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Exploring the Clothing Feedback Mechanism in the Interaction Between Medical Students' Emotional States and Humanistic Education Using a Support Vector Machine Model

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ABSTRACT This study presents an analytical framework combining weighted multi-kernel Support Vector Machine (SVM) and multimodal feature fusion to quantify the impact of clothing on medical students' emotional states in humanistic education contexts. From the perspective of textile psychology and sensory engineering, visual clothing attributes (HSV color space, LBP texture, and deep style features from ResNet-50) are integrated with physiological signals (ECG, galvanic skin response) to construct a high-dimensional multimodal feature vector. Principal Component Analysis (PCA) and Sequential Forward Selection (SFS) are applied for dimensionality reduction and optimal feature selection, while an improved Grey Wolf Optimizer (I-GWO) automatically tunes the weighted multi-kernel SVM hyperparameters. Experimental results demonstrate that the framework achieves an emotion recognition accuracy of 89.7%, with color brightness identified as the most critical driver of positive emotions and empathy. Analysis across different teaching scenarios—doctor-patient communication, ethical debate, and narrative reflection—reveals that context moderates the clothing-emotion relationship, providing precise quantitative evidence for optimizing educational strategies. The proposed approach is suitable for integration with antenna-enabled smart clothing systems, wireless sensing networks, and edge-computing platforms, enabling real-time monitoring of student emotional states and data-driven enhancement of medical humanities teaching environments.

INDEX TERMS weighted multi-kernel svm, multimodal feature fusion, smart clothing systems, wireless sensing networks

I. INTRODUCTION

With ongoing advances in educational technology through multimodality, the way to assess the impact of medical humanities education must transition from using subjective judgments to objective measures. Accurate evaluation of student/teacher interaction as a means to foster empathy and the competency needed to work in a professional environment is a vital part of improving the quality of education for future physicians. From the perspective of textile science and engineering, clothing is not merely a covering but a complex interface of multimodal information, where visual attributes (such as color and pattern) and tactile-textural properties (such as fabric weave and surface roughness) act as critical stimuli for human psychological and physiological responses.

Assessment methods of student/teacher interactions are primarily dependent on subjective ratings and interviews. Therefore, measures of non-verbal behaviours, such as student's clothing, are not adequately captured and interpreted, and this leads to difficulty interpreting how non-verbal behaviours such as clothing may affect students' emotional states, and thus the limited nature of current educational assessment measures. In particular, the area of clothing as a high-dimensional carrier of textile design elements—functioning as a primary means of individual's expression and situational feedback—has yet to be fully evaluated with respect to its psychophysiological connections with specific educational instances. While textile researchers have long studied the sensory comfort of fabrics, the "emotional comfort" and feedback mechanisms triggered by specific clothing attributes in pedagogical environments remain underexplored. Medical humanities education plays a key role in developing medical students' empathy and professional competence through training and preparation, while measures to assess how effective medical humanities education is taught remain an area of focus within educational research. At this time, evaluation of medical humanities education primarily relies on subjective evaluation scales and interviews [1,2]. In addition, qualitative research has resulted in learning about how the teaching of medical humanities affects the development of medical students through qualitative analysis [3]. Furthermore, within medical humanities education, which often requires heightened empathy and compassion, there is a notable lack of objective methods to capture and quantify an individual's emotional states during teaching activities. Especially at the level of nonverbal behavior, clothing serves as an important carrier of individual daily expression and situational feedback [4]. Its psychophysiological connection mechanism in specific educational environments has not been fully explored [5]. In the field of medical education research, scholars have confirmed that emotional states have a significant impact on learning outcomes and practical performance [6,7]. And some studies have gradually begun to focus on the regulatory role of environmental factors in the learning process [8]. However, existing literature is mostly focused on verbal communication or macro-environmental design, and there is a lack of systematic empirical research on how clothing, as an embodied and adjustable nonverbal element, reflects and affects the emotional and cognitive states of medical students in humanities courses. This research gap limits the comprehensive understanding of the teaching interaction feedback mechanism.

In terms of analytical methods, machine learning models offer new possibilities for solving the abovementioned problems. SVM has shown great potential in the fields of affective computing and behavior recognition due to its excellent robustness in handling small samples, high-dimensional data and nonlinear classification problems [9,10]. Some studies have successfully used SVM to classify emotions based on physiological signals and facial expressions [11]. However, most works have failed to effectively integrate the visual attributes of clothing into the analytical framework, focusing mainly on personalized clothing recommendations rather than educational interventions [12]. Current multimodal fusion research also focuses on audio and video signals, with insufficient attention paid to the feature modeling and systematic fusion of clothing attributes [13]. This disconnect between models and applications makes it difficult for existing technologies to quantitatively analyze the intrinsic relationship between clothing and emotional states in the context of structured educational interventions. Existing literature often fails to bridge the gap between textile informatics and educational psychology, making it difficult to quantitatively analyze how the intrinsic parameters of clothing—such as the HSV color space distribution and LBP texture features of fabrics—interact with emotional states in structured educational interventions.

