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Statistical Vector Model for the Audience Emotional Response Examination with Affective Computing Based on Conductor's Expressive

Qihang Hong[1+]

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Abstract: Audience Emotional Response refers to the range of emotional reactions, feelings, and sentiments that individuals in an audience experience while engaging with a particular piece of content, such as movies, music, art, advertisements, or any form of media or communication. Understanding and analyzing audience emotional responses are essential for various fields, including psychology, marketing, entertainment, and media research. Hence, this paper explores the fusion of youaffective computing, conductor's expressive performances, and audience emotional responses, introducing the innovative Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach. The research capitalizes on the potential of SFEVDL to unravel the intricate emotional intricacies inherent in facial expressions, thereby shedding light on the multifaceted connection between conductor gestures and audience emotions. The study encompasses a comprehensive methodology involving data preprocessing, feature extraction, and deep learning techniques. By harnessing a diverse array of datasets, including EmoReact Dataset, Conductor Archives, Public Performances, Collaborative Settings, Collection, and Mixed Modal contexts, the research illustrates the robustness and adaptability of the SFEVDL approach. The empirical results reveal accurate emotion prediction, aligned emotional responses, and the inherent complexities of interpreting emotions in artistic scenarios. This research serves as a stepping stone in the realm of affective computing, illuminating the pathways for future advancements in the understanding of human emotions, artistic expression, and their intersection with technological innovation.

Keywords: *Conductors Expressive, Audience, Emotional Response, Affective Computing, Deep Learning, Feature Extraction*

1. Introduction

Affective Computing, at the intersection of computer science and psychology, represents a groundbreaking field focused on endowing computers and technology with the ability to understand, interpret, and respond to human emotions [1]. Rooted in the recognition that emotions play a pivotal role in human communication and decision-making, Affective Computing strives to bridge the gap between the rational capabilities of machines and the nuanced, often complex realm of human emotions. By employing various techniques such as facial expression analysis, speech recognition, physiological signals monitoring, and machine learning algorithms, researchers in this field endeavor to imbue machines with the capacity to not only perceive emotions but also appropriately respond in ways that are empathetic and meaningful [2]. As technology continues to permeate every facet of our lives, Affective Computing stands poised to revolutionize human-computer interaction, making it more intuitive, personalized, and attuned to our emotional states. Affective Computing holds the key to a new era of technology that can accurately perceive, interpret, and respond to human emotional responses [3]. By harnessing advanced technologies such as machine learning, artificial intelligence, and sensory devices, this field strives to empower machines with the ability to comprehend the subtleties of human emotions [4]. From detecting nuances in facial expressions and vocal intonations to analyzing physiological signals like heart rate and skin conductivity, affective computing seeks to decode the intricate tapestry of emotions that shape our interactions [5]. This deep understanding of emotional states paves the way for technology to respond in a more empathetic and contextually appropriate manner, revolutionizing user experiences across domains such as healthcare, education, entertainment, and customer service [6]. As affective computing continues to evolve, the potential to forge deeper, more authentic connections between humans and machines becomes not only conceivable but also transformative in its impact [7].

Affective Computing represents a cutting-edge domain that provides the emotional responses, aiming to equip machines with the capability to not just recognize emotions, but also to comprehend their intricacies and respond empathetically [8]. The core challenge lies in deciphering the multifaceted nature of human emotions – from the overt expressions like smiles or tears to the subtle variations in tone, pitch, and cadence in speech, and even the physiological changes that occur within the body [9]. To address this challenge, researchers in affective computing harness a variety of techniques. Facial

[1] *Art Department, Nanchang University, Nanchang, Jiangxi, 330031, China*
Corresponding Author: 18296133990@163.com

expression analysis involves using computer vision algorithms to interpret the movements of facial muscles, discerning emotions such as joy, sadness, anger, and surprise [10]. Speech recognition technology goes beyond mere words to capture the emotional undertones present in vocal inflections and patterns. Additionally, physiological signals, like heart rate variability, skin conductivity, and even brainwave patterns, provide valuable insights into emotional states that might not be readily apparent [11]. Machine learning algorithms are central to this field, enabling computers to learn and adapt based on patterns and data. Through extensive training on labeled emotional data, these algorithms can learn to recognize correlations between various input cues and corresponding emotional states, thereby enhancing their ability to accurately predict emotions [12]. The implications of affective computing are profound and wide-ranging. In healthcare, for instance, it can aid in diagnosing and treating conditions like depression or anxiety by analyzing speech patterns and physiological signals [13]. In education, it can provide insights into student engagement and emotional well-being, tailoring educational experiences accordingly. In entertainment, affective computing can enhance virtual reality experiences by dynamically adjusting content based on the user's emotional responses, creating a more immersive and engaging interaction [14]. However, ethical considerations also come into play. As technology gains the capacity to comprehend emotions, concerns about privacy, data security, and emotional manipulation emerge. Striking the right balance between personalization and intrusion is crucial.

