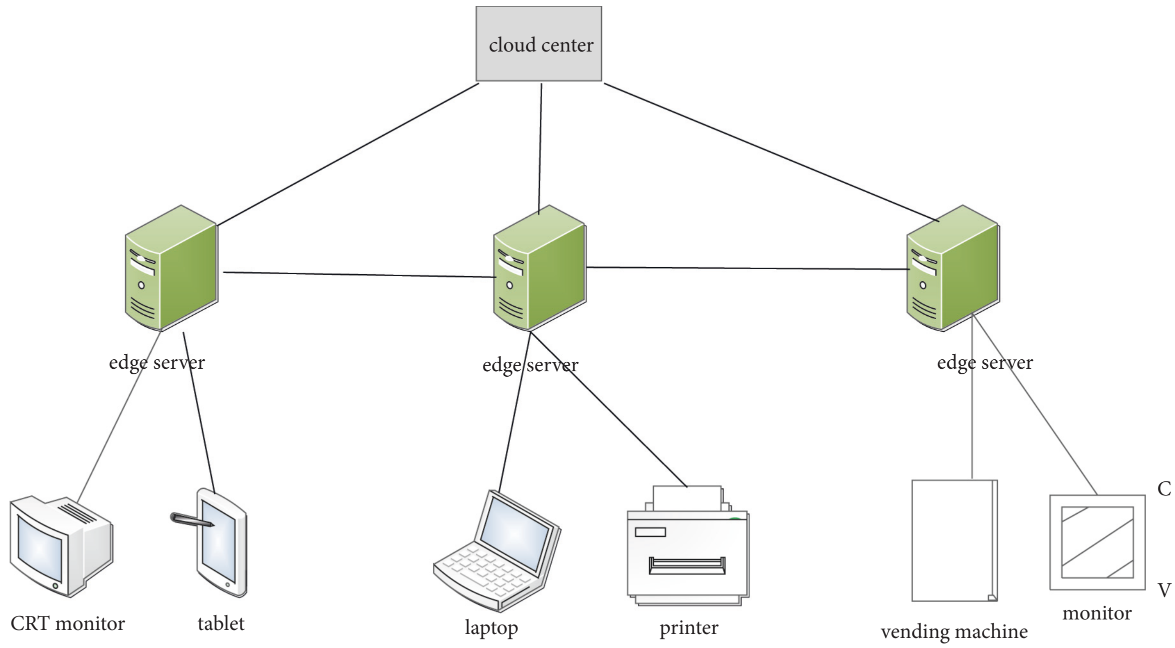

Figure 1: Network model.

data in this formula. If other expressions are used for data calculation, the amount of data will be greatly increased.

The rest of the calculation data with a data size of D is uploaded to the cloud server for processing and calculation through the optical cable or optical fiber through the backhaul link, so the transmission delay is given by

$$t_{k,j}^{\text{tran,c}} = \frac{\left(1-\eta_{k,j}\right)D_{k,j}}{W_k}. \tag{2}$$

2.2.2. Cloud Server Latency Model. When the cloud server receives all the computing data uploaded by EN, it will plan appropriate resources for each computer and issue instructions to the following computers for information processing [19]. Similar to the time delay model of EN, let $f_{k,j}^{\text{comp , c}}$ denote the cloud computing resources allocated to the jth mobile device associated with the kth edge node. Therefore, the calculation time delay generated by processing the remaining size of the calculation data of the jth mobile device related to the kth edge node on the cloud server is given by

$$t_{k,j}^{\text{comp,c}} = \frac{\left(1-\eta_{k,j}\right)D_{k,j}Z_{K,J}}{\int_{k,j}^{\text{comp,c}}}. \tag{3}$$

This formula can calculate the time delay for the cloud server to calculate the sentiment analysis. It can be observed that the time required for the cloud server to calculate the music emotional expression analysis is relatively large, so the use of edge computing has a good advantage.

$(1-\eta_{k,j})D_{k,j}$ is established to calculate the rest of the data. The data ratio $D_{k,j}f_{k,j}^{\text{comp,e}}$ of the emotional compression resources occupied by the jth mobile device related to the Kth SBS is represented in the formula $(1-\eta_{k,j})$, which represents the data sequence of the jth mobile device related to the Kth SBS. The size of the rest of the data can be calculated using this formula.

2.3. Compression Rate and Distortion Rate of Emotional Data. Let $ZR_{k,j}$ denote the data compression rate of the jth mobile device related to the kth SBS, and its expression is as follows:

$$ZR_{k,j} = \frac{D_{k,j} - D_{k,j}^{\text{com}}}{D_{k,j}}. \tag{4}$$

Among them, $D_{k,j}^{\text{com}}$ represents the data size of the data computing task of the jth mobile device related to the Kth SBS after CAE compression.

Let DIS denote the data distortion compression ratio of the jth mobile device related to the Kth SBS, and its expression is as follows:

$$\text{ZIS}_{k,j} = \sqrt{\frac{\sum_{i=1}^{Lj}\left(O_{k,j}^{i} - \varnothing_{k,j}^{i}\right)^2}{\sum_{i=1}^{Lj}\left(O_{k,j}^{i}\right)^2}}, \tag{5}$$

where in $O_{k,j}^{l}$and $\phi_{k,j}^{l}$represent the initial data sequence and the restored data sequence of the jth mobile device related to the kth SBS, and $L_j$represents the calculated data length of the jth mobile device related to the kth SBS.

Using this algorithm can greatly reduce the time of emotional expression analysis and greatly improve the analysis efficiency.