The research motivation and core contributions of this paper are as follows:

(1) Methodologically: A weighted multi-kernel SVM is applied. Through a kernel function weighted fusion strategy, it better handles the heterogeneity and nonlinear relationships among multimodal features, overcoming the limitations of traditional SVM in handling complex feature fusion.

(2) Problem Focus: To fill the existing research gap with reference to "How does the emotional state of medical students change from different contexts of humanities education based on their clothing attributes (quantitatively)?", an entire research framework has been developed from the point of view of data collection, feature fusion, model analysis, etc.

(3) Experimental Design: By using the methodology of multi-scenario teaching simulation; clothing variables were systematically manipulated for each scenario and multimodal data sets collected synchronously, thus ensuring the ecological validity and interpretability of the data.

(4) Interpretability Analysis: The use of shap provides insight into post hoc analysis of how the decision making process works for both the multiclass weighted multi-kernel SVM model, and quantifies the importance of each clothing attribute, which renders increased credulity and interpretability of the conclusions made by the weighted multi-kernel SVM model.

The experimental findings in this paper demonstrate that the multiclass weighted multi-kernel SVM model develops statistically significantly better emotion recognition accuracy than several other mainstream benchmark models and highlights the role of clothing attributes, with an emphasis on colour brightness as an essential clothing attribute that engenders positive emotions and empathy, especially in teaching contexts that require the highest degree of utilisation of emotional investment (narrative reflection).

II. EXPERIMENT

A. MATERIALS AND METHODS

1) Experimental Design and Participants

This research analysed pre-existing experimental data (DEAP, Database for Emotion Analysis using Physiological Signals) retrospectively as a reference for methodological design to inform the methodological framework; however, the actual data used in this study were collected from a custom-designed controlled experiment simulating a medical humanities classroom, as described in the following sections. This approach ensured alignment between the experimental variables (e.g., clothing attributes) and the research objectives, while adopting DEAP's rigorous physiological data acquisition standards. Ethical practices were followed. Participants had vision that meets standards. They did not have colourblindness. They did not have evidence of prior mental conditions. All participants consented to take part when data collection was initiated. Data collected followed Ethical Approval under the Declaration of Helsinki. Data were gathered in a structured, standardised instructional environment. The room was simulated based on a standard seminar room for a medical education class. The intention was to provide participants with three examples of standard methods used to educate humanities. The three methods were: role-play (the interactions between patient and provider), group discussion (a forum to have various points of view), and personal statement (writing reflective articles on what they have learned from their experiences). Each scenario was provided with a standard format for both content and use and took place over a period of 10 to 15 minutes, respectively. The clothing of the participants had been varied by supplying four pre-defined, standardised combinations labelled F1 through F4, which systematically included various combinations of colour (cool or warm) and style (formal or informal). A summary of the parameters is included in Table 1.

TABLE 1. Visual Attribute Parameters of Standardized Clothing Combinations

Clothing id	Hue type	Brightness (Mean ± SD)	Saturation (Mean ± SD)	Style type
F1	Cool	0.45 ± 0.05	0.60 ± 0.05	Formal
F2	Cool	0.65 ± 0.05	0.50 ± 0.05	Informal
F3	Warm	0.55 ± 0.05	0.70 ± 0.05	Formal
F4	Warm	0.75 ± 0.05	0.55 ± 0.05	Informal

Note: SD=Standard Deviation, id=identification,In this paper, 'formal' and 'informal' styles are operationally defined based on a pre-validated set of clothing items consistent in cut and material within each category, with the visual attributes (hue, brightness) serving as quantifiable correlates rather than sole determinants of style. This approach allows for systematic manipulation while acknowledging style as a multimodal construct.

In Table 1, there are four factors; F1 is defined as 0.45 lightness, 0.60 saturation, cool tone, and formal; F2 is defined as 0.65 lightness, 0.50 saturation, cool tone, and informal. Therefore, these two factors are cool tone lightness with low formality and cool tone lightness with high informality. The other two factors; F3 is defined as 0.55 lightness, 0.70 saturation, warm tone, and formal; F4 is defined as 0.75 lightness, 0.55 saturation, warm tone, and informal. Therefore, these two factors represent warm tone lightness with low formality and warm tone lightness with high informality. The overall structure creates a systematic experimental design that varies from cool tones/lightness and establishes the formal/informal styles, with controlled variables for use in future quantitative analyses examining clothing colour lightness and positive emotion, and the influence of style formality on anxiety.

The three target emotion categories for classification were defined based on the dominant emotional experience reported and induced within the simulated teaching scenarios: 'Negative' (anxiety, tension), 'Neutral' (calm, objective), and 'Positive' (engagement, empathy). This categorical framework guided the labeling of multimodal data segments and the model training objective.