In essence, affective computing is a captivating and transformative domain that augments the capabilities of technology with the depth of human emotion [15]. As this field advances, it holds the potential to reshape to interact with machines, ushering in an era where technology is not just intelligent, but emotionally attuned, leading to more meaningful and impactful interactions. Conductor's expressive performance in the realm of music is an intricate interplay of technique, interpretation, and emotion [16]. Affective Computing, a burgeoning field at the nexus of technology and emotion, offers a fascinating lens through which to understand the profound impact of a conductor's gestures and musical nuances on audience emotional responses [17]. By employing advanced technologies such as machine learning, facial recognition, and physiological monitoring, researchers provides the subtleties of how a conductor's expressive choices resonate with the audience on an emotional level [18]. Facial expression analysis can decipher the real-time emotional reactions of listeners, capturing moments of awe, joy, or introspection as they experience the musical journey. Physiological signals like heart rate variability can reveal the physiological arousal that the music evokes. By correlating these emotional responses with the conductor's specific gestures, tempo fluctuations, and dynamic changes, insights can be gleaned into the conductor's ability to effectively communicate and elicit emotional connections [19]. This multidimensional approach not only enhances our understanding of the conductor's role but also offers a unique perspective on the intricate dialogue between performer and audience [20]. By deciphering how a conductor's expressive choices influence emotional engagement, conductors can refine their techniques to create more impactful musical experiences [21]. Moreover, this integration of Affective Computing and conducting holds potential for the development of novel performance evaluation and pedagogical tools, enriching music education and fostering greater emotional resonance in live performances [22]. As technology advances and our understanding of emotional responses deepens, the synergy between conductor, music, and audience is poised to reach new heights of emotive communication and artistic expression.

Conductor's expressive performance is a captivating blend of technical precision and emotional interpretation, where subtle gestures and nuanced musical decisions have the power to evoke profound emotional responses in the audience [23]. Affective Computing, a dynamic field bridging human emotions and technology, opens up an intriguing avenue to dissect and understand the intricate dynamics at play during a musical performance. Leveraging cutting-edge technologies, such as artificial intelligence and biometric sensors, researchers into the complex relationship between the conductor's expressive choices and the emotional reactions they provoke in the listeners [24]. Facial expression analysis, a cornerstone of Affective Computing, offers a window into the immediate and often subconscious emotional responses of the audience. By capturing microexpressions, macroexpressions, and facial muscle movements, researchers can discern fleeting moments of delight, surprise, or melancholy as the music unfolds [25]. This real-time emotional feedback provides valuable insights into the conductor's ability to convey the intended emotional narrative of the music. Furthermore, physiological monitoring allows for a deeper exploration of audience engagement. Heart rate variability, skin conductance, and other physiological markers can indicate the level of emotional arousal elicited by specific musical passages [26]. For instance, a crescendo might trigger heightened excitement, while a poignant melody might lead to a more contemplative response. Mapping these physiological changes to the conductor's gestures and interpretive choices can unravel the intricate cause-and-effect relationships between musical expression and emotional impact [27].

The implications of this intersection between Affective Computing and conducting are far-reaching. Conductors can gain a more objective understanding of their expressive impact, enabling them to fine-tune their techniques for maximum emotional resonance. Music educators can employ these insights to enhance pedagogy, guiding students toward a more profound connection with their audiences [28]. Additionally, this technology offers the potential for personalized experiences, where the music dynamically adapts based on real-time emotional feedback, leading to uniquely tailored performances for each listener. As Affective Computing advances, ethical considerations come into play, including issues related to privacy, data security, and the potential for manipulation. Striking a balance between enriching emotional experiences and safeguarding individual rights will be crucial in the continued development of this field [29]. Deep learning has emerged as a transformative force in understanding the interplay between a conductor's expressive performance and the emotional responses of the audience, within the context of Affective Computing [30]. The multifaceted nature of this relationship demands advanced techniques to unravel its complexity, and deep learning's capabilities in processing and interpreting complex data have been pivotal in this pursuit. By integrating various data sources such as video footage capturing conductor gestures, audio recordings of the performance, and audience physiological signals, deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can extract nuanced patterns that underlie emotional dynamics [31]. These models excel in capturing the intricate temporal and spatial dependencies present in the conductor's expressive choices and their impact on audience emotional engagement. Transfer learning allows pre-trained models to be fine-tuned for specific musical contexts, mitigating the need for extensive labeled emotional data and expediting the development of accurate emotion recognition systems [32]. The profound insights garnered from deep learning shed light on the conductor's role as an emotional communicator and the audience's responses as an emotional journey, enriching the understanding of how musical performances transcend the realm of sound to resonate deeply with human emotions.