2.4. Algorithm for Rational Allocation of Resources. We know that the amount of data generated by computing the expression and analysis of music emotion is very large. The more the data are consumed, the more serious the waste of resources will be. The more serious the waste of data, the greater the cost [20]. Therefore, first, the researchers have made cost compression requirements for application services arranged by providers on edge servers, and studied the cost constraints of keeping the expected cost of the system within a controllable range at any time [21] as follows:

$$\lim_{T \longrightarrow \infty} \frac{1}{T} \sum_{t=1}^{T} E(t) \le E_{\text{avg}}, \tag{6}$$

where E_{avg}represents the long-term overhead cost within the system.

Second, in order to achieve a balance between budgeted costs and user experience delays, virtual queues are introduced through planning cost budgets to keep costs stable. The virtual queue is as follows:

$$Q(t+1) = \min\left[Q(t) + E(t)\right]. \tag{7}$$

There is an error in the calculation in formula (7). Therefore, the following formula is formulated:

$$Q(t+1) = \max\left[Q(t) + E(t) - E_{\text{avg}}, 0\right]. \tag{8}$$

$E_{\text{avg}}, 0$ is missing in formula (7), which makes the calculation of emotional data never reach the balance between the expected cost and the user experience time delay, resulting in errors in the calculation. By adding $E_{\text{avg}}, 0$ to formula (7), the data imbalance calculated by the virtual queue is solved. Finally, the quadratic Lyapunov and Lyapunov drift functions are used to represent the squeeze increase in the virtual queue at the current time t-1 and time t, respectively. The formula is as follows:

$$L(Q(t)) = Q(t)^2 (Q(t)) \triangleq E\left[L(Q(t)) - L(Q(t-1)) \mid (Q(t))\right]. \tag{9}$$

In order to obtain the most complete resource allocation scheme at present, the basic process is to first express the real-time resource allocation problem according to Lyapunov's theory combined with drift function and penalty function. The function expression for adding the Lyapunov penalty to the drift function is as follows:

$$(\Delta Q(t)) + VE\left[D_{\text{total}}(t) + D_m(t) \mid (Q(t))\right]. \tag{10}$$

2.5. Unlabeled Learning. There are also many words about emotion, and the resulting free translations also have many interpretations. Therefore, it is very difficult to label deep learning data, and the use of unlabeled deep reinforcement learning can effectively improve the accuracy of sentiment classification [22]. The basic learning model is shown in Figure 2.

In this model, $s(t)$ represents the approximate type of music emotion analyzed by the user at time t; $a(t)$ represents the data processing time according to the environmental state$s(t)$. $r(t)$ represents the processing implementation of the data processing $a(t)$ by the external network speed. The model adopts the Q-learning mechanism to asymptotically learn the selection process of the global optimal data processing, and the improvement of the action value can be realized iteratively more quickly, as shown in the following:

$$\begin{cases} Z(t) = r(t) + \gamma \max\limits_{a(t+1)\in A} Q_i(s(t+1)), a(t+1) - Q(s(t), a(t)), \\ \mathrm{Q}_{\mathrm{i}+}(\mathrm{s}(\mathrm{t}), \mathrm{a}(\mathrm{t})) = \mathrm{Q}_{\mathrm{i}}(\mathrm{s}(\mathrm{t}), \mathrm{a}(\mathrm{t})) + \varphi \mathrm{Z}(\mathrm{t}). \end{cases} \tag{11}$$

Among them, l is the number of iterations, φ is the learning value, γ is the discount factor, and $Q_l(.)$represents the optimized data value to be evaluated. In order to obtain the optimal unloading decision, the following must be satisfied:

$$\begin{cases} Z(\mathrm{t}) = \mathrm{r}(\mathrm{t}) + \gamma \max\limits_{a(t+1)\in A} Q_i(s(t+1)), a(t+1) - Q(s(t), a(t)), \\ \mathrm{Q}_{\mathrm{i}+}(\mathrm{s}(\mathrm{t}), \mathrm{a}(\mathrm{t})) = \mathrm{Q}_{i}(\mathrm{s}(\mathrm{t}), \mathrm{a}(\mathrm{t})) + \varphi \mathrm{Z}(\mathrm{t}). \end{cases} \tag{12}$$

So, for each update l, the minimization of the perfect data objective is shown as the objective function used to implement the update of the DNN weights and biases as follows:

$$\min\left(r(t) + \gamma \max_{a(i+1)\in A} Q_i(s(t+1), a(t+1) - Q_i(s(t), a(t))\right). \tag{13}$$

2.6. Classification of Music Emotions. Music can be seen everywhere in life. If you listen to this music, you will feel excited, depressed, and happy. So if we want to listen to happy or exciting music in our spare time, we can click into some software to order songs. Yet, we know that we do not know the specific emotion according to the name of the song, but if we directly input the emotion type, such as the song of joy and happiness, the system will directly match the name of the corresponding emotional song. For example, this function is available in NetEase Cloud and QQ Music, which greatly improves the user experience. The flow chart of its music emotional classification model is shown in Figure 3.