To create the initial data collection, a fully balanced Latin square design was used to assign the clothing and situational sequences. The participants wore the specified clothing combinations for each situation, which was also necessary to complete each task in the teaching scenario.

2) Multimodal Data Acquisition and Preprocessing

This research paper used three different types of data (physiological/biophysical data, behavioral data, and subjective rating scale data) that have previously been collected over time to analyze the emotional condition of medical students. All data streams were timestamped and synchronized to a common master clock (National Instruments PXIe-6674T) during the first phase of acquisition, with all data sampled at no less than 1000Hz. Consequently, data segments were aligned precisely for the retrospective analysis.

Physiological data were obtained from historical datasets of electrocardiogram and skin activity recorded using the Biopac MP160 system. Electrocardiogram signals were acquired using the ECG100C (Electrocardiogram) module, with electrodes placed in the standard lead II. Skin activity was acquired using the GSR100C (Galvanic Skin Response) module, with electrodes attached to the fingertips of the nondominant index and ring fingers of the participants. In retrospective analysis, the raw electrocardiogram signals were first filtered by a 0.5–35 Hz bandpass filter to remove baseline drift and high-frequency noise, and then the Pan-Tompkins algorithm was used to detect R waves and calculate heart rate variability indices [14]. After the raw skin activity signals were filtered by a 0.05–5 Hz bandpass filter, peak detection was performed to extract skin activity response features.

Behavioral data were derived from participants' frontal video recordings using a Logitech C920 HD camera (1920 × 1080 resolution, 30 fps). The video streams were used to extract two types of features: (1) Facial expression features: the intensity of 49 facial motion units in each frame was detected using the OpenFace 2.0 toolkit; (2) Clothing image features: frames containing the upper body clothing area were extracted from the video for subsequent visual attribute analysis.

Subjective scale data were derived from participants' completed records on the Chinese version of the Positive and Negative Emotion Scale and the Jefferson Empathy Scale (Medical Student Version) after the experiment, providing self-reported scores for emotional experience and empathy ability.

3) Feature Extraction and Vector Construction

Based on retrospective historical multimodal data, this paper systematically extracts visual features, physiological response features, and facial movement features of clothing to construct a numerical representation for emotion state classification. The extraction of clothing features focuses on three dimensions: color, texture, and style, as shown in Figure 1.

In Figure 1, color features are calculated in the HSV (Hue, Saturation, Value) color space, including histogram statistics (mean, SD, skewness) and the area ratio of the dominant

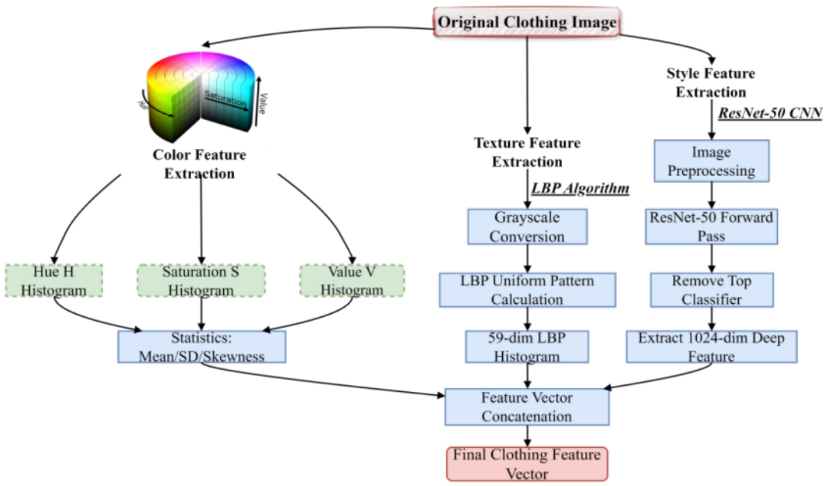

FIGURE 1. Technical Architecture for Clothing Feature Extraction. (Note: LBP=Local binary patterns, CNN=Convolutional Neural Network, ResNet=Residual Network)

color regions for the three channels of hue (H), saturation (S), and value (V). Texture features are described using the LBP algorithm, obtaining a 59- dimensional texture distribution vector by calculating the LBP uniform pattern histogram of the image region. Style features are extracted based on a ResNet-50 convolutional neural network model pre-trained on the ImageNet dataset. By removing its top-level classifier, the 1024-dimensional activation vector before the last fully connected layer is used as the deep semantic representation of the clothing style.

Physiological features were extracted from both electrocardiogram (ECG) and skin conductance signals. A series of heart rate variability indices, including time-domain and frequency-domain indices, were calculated from the ECG signals. Skin conductance features were primarily extracted from skin conductance response signals, including the peak value of the skin conductance response (SCR) within a specific time window, the frequency of SCR occurrences, and the integral area of the SCR signal. Facial expression features were quantified using the facial motion unit intensity values output from the OpenFace 2.0 toolbox. This paper selected the average and peak intensities of eight core motion units highly correlated with basic emotional expressions over time as features.