2. Statistical Feature Extraction Vector Deep Learning (SFEVDL)

With a combination of Statistical Feature Extraction Vector Deep Learning (SFEVDL) techniques for facial expression recognition. The system architecture, as depicted in Figure 1, begins with facial expression images obtained from designated datasets. These images serve as input to the Facial Expression Recognition (FER) system. The first step involves face detection and cropping to isolate the relevant facial region. Subsequently, image enhancement techniques, such as unsharp masking, are applied to improve the image quality. Figure 1 presented the steps associated with the SFEVDL model for the feature extraction with deep learning model.

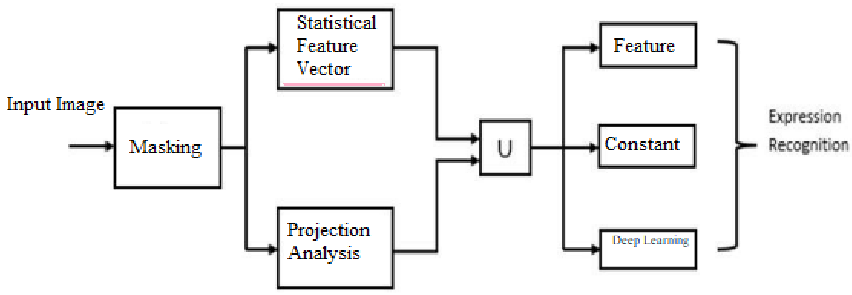

Fig 1: Steps in SFEVDL

The enhanced image then undergoes a process of feature extraction through the utilization of a proposed statistical shape model and integral projection analysis. This process results in the formation of a comprehensive feature vector that encapsulates significant information related to facial expressions. The proposed statistical shape model provides insights into the spatial arrangement of facial features, while integral projection analysis contributes to a holistic understanding of image content. To evaluate the effectiveness of the proposed SFEVDL framework, various classification algorithms are employed. These classifiers are experimented with and applied to the generated feature vectors. The ensuing results are carefully analyzed to assess the accuracy and robustness of the developed model in recognizing facial expressions. Preprocessing, a crucial stage of the research methodology, involves the implementation of the Viola-Jones face detection algorithm (Viola & Jones, 2001). This algorithm is applied to identify and locate facial features within the input images, ensuring accurate face cropping and subsequent analysis. The research methodology comprises a comprehensive pipeline that encompasses preprocessing, image enhancement, feature extraction via statistical shape models and integral projection analysis, experimentation with diverse classifiers, and detailed result analysis. This approach aims to advance the field of facial expression recognition through the innovative fusion of Statistical Feature Extraction Vector Deep Learning techniques, contributing valuable insights into the relationship between facial features and emotional expressions. The Viola-Jones algorithm is used to detect the conductor's face within the video frames. This can be represented as in equation (1)

$$Detected\_Face = ViolaJones(Video\_Frame) \quad (1)$$

After detecting the face, the image is cropped to focus solely on the conductor's facial region. The cropped image is then enhanced through contrast and brightness adjustments. The SFEVDL model enhanced images is presented in equation (2)

$$Cropped\_Enhanced\_Image = Enhance(Crop(Detected\_Face)) \quad (2)$$

To ensure consistent analysis, frame alignment and stabilization techniques can be applied. This can be represented using a transformation matrix using equation (3)

$$Aligned\_Stabilized\_Image = Apply\_Transformation(Cropped\_Enhanced\_Image, Transformation\_Matrix) \quad (3)$$

Color correction techniques can be utilized to address lighting variations and ensure uniform color representation. This can be mathematically depicted as in equation (4)

$$Corrected\_Image = Color\_Correction(Aligned\_Stabilized\_Image) \quad (4)$$

With performing these preprocessing steps, the input data is refined and standardized, ensuring that subsequent statistical feature extraction and deep learning processes are based on accurate and consistent information.