3. Algorithm Research Based on Emotional Data Processing

With the continuous development of information technology, the processing of emotional data is becoming faster and faster, and its requirements for the speed and quality of

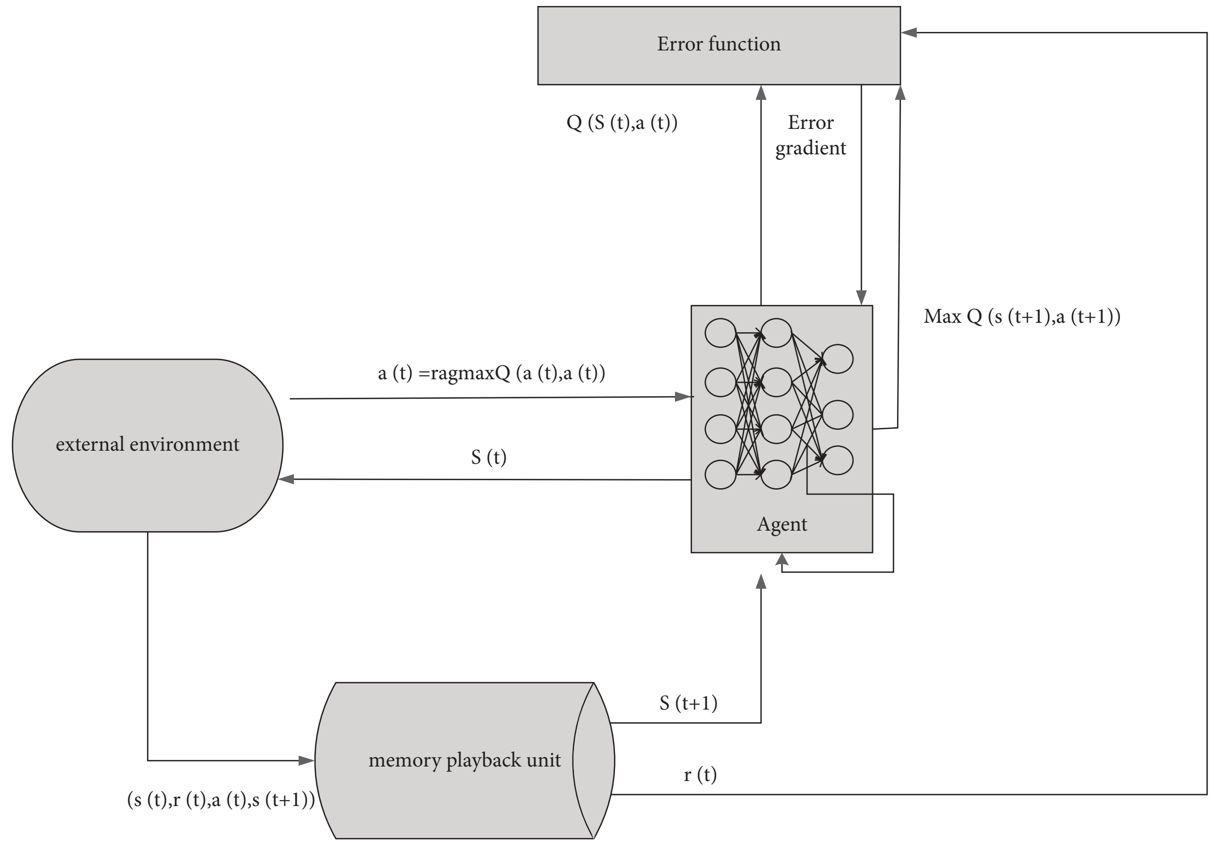

Figure 2: Learning model.

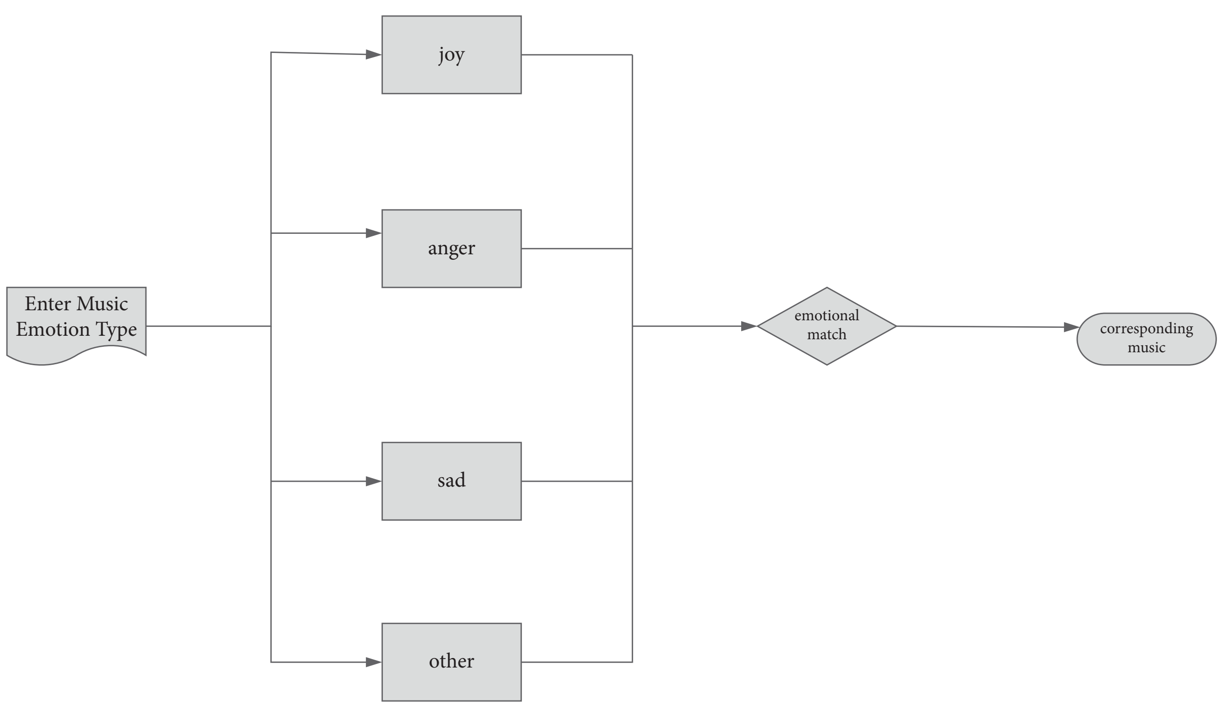

Figure 3: Classification flow chart for searching music emotion.

data processing are also getting higher and higher. Therefore, it is very meaningful to establish an efficient set of emotional data processing algorithms to quickly parse out emotional data. This chapter takes the data transmission efficiency of mobile devices, the delay of data transmission, and the accuracy of data processing as the starting point of the research, and designs the corresponding allocation algorithm. Improving the efficiency of data in all aspects and providing users with higher quality is the purpose of our research, and the addition of algorithms will make the processing of emotional data more logical and efficient.