While deep networks implicitly capture low-level attributes, explicit handcrafted features provide interpretable, domain-specific descriptors for clothing attributes. To address potential redundancy between the deep semantic features from ResNet-50 and the manually engineered color (HSV) and texture (LBP) features, the subsequent application of Principal Component Analysis (PCA) for dimensionality reduction and Sequential Forward Selection (SFS) for feature optimization specifically mitigates collinearity and selects the most discriminative feature subset, thereby refining the model architecture and enhancing its efficiency. To eliminate the impact of differences in physical dimensions and numerical ranges among different features, Z-score standardization was applied to all features. Given the high dimensionality of the feature vectors, PCA was subsequently used to reduce the dimensionality of the standardized feature set, projecting the original features into a lower-dimensional space while retaining 95% of the variance contribution. Finally, the dimensionality-reduced features from the three modalities were concatenated and combined to form a unified feature vector, which served as the model input.

However, simple feature fusion may apply redundant information, which could degrade model performance. Therefore, the SFS algorithm is applied for feature optimization. The SFS algorithm uses the average classification accuracy of five-fold cross-validation as its evaluation criterion. It employs a greedy search strategy, starting with an empty feature set, iteratively adding the single feature that best improves model performance under the current conditions. This process continues until adding a new feature no longer significantly improves classification performance.

4) Construction of an Advanced Weighted Multi-kernel SVM Model

This paper uses SVM as the core classifier, and its basic goal is to find an optimal hyperplane that maximizes the margin between samples of different emotion categories on the hyperplane [15]. The optimization problem can be expressed as:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \tag{1}$$

$$\text{subject to } y_i(w\cdot\phi(x_i)+b) \geq 1-\xi_i, \quad \xi_i \geq 0, \quad i=1,\ldots,n \tag{2}$$

w is the weight vector; b is the bias term; ξ_i is the slack variable; C is the regularization parameter used to balance classification error and model complexity; and $\phi(x_i)$ represents the kernel function that maps the input features to a high-dimensional space. y_i is the true class label, and x_i refers to the feature vector of the sample.

Regarding kernel function selection, this paper compares the performance of linear kernels, polynomial kernels, and radial basis function kernels in processing this feature set. It was found that the radial basis function kernel is more stable in mapping nonlinear feature relationships, and therefore it was determined as the fundamental kernel function of the model. Its mathematical expression is:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \tag{3}$$

γ is the kernel function parameter, controlling the range of influence of a single sample on the classification boundary.

C and γ are optimized using a grid search combined with five-fold cross-validation. The search range for C is set to $[2^{-5}, 2^{15}]$, varying on a logarithmic scale to balance classification error and model complexity. The search range for parameter γ is set to $[2^{-15}, 2^{3}]$, also using a logarithmic scale. For each (C, γ) parameter combination, its average classification accuracy on the cross-validation set is calculated as a performance evaluation metric. The final optimal parameter combination is determined based on the highest cross-validation accuracy. Using this optimal parameter combination, the model is retrained on the entire training set to obtain an SVM classifier used for final test set evaluation and feature parsing. The trend of loss and accuracy changes during SVM training is shown in Figure 2.

Figure 2 shows that the training loss decreased rapidly and approximately linearly from around 1.2 to around 0.1 with slight random fluctuations. The training accuracy rapidly increased from an initial low value to around 0.9, while the validation accuracy increased synchronously but eventually stabilized at 0.88, slightly lower than the training accuracy. These changes clearly demonstrate the convergence process of the model training: the rapid decrease in training loss indicates that the model effectively learned the data features; the steady increase in training accuracy reflects the continuously improving model fitting ability; and the validation accuracy being slightly lower than the training accuracy indicates a slight overfitting phenomenon. However, the overall training process stabilized after about 50 cycles, proving that the model reached a good convergence state and possessed a certain generalization ability.

However, SVM has significant limitations when processing heterogeneous multimodal data. A single kernel function cannot simultaneously capture the optimal representation of different feature spaces. Therefore, a weighted multi-kernel SVM framework is applied, combined with an intelligent optimization algorithm to achieve automatic hyperparameter optimization. At the principle level of weighted multi-kernel SVM, an innovative kernel function combination strategy is designed, its mathematical expression being:

$$K_{combined}(x_i, x_j) = \eta \cdot K_{linear}(x_i, x_j) + (1-\eta) \cdot K_{RBF}(x_i, x_j) \tag{4}$$