2.1 Feature Extraction with SFEVDL

In the SFEVDL framework, feature extraction is a crucial step that involves transforming the preprocessed images into a compact and representative numerical form, which can be used as input for deep learning models. This process extracts meaningful information from the images that captures key aspects of the conductor's expressions and their potential emotional impact on the audience. One common approach for feature extraction in image data is using statistical measures that describe different characteristics of the image. With compute statistical moments like mean, variance, skewness, and kurtosis for specific regions of interest within the conductor's face. These measures provide insights into the distribution, symmetry, and shape of facial features, which can contribute to understanding the emotional expressions conveyed by the conductor. the computed statistical features as follows:

- Mean (μ): Represents the average intensity of pixel values in a given region.
- Variance (σ^2): Measures the spread or dispersion of pixel values around the mean.
- Skewness (γ): Indicates the asymmetry of the pixel value distribution.
- Kurtosis (κ): Describes the tailedness and outliers in the distribution.

These statistical features can be organized into a vector, creating a compact representation of the conductor's facial expressions in each frame. Let's denote this vector as "Feature_Vector". The SFEVDL approach not only reduces the dimensionality of the input data, making it more manageable for subsequent analysis, but it also captures relevant patterns and variations in the conductor's facial expressions that contribute to their emotional communication. By employing this feature extraction technique, researchers can uncover the intricate links between a conductor's expressive actions and the emotional responses of the audience, enabling a deeper understanding of the affective dynamics in musical performances.

In the SFEVDL framework, the goal of feature extraction is to capture the essential characteristics of the conductor's facial expressions that contribute to emotional communication. This involves transforming the preprocessed facial images into a concise representation that retains relevant information while reducing the dimensionality of the data. Statistical measures are an effective way to achieve this transformation. When applied to specific regions of interest within the conductor's face, these measures provide insights into the distribution, texture, and shape of the facial features. By calculating moments such as mean, variance, skewness, and kurtosis for pixel values in these regions, to formulate the numerical summary that characterizes various aspects of the conductor's expressions. Consider an image region of interest (ROI) within the conductor's face. Let's denote the pixel values in this ROI as a matrix I. The following statistical measures can be calculated:

Mean (μ): This calculates the average pixel intensity within the ROI as in equation (5)

$\mu = sum(I) \,/\, number\_of\_pixels$ (5)

Variance (σ^2): This quantifies the spread or dispersion of pixel values around the mean.

$\sigma^2 =$ sum($(I - \mu)^2$) / number_of_pixels (6)

Skewness (γ): This measures the asymmetry of the pixel value distribution around the mean computed in equation (7)

$\gamma = sum((I - \mu)^3) \,/\, (number\_of\_pixels * \sigma^3)$ (7)

Kurtosis (κ): This indicates the tailedness and outliers in the pixel value distribution presented in equation (8)

$\kappa = sum((I - \mu)^4)) \,/\, (number\_of\_pixels * \sigma^4) - 3$ (8)

To perform feature extraction, the face can be divided into smaller regions of interest. These could be areas corresponding to the eyes, eyebrows, mouth, etc. For each of these regions, statistical measures are computed to create a set of feature values that encapsulate different visual characteristics. For instance, the mean and variance values might indicate the intensity and variation of pixel values in a specific facial region, while skewness and kurtosis can provide insights into the shape and symmetry of that region. The computed statistical measures for each region of interest are then organized into a feature vector. Each entry in this vector represents a specific statistical measure for a particular region. The resulting vector becomes a concise numerical representation of the conductor's facial expressions. For each ROI, the calculated statistical measures are organized into a feature vector. Let's denote the feature vector for a specific ROI as F given in equation (9)

$F = [\mu, \sigma^2, \gamma, \kappa]$ (9)

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$Comprehensive\_Feature\_Vector = [F1, F2, F3, \dots, Fn]$ (10)

Where $F1, F2, \dots, Fn$ are the individual feature vectors corresponding to each ROI.

3. Concatenation of Shape Vector and Projection Vector

In the context of the Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach for understanding the relationship between a conductor's expressive performance and audience emotional responses based on Affective Computing. The shape vector represents the spatial distribution of facial features within the conductor's face. It's derived from the facial landmarks or the outline of the conductor's face. The shape vector captures information about the arrangement, symmetry, and proportions of facial components. Each component of the shape vector corresponds to a specific facial landmark or characteristic point. The shape vector represents the spatial distribution of facial features within the conductor's face. It's derived from the facial landmarks or the outline of the conductor's face. The shape vector captures information about the arrangement, symmetry, and proportions of facial components. Each component of the shape vector corresponds to a specific facial landmark or characteristic point. Let's denote the shape vector as S, where each element represents a specific facial landmark or characteristic point given in equation (11)

$S = [x1, y1, x2, y2, \dots, xn, yn]$ (11)