3.1. Music Emotional Assignment Algorithm on Edge Computing. The four kinds of time delays included in the edge computing network model are cloud server computing delay, edge node computing data delay, transmission time delay between edge service computer and cloud server, and mobile device transmission delay. The edge node can only perform the data distribution task after the EN has accepted the emotional computing data. In practical application statistics, some emotional computing data are closely related to other related data. The cloud server waits for the data transmission between the edge node and the cloud server before the emotional computing data task, which can improve the accuracy of emotional computing. The calculation result of sentiment data is in itself, so the time delay required for the processing time to return the calculation result can be excluded from the calculation time.

The overall time delay of the calculation data time of the jth mobile device emotion related to the kth SBS by the design model is given by

$$t_{k,j}^{\text{total}} = t_{k,j}^{\text{tran},e} + \max\left\{t_{k.j}^{\text{comp},e}, t_{k.j}^{\text{tran,c}}, t_{k.j}^{\text{comp,c}}\right\}. \quad (14)$$

The refinement goal of the design in this section is to calculate the sum of all mobile device delays for data minimization, and use this sum of data transmission time delays as the time delay criterion. Each mobile device is assigned a weight factor $\lambda_{k,j} \in [0,1]$, which represents the order of computing data between mobile devices and satisfies the following formula:

$$\sum_{k=1}^{M}\sum_{j=1}^{I_k}\lambda_{k,j} = 1. \quad (15)$$

Therefore, the computation of the perfection problem can be formulated as follows:

$$P1: \min_{\substack{\text{ZR,H,T,}\\ \mathbb{F}^{\text{comp},e},\, \mathbb{F}^{\text{comp},c}}} \sum_{k=1}^{M}\sum_{j=1}^{I_k}\lambda_{k,j}t_{k,j}^{\text{total}}, \quad (16)$$

$$C1: \sum_{k=1}^{M}\sum_{j=1}^{I_k}\tau_{k,j} \le T, \quad (17)$$

$$C2: 0 < DIS_{k,j} \le \text{DIS}_{k,j}^{\text{out}}, \forall k, j1 \le k \le M, 1 \le j \le I_k, \quad (18)$$

$$C3: 0 \le \eta_{k,j} \le 1, \forall k, j1 \le k \le M, 1 \le j \le I_k, \quad (19)$$

$$C4: \sum_{j=1}^{I_K} f_{k,j}^{\text{comp,c}} \le F_{\text{k}}^{\text{comp,c}}\ ,\ f_{k,j}^{\text{comp,c}} \ge 0, \forall k1 \le k \le M, \quad (20)$$

$$C5: \sum_{k=1}^{M}\sum_{j=1}^{I_k} f_{k,j}^{\text{comp,c}} \le F^{\text{comp,c}}\ ,\ f_{k,j}^{\text{comp,c}} \ge 0. \quad (21)$$

Equation (17) indicates that in a TDMA frame, the total amount of transmission time slots allocated to all devices does not exceed the frame length T. Constraint formula (18) indicates that the data distortion rate of any mobile device cannot exceed the maximum distortion rate of the data capacity. The restriction formula (19) represents the data range of the division ratio of the emotional calculation data of each mobile device. Constraint formulas (20) and (21) indicate that the total amount of edge emotional computing resource data allocated to all mobile devices does not exceed the maximum emotional data computing capacity of the cloud server and each edge server. Among them, the data compression rate vector $ZR = \left\{ZR_{k,j}11 \le k \le M, 1 \le j \le I_k\right\}$ of all mobile devices is represented; $H = \left\{\eta_{k,j}11 \le k \le M, 1 \le j \le I_k\right\}$and $T = \left\{\tau_{k,j}11 \le k \le M, 1 \le j \le I_k\right\}$ represent the division ratio of the data amount and the number of time slots, respectively. $F^{\text{comp , e}} = \left\{f_{k,j}^{\text{comp,e}}11 \le k \le M, 1 \le j \le I_k\right\}$ represents the amount of emotional data computing resources allocated by the edge server to mobile devices, and $F^{\text{comp , c}} = \left\{f_{k,j}^{\text{comp,c}}11 \le k \le M, 1 \le j \le I_k\right\}$ represents the amount of emotional computing data resources allocated to all mobile device resources by the cloud server [23].

3.2. Perfecting the Allocation Algorithm for Affective Computing. In order to improve the coupling relationship between the target parameters and become more observant, the formula P1 is changed to the formula p1_2:

$$P1_2: \min_{\substack{\text{ZR,H,T,}\\ \mathbb{F}^{\text{comp},e},\mathbb{F}^{\text{comp,c}}}} \sum_{\text{k}=1}^{M}\sum_{\text{j}=1}^{I_{\text{k}}}\lambda_{k,j}\left[\frac{TD_{k,j}^{\text{com}}}{R_{k,j}\tau_{k,j}} + D_{k,j}\max\left\{\frac{\eta_{k,j}Z_{k,j}}{f_{k,j}^{omp,e}}, \frac{1-\eta_{k,j}}{W_k}, \frac{\left(1-\eta_{k,j}\right)Z_{k,j}}{f_{k,j}^{omp,e}}\right\}\right]. \quad (22)$$