K_{linear} and K_{RBF} represent the linear kernel and radial basis function, respectively, with η being a dynamic weighting coefficient that satisfies the constraint $0 \leq \eta \leq 1$. This dual-kernel architecture can automatically adjust the contribution ratio of the kernel function according to the distribution characteristics of the actual data, achieving optimal kernel mapping for different modal features, thus theoretically guaranteeing the adaptive modeling capability for the feature structure of heterogeneous multimodal data. Based on grid search, an intelligent hyperparameter optimization framework based on the improved Grey Wolf Optimizer (I-GWO) is applied [16]. The I-GWO algorithm applies two key improvements on the standard Grey Wolf Optimizer: first, an adaptive convergence factor adjustment mechanism, which enables the algorithm to maintain a strong global exploration capability in the early stage of iteration to avoid getting trapped in local optima, and enhances the local development accuracy in the later stage of iteration to accelerate convergence; second, a random perturbation strategy, which injects controllable randomness into the population position update process to effectively avoid premature convergence. The optimization process uses the average classification accuracy of five-fold cross-validation as the fitness function to ensure that the selected hyperparameter combination has good generalization performance.

III. RESULTS AND DISCUSSION

A. VALIDATION OF THE WEIGHTED MULTI-KERNEL SVM EMOTION RECOGNITION MODEL

To verify the effectiveness of the weighted multi-kernel SVM (M5) in the emotion recognition task for medical students, this paper retrospectively compares it with four benchmark models—logistic regression (M1), multilayer perceptron (M2), deep belief network (M3), and visual transformer (M4)—based on historical datasets, comparing the performance of the five models on four evaluation metrics. All models used the same training and test sets, and a five-fold cross-validation process was employed to ensure the stability of the evaluation results. The results are shown in Figure 3. It is important to note that the reported accuracy of 89.7% refers to the performance on the independent test set, whereas the validation accuracy of 0.88 (88%) mentioned in the context of Figure 2 pertains to a held-out validation set during the model tuning phase, explaining the numerical difference.

Figure 3, with model type as the Y-axis, shows the performance of all models (M1 (77.2%, 76.8%, 77.1%, 76.9%)), M2 (82.1%, 81.5%, 82.0%, 81.7%), M3 (85.3%, 84.7%, 85.2%, 84.9%), M4 (86.9%, 86.2%, 86.7%, 86.4%), and M5 (89.7%, 89.3%, 89.5%, 89.4%)) from bottom to top along the Y-axis. Furthermore, the values for each model across the four indicators remain highly consistent. This

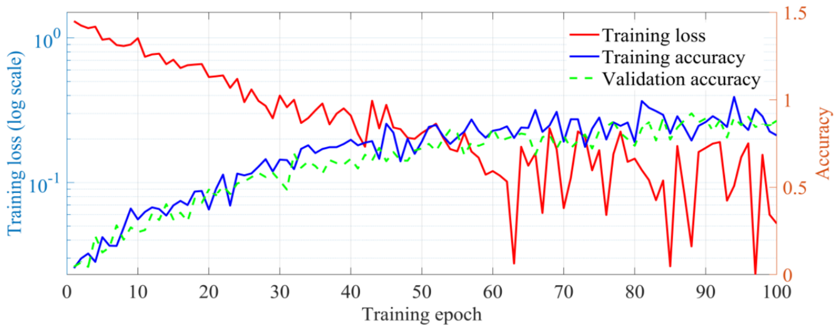

FIGURE 2. Trends in Model Training Loss and Accuracy

pattern of change indicates that: First, there is a positive correlation between the complexity of the model architecture and the classification performance. The weighted multi-kernel SVM model in this paper improves the accuracy by 2.8 percentage points compared with the best baseline model. Second, the slight differences between the models in different metrics reflect the balance between precision and recall in the emotion classification task, proving that multimodal feature fusion effectively improves the model's comprehensive discrimination ability.

To further reveal the classification mechanism of the model in the feature space, the classification boundary and sample distribution of the weighted multi-kernel SVM model were displayed through 3D feature space projection, so as to transition from quantitative evaluation to visual verification and enhance the interpretability of the emotion classification mechanism. Figure 4 shows the generation of multimodal feature data after dimensionality reduction using principal component analysis.

In Figure 4, the horizontal, vertical, and Z-axis represent the first three principal components (PC1, PC2, and PC3), with variance contributions of 32.5%, 18.7%, and 9.3%, respectively. The data points represent the distribution of samples in the reduced-dimensional feature space. Correctly classified samples are indicated by red, green, and blue colors to represent the three emotion categories (red for category 1, green for category 2, and blue for category 3), while misclassified samples are highlighted with black crosses. The data distribution shows that correctly classified points form clear clusters in their respective principal component spaces, while misclassified points are mostly distributed in the category boundary regions. This reflects partial overlap in the feature spaces, indicating that the model's ability to distinguish boundary samples still has room for improvement.