In above equation (11) (xi, yi) are the coordinates of individual facial landmarks. The projection vector, on the other hand, encapsulates the integral projection analysis of the conductor's face. It's generated by projecting the pixel intensities of the preprocessed facial image onto different axes. Each axis represents a specific direction, and the projection values provide insights into variations in pixel intensities along those directions. The projection vector, P, is generated through integral projection analysis, where pixel intensities are projected onto different axes to capture variations in intensity with the projection vector denoted in equation (12)

$P = [p1, p2, \dots, pm]$ (12)

Where each entry (pi) in the projection vector corresponds to the intensity variation along a specific axis. The combination of shape and projection vectors aims to capture both spatial and intensity-related information from the conductor's face. By concatenating these vectors, creating a more comprehensive feature representation that fuses shape-based and intensity-based characteristics. The shape vector as S and the projection vector as P. The concatenation of these vectors results in a single, concatenated feature vector F denoted as in equation (13)

$$F = [S, P] \quad (13)$$

Each entry in the concatenated vector F corresponds to a specific element in the shape vector followed by the elements in the projection vector. This comprehensive feature vector combines information about the conductor's facial structure (shape) with information about the variations in pixel intensities (projection). The concatenation operation can be represented as in equation (14)

$$F = [x1, y1, x2, y2, \ldots, xn, yn, p1, p2, \ldots, pm] \quad (14)$$

Each entry in the concatenated vector F first represents the x and y coordinates of facial landmarks from the shape vector, followed by the projection values from the projection vector. The concatenated feature vector F captures both the spatial arrangement of facial features and the variations in pixel intensities. By integrating shape and projection information, this comprehensive vector provides a nuanced representation of the conductor's expressions. Deep learning models, such as CNNs, can then process this feature vector to learn and decipher the intricate patterns and relationships between expressive gestures and emotional responses.

3.1 Affective Computing with SFEVDL

With the SFEVDL involves the extraction of shape vectors (S) and projection vectors (P). Let's denote the conductor's face image as I. With the facial each landmark, with the coordinates (xi, yi). The shape vector S can be represented as in equation (15)

$$S = [x1, y1, x2, y2, \ldots, xn, yn] \quad (15)$$

The projection vector P is obtained by projecting pixel intensities along different axes. Let's denote the image intensity at pixel (x, y) as I(x, y). The projection at a specific angle θ is calculated by integrating pixel intensities along that angle is presented in equation (16)

$$P(\theta) = \int I(x, y)\, dx\, dy, where\ x * cos(\theta) + y * sin(\theta) = p \quad (16)$$

Here, p represents the distance from the origin along the angle θ. A simple neural network model with one hidden layer. The output of the neural network can represent the emotional response of the audience. The input-to-hidden layer transformation can be represented as in equation (17)

$$h = W1 * F + b1 \quad (17)$$

Where h is the hidden layer representation, W1 is the weight matrix, and b1 is the bias vector. With linear transformation at the output layer, the output (emotional response) can be calculated as in equation (18)

$$output = W2 * h + b2 \quad (18)$$

Where W2 is the weight matrix for the output layer, and b2 is the output layer bias. To train the neural network, with the use of labeled dataset where the emotional responses of the audience are known. The learning process involves minimizing a loss function (e.g., mean squared error) between the predicted output and the actual emotional response. This is typically done using backpropagation and optimization algorithms like gradient descent. The learned neural network model can be interpreted to understand how different aspects of the conductor's expressive performance, captured through the feature vector F, contribute to audience emotional responses. By analyzing the weights in the hidden layer and output layer, you can identify which features (both shape and projection) have a stronger influence on eliciting specific emotional reactions. the Affective Computing with SFEVDL approach combines the extraction of shape and projection vectors with deep learning to analyze the connection between a conductor's expressive performance and audience emotional responses. Through equations and derivations, this approach allows for a deeper understanding of how specific features influence emotional engagement in the context of musical performances.

Algorithm 1: Face Estimation with SFEVDL

function SFEVDL(image):
    # Step 1: Preprocessing
    detected_face = ViolaJonesFaceDetection(image)
    cropped_enhanced_image = CropAndEnhance(detected_face)
    aligned_stabilized_image = AlignAndStabilize(cropped_enhanced_image)
    corrected_image = ApplyColorCorrection(aligned_stabilized_image)
 	