s.t.*C1.C2.C3.C4.C5*

Through the sentiment calculation data, it is found that the parameter vector CR is only related to the restriction condition C2, and is not related to the parameter of *i*. The larger the data compression rate ($\mathbb{CR}_{k,j}$) of the *j* of the behavioral device, the smaller the value of ($D_{k,j}^{\text{com}}$) The data value in equation (21) will also become smaller, but the distortion rate of the data will also increase with the data. On the contrary, the smaller the data compression rate ($\mathbb{CR}_{k,j}$)

of the j of the behavioral device, the larger the value of $(D_{k,j}^{\mathrm{com}})$, the data value in equation (22) will also become larger, but the distortion rate of the data will also become smaller with the data. Therefore, when the constraint condition C2 is satisfied, the obtained maximum data compression rate parameter set CR can be calculated. It should be noted that the equipment models of computer equipment are different, and the format, size, method, etc., of emotional computing data are also different. Therefore, there is no joint relationship formula for the data compression rate and distortion of behavioral devices. In order to solve this problem, the convolutional autoencoder obtains the structural diagram of the relationship expression between the distortion rate and the data compression rate. The convolutional autoencoder is shown in Figure 4.

This model is mainly composed of input layer, convolutional layer, max pooling layer, deconvolutional layer, upsampling layer, and output layer. The four layers, input layer, convolutional layer, max pooling layer, and bottleneck layer, are used to compress emotional data. The input layer is used to process the input data for emotional data compression; the convolutional layer and the maximum pooling layer are the preparatory processing for emotional data compression; and the bottleneck layer is the last layer for emotional data compression processing. In this layer, the result of computing sentiment data can be obtained. The output compression set $\Phi_{k,j}$ consists of the output layer, the upsampling layer, and the deconvolutional layer. These three layers run at the edge two-point node, and their role is to restore the data sequence $O_{k,j}^{l}, 1 \leq l \leq L_j$. So, the data compression ratio of the behavioral device determines the size of the bottleneck layer. The nonlinear relationship between the emotional data distortion rate of $\Phi_{k,j}$behavioral device j and the data transmission sequence is as follows:

$$\mathrm{DIS}_{k,j} = \mathrm{c}_1 \phi_{k,j}^{c_2}. \tag{23}$$

The parameters c1 and c2 are associated with the task data set received by the behavioral device.

Therefore, the main process of the approximate relationship between data compression rate and distortion rate mapping method is as follows: the first step is to calculate the behavioral device j and use the formula as the loss function of CAE; the second step is to calculate the CAE models of n different data compression rates, and finally use the formula as the loss value of n average functions. After testing the data set, the loss value of n average functions is obtained as the data distortion rate of behavioral device j under n different compression cases. By fitting data with different compression ratios and distortion ratios, the approximate relationship between the compression ratio and the distortion ratio of behavioral device j is obtained as follows:

$$\mathrm{DIS}_{k,j}^{i} = \psi\left(ZR_{k,j}^{i}\right), 1 \leq i \leq n. \tag{24}$$

Finally, a function $\psi(ZR_{k,j})$approximation is used to express the relationship between the data distortion rate and the compression rate of the behavioral device, so the most perfect data compression rate of the behavioral device j is expressed as follows:

$$ZR_{k,j}^{*} = \psi^{-1}\left(\mathrm{DIS}_{k,j}^{\mathrm{out}}\right), \tag{25}$$

where $\psi^{-1}(.)$represents the inverse function of $\psi(.)$.

The use of the compressed parameter vector ZR replaces and refines the data and reduces to the following formula:

$$\begin{aligned} P1_3\colon \quad & \min_{\substack{\mathrm{ZR,H,T,} \\ \mathbb{F}\,\mathrm{comp,e},\ \mathbb{F}\,\mathrm{comp,c}}} \sum_{\mathrm{k}=1}^{M} \sum_{\mathrm{j}=1}^{I_{\mathrm{k}}} \Delta_{k,j} \left[\frac{T}{R_{k,j}\tau_{k,j}} + \frac{\lambda_{k,j} D_{k,j}}{\Delta_{k,j}} \max \left\{ \frac{\eta_{k,j} Z_{k,j}}{f_{k,j}^{omp,e}}, \frac{1-\eta_{k,j}}{W_k}, \frac{\left(1-\eta_{k,j}\right) Z_{k,j}}{f_{k,j}^{omp,e}} \right\} \right], \\ & \mathrm{s.t.C1.C3.C4.C5} \\ & \Delta_{k,j} = \lambda_{k,j}\left(1 - \Psi^{-1}\left(DIS_{k,j}^{\mathrm{out}}\right)\right)_{k,j}. \end{aligned} \tag{26}$$

The following is the expression that minimizes the sum of weighted transmission delays for behavioral devices stC1:

$$\min_{T} \sum_{\mathrm{k}=1}^{M} \sum_{\mathrm{j}=1}^{I_{\mathrm{k}}} \frac{\lambda_{k,j}\left(1 - \psi^{-1}\left(\mathrm{DIS}_{k,j}^{\mathrm{out}}\right) D_{K,J} T\right)}{R_{k,j}\tau_{k,j}}. \tag{27}$$

It is worth noting that this formula is obtained by simplifying the data compression parameter vector ZR after replacement, and this formula can only be established according to formula (25).