B. ANALYSIS OF KEY CLOTHING FEATURES BASED ON SHAP AND ITS EMOTION-DRIVEN MECHANISM

To gain a deeper understanding of the mechanism by which clothing attributes influence emotional state, this paper uses the SHAP method to analyze a trained weighted multi-kernel SVM model. Figure 5 shows the global feature importance ranking; the higher the SHAP value, the higher the feature importance.

The ranking of the major characteristics of seven clothing items is shown in Figure 5; the characteristics that are ranked the most important were colour brightness (0.152), hue standard deviation (0.121), texture complexity (0.098), average colour saturation (0.087), formality (0.076), colour contrast (0.064) and texture uniformity (0.053). Each of the feature's CI (Confidence Interval) lengths corresponds with the length of its horizontal line; the data represents a distinct hierarchy and shows that colour brightness was the most important feature; it also had the widest CI of any feature. The remaining features can be identified by the sequential decline of their importance and their subsequently narrower CIs, and it appears evident that colour features are more prominent in the overall analysis of clothing than any other feature, with colour brightness being the most important contributor to the model's predictions. Although features such as texture and formality are of diminishing importance, they are also estimated with greater accuracy and stability than colour features. Overall, this demonstrates the degree to which colour characteristics affect the feature ranking of clothing and how accurately the ranking of features can be assessed.

In order to further explore the impact of SHAP on emotional responses due to color brightness, this paper selects another component associated with visual properties that correlate with emotional states-occurrence of visually saturated colours. In conjunction with SHAP's macro-level ranking of the importance of the relationship between colour saturation and emotional responses, this paper presents the relationship between colour saturation and emotional responses, as shown in Figure 6.

The two-part analysis of emotional state versus visual characteristics in Figure 6. In Figure 6 (a), as people are experiencing a change from negative emotions to positive emotions, then the average brightness of color selection increases considerably (mean 0.3 for negative group, mean 0.5 for neutral group, and mean 0.7 for positive group). Also, the group of individuals experiencing positive emotions had a relatively lower SD of color brightness than did the individuals who experienced negative emotional states,

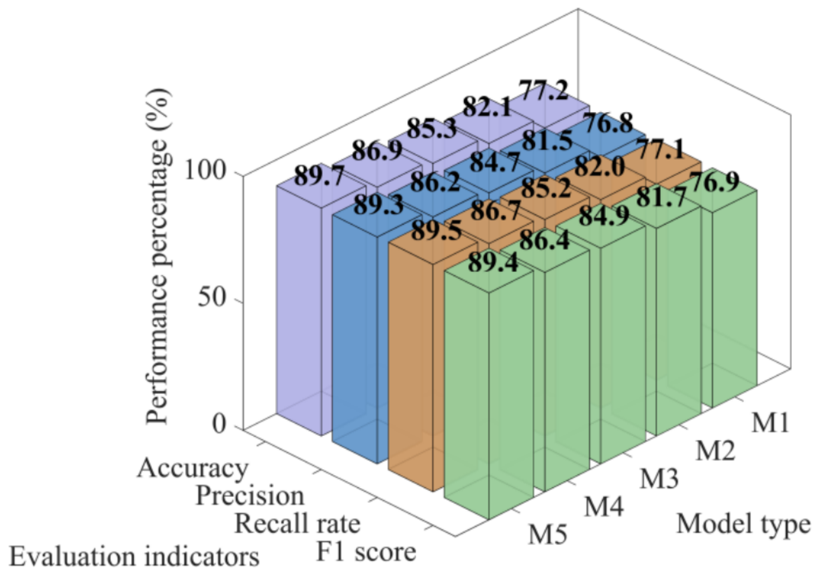

FIGURE 3. Performance Comparison of Multiple Models in the Emotion Classification Task

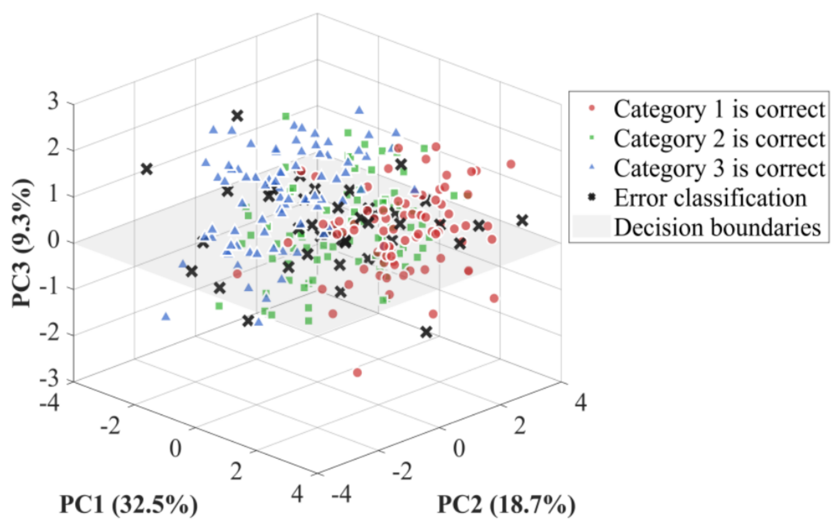

FIGURE 4. 3D Feature Space Projection and Classification Results of the Weighted Multi-kernel SVM Model