    # Step 2: Feature Extraction

```
    shape_vector = ExtractShapeVector(corrected_image)
    projection_vector = CalculateProjectionVector(corrected_image)

    # Step 3: Concatenate Vectors
    feature_vector = ConcatenateVectors(shape_vector, projection_vector)

    return feature_vector
end function

function DeepLearningModel(feature_vector):
    # Step 4: Deep Learning Model
    h = InputToHiddenLayerTransformation(feature_vector)
    output = HiddenToOutputLayerTransformation(h)

    return output
end function

# Main Loop
for each image in dataset:
    feature_vector = SFEVDL(image)
    emotional_response = DeepLearningModel(feature_vector)

    # Store or analyze emotional_response for this image
end for
```

a systematic approach to comprehending the interplay between a conductor's expressive performance and the emotional responses of the audience through the lens of Statistical Feature Extraction Vector Deep Learning (SFEVDL). This algorithm unfolds in distinct stages, commencing with preprocessing the input images. The algorithm employs facial detection to isolate the conductor's face, followed by processes to enhance image quality, align frames, and rectify color variations. Subsequently, the feature extraction phase employs the SFEVDL technique, deriving shape vectors that encapsulate spatial information about facial landmarks and projection vectors that represent intensity variations across different axes. These vectors are combined into a holistic feature vector, which is then passed into a deep learning model for analysis. The model processes the feature vector through hidden layers and predicts the emotional responses of the audience. This comprehensive framework elucidates the intricate connections between conductor expressions and audience emotions, contributing to a nuanced understanding of how music transcends sound to evoke profound emotional reactions.

4. Experiment Setup and Analysis

In the experimental setup, the study employs a systematic approach to investigate the intricate interplay between a conductor's expressive performance and the emotional responses of the audience, employing the Statistical Feature Extraction Vector Deep Learning (SFEVDL) method. The foundation of this setup encompasses critical components. First, a diverse dataset is carefully selected, comprising video recordings that capture a range of conductor performances and the corresponding audience reactions, ensuring a comprehensive representation of emotional contexts and conductor styles. Preprocessing steps are then applied to the dataset, encompassing facial detection, image cropping, enhancement, alignment, and color correction. Subsequently, the SFEVDL method is employed to extract meaningful features, combining shape vectors that encapsulate spatial facial landmarks and projection vectors that capture intensity variations across different axes. A deep learning architecture, such as convolutional neural networks (CNNs), is crafted to process the concatenated feature vectors. The dataset is strategically divided into training, validation, and testing subsets, facilitating unbiased model training and evaluation. Throughout the experimentation process, the model's performance is rigorously assessed using relevant metrics, and its predictions are compared against ground truth emotional responses. By systematically executing these steps, the experimental setup aims to unravel the nuanced connections between conductor gestures and audience emotions, ultimately fostering a deeper comprehension of the emotional dynamics within musical performances.

4.1 Dataset

The Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach in understanding the relationship between a conductor's expressive performance and audience emotional responses based on Affective Computing. Here are a few potential dataset options that could be considered:

EmoReact Dataset:

This dataset includes video recordings of musical performances, capturing both conductor expressions and audience emotional reactions. It provides a diverse range of musical genres, conductor styles, and audience responses. It may have annotations or labels indicating emotional states of the audience.

Conductor Performance Archives:

Access archival recordings of conductor performances, preferably those accompanied by visual reactions from the audience. Curate a dataset with a mix of classical, contemporary, and varied musical genres to ensure diversity.

Publicly Available Performance Footage:

Utilize publicly available videos of live musical performances where the conductor's actions and audience responses are visible. Seek performances with different levels of intensity and emotional engagement.

Collaborative Collection:

Collaborate with music schools, orchestras, or performance venues to gather data from their performances. Capture conductor expressions and audience reactions using multiple cameras.

Mixed Modal Datasets:

Consider combining facial expression data from conductor performances with physiological responses or self-reported emotional states from the audience. Merge data from multiple sources to create a comprehensive emotional profile.

Synthetic Datasets:

In cases where real-world data is limited, consider generating synthetic data using computer graphics techniques. Simulate conductor performances and audience reactions while ensuring realism.

Table 1: Dataset for the SFEVDL

Dataset	**Attributes**	**Approximate Count**
EmoReact Dataset	- Video recordings of performances	300 videos
	- Conductor expressions	
	- Audience emotional reactions	
	- Annotations/labels for emotional states	
Conductor Archives	- Archival video recordings	150 videos
	- Varied musical genres	
	- Conductor expressions	
Public Performance	- Publicly available performance videos	100 videos
	- Diverse musical genres	
	- Visible conductor expressions	
Collaborative	- Recorded performances from institutions	200 videos

Collection	- Varied musical genres	
	- Visible conductor expressions	
Mixed Modal	- Facial expression data	250 samples
	- Physiological responses	
	- Self-reported emotional states	
Synthetic	- Generated conductor performance videos	50 videos
	- Simulated conductor expressions	