3.3. Analysis of Data Results. In order to further test the compression method of emotional data, not only can the original data be compressed with high quality, but also the absolute error between the test accuracy of the restored data and the accuracy of the original data mapping is within the allowable range, the emotional recognition model constructed in this study is an executable scheme, and its main function is to perform emotional preparatory data processing on the restored data and the initial data. This model is divided into three max pooling layers, four convolutional layers, and three fully connected layers [24]. The convolutional layer uses a 3∗3 convolutional kernel, the padding mode is S AME, the sliding step size is 1, and the activation function is RELU. The ratio of the 2886 pieces of characteristic data tested using the SEED data set is 4:3 between the planning test data set and the calculation data set, and the calculated accuracy is 88.63%. In order to prove that the data set of restored emotional features has a good

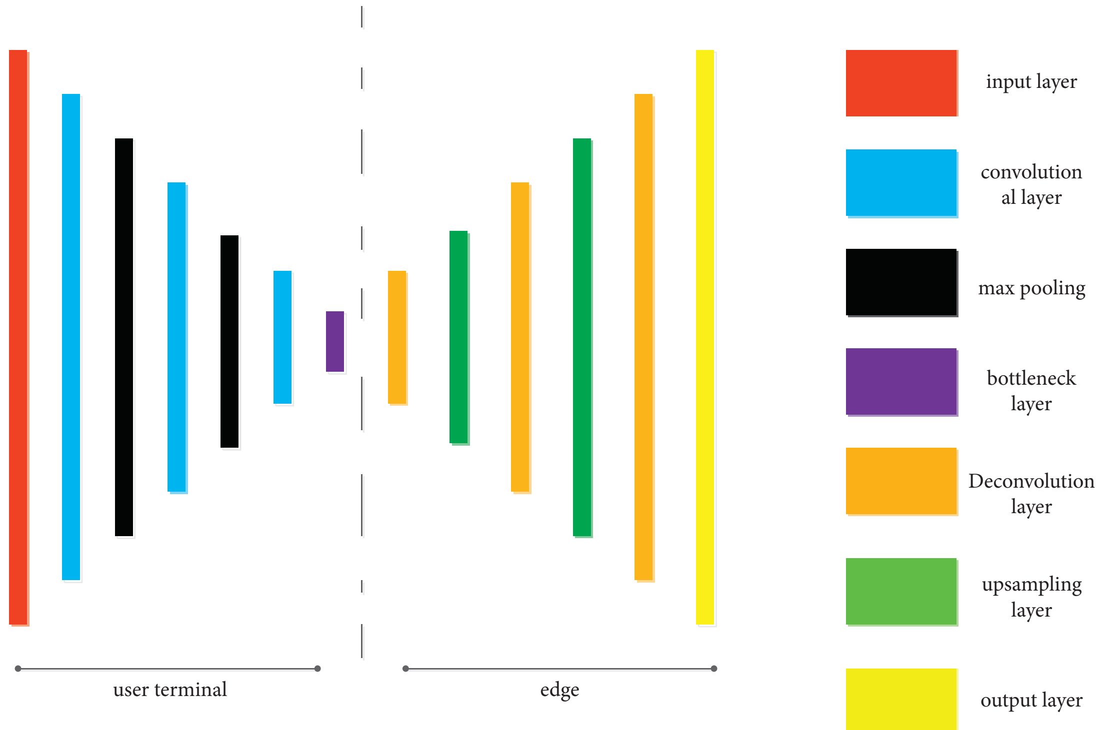

Figure 4: Convolutional autoencoder.

accuracy in the emotional model, the restored emotional feature data are inputted into the model, and the accuracy of user emotion recognition will be obtained as shown in Table 1.

It can be seen from the figure that with the gradual increase in the compression ratio, the obtained accuracy and absolute error are also gradually increased. For example, when CR = 0.25, the accuracy is 88.71%, and the absolute error $\delta = 3\%$; when CR = 0.75, the accuracy is 88.59%, and the absolute error $\delta$is = 1.09%. The accuracy obtained by the parameters of the initial model used will also be different, which will lead to a small range of fluctuation errors in the accuracy of the final recognition.

In the edge computing network, the signal range radius of edge nodes is $R = 500$ m and the frequency bandwidth is $B = 10$ MHz. The size of the data calculation task generated by each behavioral device is distributed in [0.1, 0.5] Mbits, the CPU cycle per bit must be distributed within [500, 1000] CPU cycles/bit, and other simulation parameters are set as shown in Table 2.

Why do the parameters in Table 2 take such values? Due to the fading of small-scale blocks and the mobility characteristics of mobile devices in the communication model, the results of each operation are random, and the results of each calculation of emotional data are uncertain. Therefore, the value of emotional data is calculated by the mathematical method of statistical averaging to obtain the average value of all data as the final value of the parameter.

Table 1: Accuracy and absolute error of compression ratio restored data.

Compression ratio	Accuracy (%)	Absolute error (%)
C $R = 0.10$	88.66	0.02
C $R = 0.25$	88.71	0.03
C $R = 0.50$	88.90	0.78
C $R = 0.75$	89.59	1.09
C $R = 0.95$	89.44	1.29

Table 2: Simulation parameter settings.

Parameter	Value
Background noise power, N	−174d Bm/Hz
Edge node computing capability	$[2 \times 10^{10}, 10 \times 10^{10}]$CPU cycle/s
Cloud computing capabilities	$[1 \times 10^{11}, 8 \times 10^{11}]$CPU cycle/s
T DMA frame length, T	0.1 s _
Path loss model	$128.1 + 37.6 \times \log_{10}(d(km)/1000)$dB
User's transmit power	0.25 W _

4. Performance Testing and Application Verification

Through the descriptions in the previous chapters, in view of the problems faced by the intelligent analysis of emotions in music performances today, in this section, the scheme through specific experimental data will be verified. In order to make the experiment more accurate, it is necessary to use the test tool to meet the calculation needs. The main contents of the test in this section include the processing of data delays in the recognition of music emotional expressions, the optimal configuration scheme for analyzing emotional data, and testing the different emotions expressed by music performances. If the emotion of the music can be analyzed, then this model is useable.