indicating that when individuals are in a positive emotional state, they have a greater affinity for high-brightness colors. In Figure 6 (b), the same pattern of emotional attitude on the distribution of saturation occurs; the average saturation of colors selected by individuals in a negative emotional state, a neutral emotional state and a positive emotional state is 0.4, 0.6, and 0.75 respectively. Furthermore, individuals in the negative emotional state group exhibited the greatest dispersion (SD=0.18) and individuals in the positive emotional state group exhibited the least dispersive (SD=0.12), indicating that the brighter the emotional state is in an individual's emotional decision-making process, the more saturated the color selection will be and the more consistent the choices will reflect the emotional state due to the influence of the emotional state upon an individual's perception of color and color selection.

C. ANALYSIS OF THE MODERATING EFFECT OF TEACHING CONTEXT ON THE ASSOCIATION BETWEEN CLOTHING AND EMOTION

In order to examine the moderating role of teaching context in the clothing emotion relationship, this study analyzed historical data via meta-analysis across three simulated teaching contexts: doctor-patient communication, ethical debate and narrative reflection. Each of these scenarios had distinct requirements for social interaction, as well as varied levels of emotional engagement. The results of the correlation analysis related to clothing characteristics and emotions will be presented in Table 2.

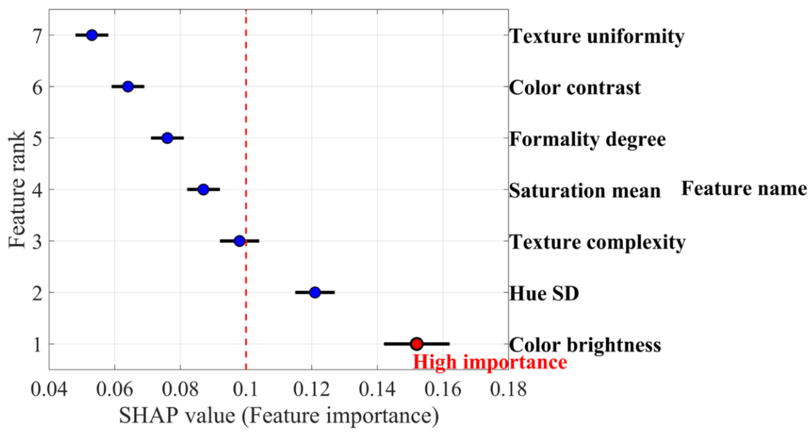

FIGURE 5. Importance of Clothing Features

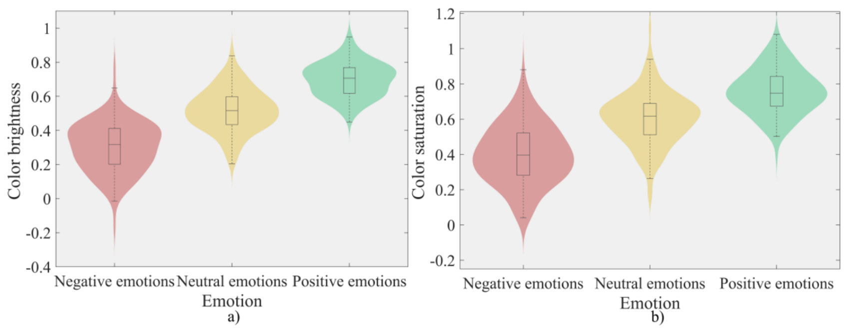

FIGURE 6. Analysis of the Relationship between Visual Features and Emotional State: (a) Color Brightness Distribution under Different Emotional States, (b) Color Saturation Distribution under Different Emotional States

TABLE 2. Correlation Analysis Results between Different Clothing Features and Emotional State and Empathy Ability

Teaching context	Clothing features	Negative emotion correlation	Neutral emotion correlation	Positive emotion correlation	Empathy score correlation
Doctor-Patient communication	Color brightness	-0.32*	0.18	0.41**	0.38**
	Color diversity	-0.25	0.22	0.29*	0.31*
	Formality of style	0.28*	0.15	-0.33*	-0.27*
Ethical debate	Color brightness	-0.19	0.24	0.35**	0.29*
	Color diversity	-0.22	0.19	0.26*	0.24
	Formality of style	0.31*	0.21	-0.28*	-0.25
Narrative reflection	Color brightness	-0.38**	0.12	0.52***	0.45***
	Color diversity	-0.29*	0.17	0.41**	0.38**
	Formality of style	0.25	0.08	-0.36**	-0.32*

Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$; the correlation coefficient is the Pearson r value.