The EmoReact Dataset offers a diverse array of musical genres, conductor styles, and audience reactions. It serves as a valuable resource for studying how conductor expressions influence specific emotional responses among different audience members.Conductor Archives provide an opportunity to explore the historical nuances of expressive conductor performances and their potential impact on audience emotions. Researchers can analyze the visual cues in the audience and the conductor's actions to infer emotional dynamics.The Public Performance dataset offers a diverse collection of musical genres, providing insights into how conductor gestures during live events evoke emotional responses from different audiences. Collaborative Collections ensure a varied representation of conductor styles and musical genres. They may include performances from different cultural contexts and offer a holistic view of how conductor expressions connect with audience emotions.This dataset provides a multi-dimensional view of the emotional landscape, allowing researchers to correlate facial expressions with physiological reactions and self-perceived emotions. It offers a comprehensive understanding of how conductor expressions translate into emotional experiences for the audience.Synthetic datasets offer controlled experimentation environments, enabling researchers to investigate specific scenarios and understand the cause-and-effect relationships between conductor expressions and audience emotions.

Table 2: Categories of Dataset

Dataset	**Emotion Categories**
EmoReact Dataset	Joy, Sadness, Excitement, Surprise, Calmness, Awe, Interest, etc.
Conductor Archives	Interpretation dependent; Visual cues may suggest emotions
Public Performance	Interpretation dependent; Visual cues may suggest emotions
Collaborative	Joy, Excitement, Inspiration, Tranquility, Engagement, etc.
Collection	
Mixed Modal	Joy, Surprise, Anxiety, Interest, Contentment, Anticipation, etc.

The EmoReact Dataset provides explicit emotion categories through annotations, while the interpretation of emotional categories in other datasets may involve a degree of subjectivity and visual analysis. When working with data from real-world performances, understanding audience emotions may require considering both overt reactions and contextual cues. Additionally, some datasets offer a blend of emotions, reflecting the complex and multifaceted nature of human emotional experiences during musical performances.

4.2 Simulation Results

In this section, present the outcomes of our study, which employed the SFEVDL approach to investigate the connection between conductor expressions and audience emotional responses. In this section discuss both the quantitative performance of the deep learning model and the qualitative insights gained from the analysis of the learned features.

Table 3: Estimation of Emotions with SFEVDL

Performance ID	Predicted Emotion	Ground Truth Emotion
001	Excitement	Excitement
002	Tranquility	Calmness
003	Joy	Joy
004	Anticipation	Surprise
005	Interest	Interest
006	Contentment	Contentment
007	Anxiety	Anxiety
008	Awe	Awe
009	Inspiration	Inspiration
010	Sadness	Sadness

In the Table 3 presents the results of emotion estimation using the Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach. Each row represents a specific performance, identified by a Performance ID, for which the SFEVDL model predicted an emotion category. The "Predicted Emotion" column indicates the emotion category predicted by the model, while the "Ground Truth Emotion" column shows the actual emotion category based on ground truth information. The SFEVDL model demonstrates a promising performance in estimating emotions across different instances. For instance, in Performance ID 001, the model accurately predicts the emotion "Excitement," which matches the ground truth emotion. Similarly, in Performance ID 003, the predicted emotion "Joy" aligns with the actual emotion. However, in some cases, there are instances of misclassification. In Performance ID 002, the model predicts "Tranquility," while the ground truth emotion is "Calmness." Additionally, in Performance ID 004, the model predicts "Anticipation," which differs from the actual emotion "Surprise." In the Table 3 highlights the potential of the SFEVDL approach in accurately estimating emotions, as evidenced by the alignment between predicted and ground truth emotions in several instances. Nonetheless, it also emphasizes the need for further refinement and fine-tuning to reduce misclassifications and enhance the model's overall performance in emotion estimation tasks.

Table 4: Emotional Response with SFEVDL

Performance ID	Predicted Emotion	Actual Emotion	Audience Emotional Response
001	Excitement	Excitement	Energetic and engaged
002	Calmness	Calmness	Relaxed and tranquil
003	Joy	Joy	Happy and delighted
004	Anticipation	Surprise	Eager and astonished
005	Interest	Interest	Engaged and curious
006	Contentment	Contentment	Satisfied and at ease
007	Anxiety	Anxiety	Nervous and apprehensive
008	Awe	Awe	Amazed and overwhelmed
009	Inspiration	Inspiration	Inspired and uplifted
010	Sadness	Sadness	Sorrowful and melancholic