4.1. Data Latency Test for Emotion Recognition

The Edge Computing Platform Cloudlet. An edge computing-based sentiment analysis system CoCo is proposed. The processing flow of testing the data delay of emotion recognition mainly includes the following: first, collecting sentimental data; second, analyzing the sentimental data collected by the model; third, sending the sentimental data to the edge server; and finally, sending the result to the cloud server for processing. In addition, edge computing is applied to analyze many problems arising from sentiment analysis for analysis and exploration. Its data stream processing mainly includes the processing time required to analyze the emotional collection data, the processing time of sending the emotional data to the edge server, and finally, after the data are processed and transformed by the analysis program, the time it takes to send the results to the cloud server for processing. In order to prevent the time speed of the analyzer from affecting the delay, it is necessary to continue to use the empty analyzer. For comparison, it is necessary to test the ideal situation; that is, the edge server directly sends the data to the cloud server after receiving the emotional data, and does not use PubSub to distribute various queue data. The ideal average total response time delay for transmitting data is 28 ms; however, through the CoCo experiment, the average response time delay is 32 ms, while the time of other additional response parts of the CoCo architecture is 4 ms. The conclusion is that the remaining data processing time brought by CoCo is only a small fraction of the total delay time, while in practice with a real analyzer, this fraction will be even smaller [25], specifically as shown in Figure 5.

A major feature of CoCo is that it supports real-time analysis and use of emotional data, so the response time delay of the system is a very critical part. CoCo works serially using multiple virtual machines, which have time to process sentiment data. So to quantify this extra processing time, it is necessary to measure the latency from when the emotional data are received from the edge server until the data are ready to be sent from the edge data server to the cloud server. To prevent the effects of this time delay, an empty analysis sentiment program is used that produces random results when receiving data. Meanwhile, since the purpose of this study is to experimentally measure the additional processing time, the adaptation mechanism is not enabled during testing. A 5-minute video will be decoded at 5FPS, resulting in an image of approximately 1599 frames. The system delay processing time is recorded for each frame. Figure 6 shows the CDF curve for all delayed processing times. It can be seen from this that the delay processing time is basically within 2–5 milliseconds, which is the inherent processing time brought by the CoCo structure.

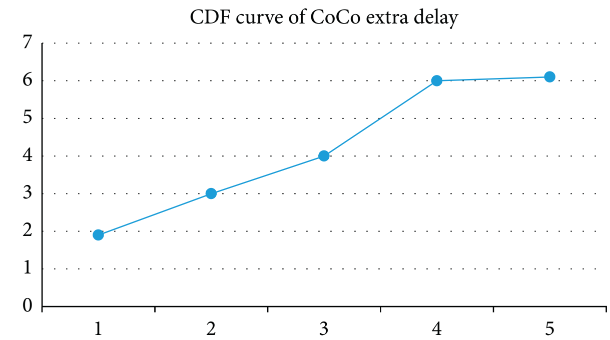

Figure 5: CDF curve of CoCo extra delay.

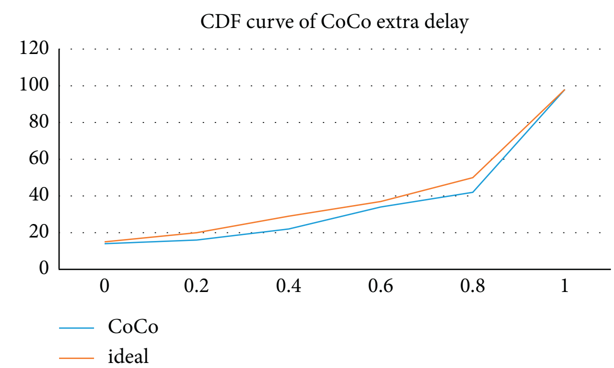

Figure 6: CDF curve of CoCo response delay.

4.2. Optimal Allocation Analysis of Testing Emotional Resources. This graph shows the time it takes to configure the Bootable Music Emotions virtual machine classification image. For music data, this sentiment analysis process is mainly for virtual machine synthesis. For Docker, the main thing is to overwrite new sentiment data to Union FS. To test its achievability, it is necessary to test multiple data requests that match the corresponding music sentiment. The experimental results show that the configuration speed of Docker is significantly faster than that of virtual machines. The performance is also good, and the increased request opportunities will not affect the configuration speed of Docker. The sentiment analysis rate of the music model is specifically shown in Figure 7.

When the emotional data are sent to the edge server, the analysis program simultaneously processes, calculates, and transforms the emotional data. The reason for this experimental result is that Docker uses the layered image technology of the Union FS. The Docker uses dynamic resource reuse to start multiple users using the same program, which solves the problem of system resource locking and saves disk space usage. A virtual machine needs to start a copy of the operating system, which is fundamentally different from a process container.

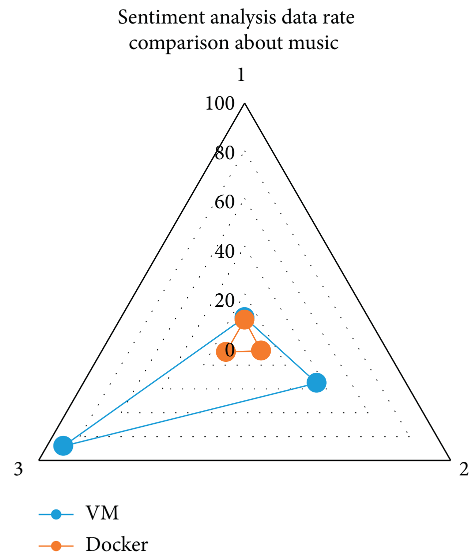

Figure 7: Comparison between VM and Docker configuration speed.