Table 2 shows that in storytelling, brightly colored clothes have a very strong impact on people's perception of the clothes they wear. When people reflect on their narratives, there is a significant positive correlation between brightly colored clothing and positive emotions ($r=0.52$, $p<0.001$), and a high correlation with individual empathy scores ($r=0.45$, $p<0.001$). This indicates that wearing brightly colored clothing in this example can promote emotional resonance with others. However, in doctor-patient communication requiring role-playing, formality of style is positively correlated with negative emotions ($r=0.28$, $p<0.05$) and negatively correlated with positive emotions ($r=-0.33$, $p<0.05$), confirming the hypothesis that formal attire may induce situational tension. Particularly noteworthy is that color brightness is significantly positively correlated with positive emotions in all scenarios (correlation coefficients 0.35-0.52), and the emotional facilitation effect of color brightness becomes increasingly prominent as the emotional intensity of the situation increases (from ethical debate to narrative reflection). This gradient pattern provides precise quantitative evidence for optimizing the teaching environment through clothing design.

The relationship between color brightness and positive emotion scores in different teaching contexts aims to visually present the context-moderating effect obtained from the correlation analysis in Table 2 through regression curves, providing the most direct visual evidence for the "context-dependent law", as shown in Figure 7.

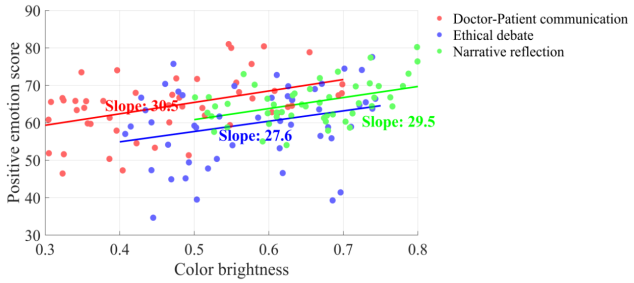

FIGURE 7. Brightness-emotion Relationship in a Specific Scene

Figure 7 shows the positive emotion score (unit: points) on the vertical axis. The data illustrates the relationship between color brightness and positive emotion in three different communication scenarios: In the doctor-patient communication scenario (red), the color brightness values are mainly distributed within [0.3, 0.7], with emotion scores ranging from approximately 45 to 83 points, and a slope of 30.5; in the ethical debate scenario (blue), the color brightness values range from 0.4 to 0.75, with emotion scores ranging from approximately 35 to 78 points, and a slope of 27.6; in the narrative reflection scenario (green), the color brightness values are concentrated between 0.5 and 0.8, with emotion scores ranging from approximately 52 to 81 points, and a slope of 29.5. The data shows that as color brightness increases, the emotion scores in all scenarios tend to rise, but the magnitude of the increase varies significantly. The slope is largest in the doctor-patient communication scenario and smallest in the ethical debate scenario. This pattern of change indicates that situational factors play an important moderating role in the color-emotion relationship.

IV. CONCLUSION

This paper presents an analytical approach that incorporates both weighted multi-kernel SVM and multimodal feature fusion, utilizing historical experimental findings to quantitatively reveal the influence of clothing feedback on emotion and interactions with humanities education among medical students. The experiments confirm the approach's ability to effectively handle heterogeneous educational datasets and suggest that 'brightness of color' is a central feature of clothing that produces positive emotion and empathy, especially within high-investment emotional contexts such as narrative reflection. Conversely, formal style clothing was shown to have a positive association with tension in the communication process between doctor and patient. The identified link between color brightness and positive emotion is contextualized within the specific cohort of medical students and controlled scenarios studied; therefore, generalization to broader populations or unstructured educational settings requires further validation. Future work should incorporate larger, diverse samples and longitudinal designs to substantiate causal inferences in the humanistic education feedback mechanism. The limitations of this research are primarily due to its reliance upon a single type of sample as well as the use of controlled experimentation. Future research should improve sample variety and establish the model's potential for use in authentic classroom environments. Future research can also be developed to include dynamic temporal models, and a greater range of physiological and social behaviours to provide a more accurate and complete knowledge representation of educational emotion recognition and intervention systems.

AUTHOR CONTRIBUTIONS

Conceptualization – ZhengTong HuangFu; methodology – Peng Wang; formal analysis – JingJing Huang; investigation – ZhengTong HuangFu; resources – Peng Wang; writing-original draft preparation – ZhengTong HuangFu and Peng Wang ; writing-review and editing – ZhengTong HuangFu; visualization – ZhengTong HuangFu; supervision – ZhengTong HuangFu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare that they have no financial conflicts of interest.

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The manuscript has neither been previously published nor is under consideration by any other journal. The authors have all approved the content of the paper.

HUMAN RESEARCH SUBJECTS

This study was approved by Hainan Vocational University of Science and Technology Ethics Committee. We secured a signed informed consent form from every participant.

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