Among them, the resource usage in the configuration process is detected, including CPU memory usage and load. The experimental results show that Docker occupies less machine resources and is much smaller than virtual machines. Therefore, it is better to use Docker to configure and calculate the corresponding music emotional data, because it saves the consumption of resources, the emotion and analysis of the music performance will be faster, and the obtained data will be more accurate. The specific situation is shown in Figures 8 and 9.

4.3. Emotional Testing Based on Music Performance. Not only the emotion that a piece of music carries, according to the difference of people's thinking and mood, but also the understanding of music emotion is different. For example, in the song "Safflower High Heels," the feeling I understand is to express the thoughts of my lover, and their understanding may be other feelings. Yet through experiments, it can be seen that most people's emotional understanding of this song can be obtained by statistical methods to obtain the data of this music emotion. Now, five people A-*E* are selected to do an emotional test on the music "Red High Heels." Table 3 shows the different emotional understandings of the song "Safflower High Heels"

From the data obtained above, it can be seen that most of the musical feelings expressed in the song "Safflower High Heels" are to express the missing feelings for the lover, and the few understood musical feelings are lyric and other emotions. It can be seen that even if it is the same music song, according to people's understanding of the emotion of the song, the emotions it expresses are also different.

Based on the application of the emotional classification method and unlabeled learning model mentioned above, a specific analysis of the emotional expression content of music can be conducted. Music emotion generally includes a

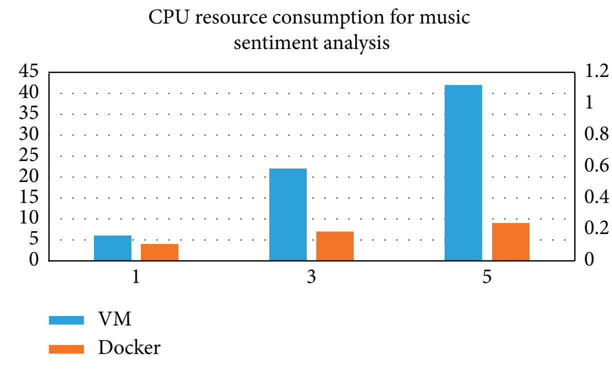

Figure 8: Profiler configures CPU resource consumption.

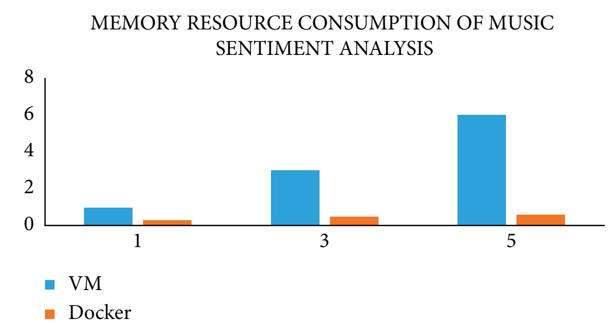

Figure 9: Resource consumption of profiler configuration memory.

Table 3: Different emotional understandings of the song "Safflower High Heels."

Id	Emotion		
	Miss	Lyrical	Other
A	✓		
B	✓		
C			✓
D		✓	
E	✓		

series of emotional factors such as joy, anger, sadness, and music, and an effective identification and extraction application have been obtained. Based on the effective solution of music emotion classification, our realization of the expression function of music emotional analysis has been well solved, as shown in Table 4.

Compared with the methods, the accuracy of the analysis efficiency of the model algorithm has been greatly improved, and it is better adapted to the needs of the expression analysis of current music emotions. The method of sampling survey is adopted to investigate the accuracy and analysis rate of sentiment analysis of 15 pieces of music. In general, the accuracy of the original music sentiment analysis is usually between 60% and 70%, as shown in Table 5; the analysis and expression accuracy of the designed model of this study have been greatly improved.

Table 4: Music analysis expresses emotion extraction.

Test spot check number	Analysis and expression of emotion
1	Happy, excited
2	Sadness, despair
3	Depression, fear
4	Anticipation, excitement
5	Sadness, anger

Table 5: Music expression analysis accurate performance calculation.

Music number	Music emotion	Accuracy	Analysis speed improvement
1	Sad	8 5.3%	1.25 _
2	Happiness	8 7.5%	1.12 _
3	Excited	8 8.6%	1.18 _
4	Joy	8 6.95	1.21 _
. . .		. . .	
1 5	Excited	8 8.5%	1.16 _

5. Conclusion

In the edge computing network, the need for emotional analysis expressed by users for music is solved by the nearest edge server, which reduces the processing time required for processing information, relieves the pressure of network congestion, and improves the quality of service for users' speed. This paper analyzes how the edge network optimizes the time delay of the music emotional system, and proposes the influence of emotional word analysis, edge computing capability, cloud computing capability, and other factors on the calculation of music emotional data. However, my knowledge is still shallow. To be optimized, in short, the impact of edge computing on music performance is very large. For example, the rapid development of Douyin in recent years has grown into almost the must-have software in every mobile phone. For example, the songs of my music software are usually obtained from Douyin. There are all kinds of music emotions in this, which greatly enriches my spiritual world. Under the development of the big era, edge computing will also develop rapidly. Although its technology is immature and there is no effective foundation as support, the development of edge computing will usher in a revolution in the expression and analysis of music emotions in the near future sexual development. The communication method between users and base stations established in this chapter is divided into multiple addresses, thereby ignoring the channel interference between users and reducing the complexity of the problem. However, in general network modeling, most users use OFDM. Therefore, the follow-up work will study how to make full use of network resources in the FDMA mode, so as to ensure the processing time delay of the system.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this work.

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