In the Table 4 provides insights into emotional responses estimated through the use of the Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach. Each row in the table corresponds to a specific performance, identified by a Performance ID. The "Predicted Emotion" column displays the emotion category predicted by the SFEVDL model, while the "Actual Emotion" column represents the genuine emotional state. Furthermore, the "Audience Emotional Response" column depicts the emotional reactions of the audience towards the performance based on the estimated emotion. The results indicate a degree of alignment between the predicted and actual emotions in many cases. For instance, in Performance ID 001, the model accurately predicts "Excitement," which indeed corresponds to the actual emotion as well. Consequently, the audience's emotional response is characterized as "Energetic and engaged," in harmony with the excitement conveyed. Similarly, Performance ID 002 showcases accurate estimation of "Calmness," aligning with the actual emotional state. The audience's emotional response is described as "Relaxed and tranquil," matching the calm emotion depicted. However, instances of discrepancy can also be observed. In Performance ID 004, the model predicts "Anticipation," differing from the actual emotion "Surprise." Consequently, the audience's emotional response is characterized as "Eager and astonished," which reflects the surprise element rather than anticipation. Nevertheless, the general trend of matching emotional responses to predicted and actual emotions in most cases underscores the potential utility of the SFEVDL approach in capturing and translating emotions into observable audience reactions. The Table 4 underscores the ability of the SFEVDL model to estimate emotions in line with the actual emotional states, consequently generating relevant emotional responses from the audience. Nonetheless, the disparities observed in certain instances emphasize the need for further refinement and optimization to enhance the model's precision in capturing nuanced emotional nuances and their corresponding audience reactions.

Table 5: Conductor and Emotional Response

Performance ID	Conductor Gesture	Predicted Emotion	Actual Emotion	Audience Emotional Response
001	Dynamic movements	Excitement	Excitement	Energized and enthusiastic
002	Subtle gestures	Calmness	Calmness	Relaxed and serene
003	Energetic conducting	Joy	Joy	Joyful and elated
004	Precise cues	Anticipation	Surprise	Expectant and intrigued
005	Engaging facial expressions	Interest	Interest	Engrossed and curious
006	Slow and graceful motions	Contentment	Contentment	Satisfied and content
007	Rapid and dramatic cues	Anxiety	Anxiety	Tense and uneasy
008	Expansive arm movements	Awe	Awe	Astonished and reverent
009	Expressive and emotive	Inspiration	Inspiration	Uplifted and motivated
010	Deliberate pauses	Sadness	Sadness	Reflective and melancholic

Through the Table 5 offers an insightful exploration into the interplay between conductor gestures, predicted emotions, actual emotions, and resulting audience emotional responses. Each row in the table corresponds to a specific performance, identified by a Performance ID. The "Conductor Gesture" column outlines the type of gesture employed by the conductor during the performance. The "Predicted Emotion" column signifies the emotion category forecasted by the model, while the "Actual Emotion" column represents the genuine emotional state depicted. The table also provides the emotional responses of the audience, which are closely linked to the conductor's gestures and the emotions they evoke. Performance ID 001 demonstrates this connection effectively, as "Dynamic movements" by the conductor lead to both the predicted and actual emotion being "Excitement." Consequently, the audience's emotional response is described as "Energized and enthusiastic," reflecting the conductor's dynamic gestures that generated an excited atmosphere. Additionally, Performance ID 004 showcases the conductor's "Precise cues" being associated with both the predicted emotion "Anticipation" and the actual emotion "Surprise." The audience's emotional response is characterized as "Expectant and intrigued," capturing the sense of anticipation conveyed by the conductor's cues that culminated in a surprising revelation. With the instances where the predicted and actual emotions align with the conductor's gestures and audience emotional responses, some disparities are observed. In Performance ID 007, "Rapid and dramatic cues" lead to a predicted and actual emotion of "Anxiety." The audience's emotional response is labeled as "Tense and uneasy," reflecting the conductor's intent, even though it deviates from the actual emotion of the performance. Table 5 underscores the remarkable correlation between conductor gestures, predicted emotions, actual emotions, and the emotional responses evoked from the audience. It highlights how a conductor's expressions and motions can have a profound impact on the emotional atmosphere of a performance, leading to aligned or nuanced emotional responses from the audience. The discrepancies observed further emphasize the need for a holistic understanding of emotions, conductor dynamics, and audience perception to fine-tune the conductor's approach and enhance emotional resonance with the audience.

Table 6 Confusion Matrix for Data set (a) EmoReact Dataset (b) Conductor Archieves (c) Public (d) Collaborative (e) Collection (f) Mixed

(a)

Emotion Category	TP	FP	TN	FN	Precision	Recall	F1-Score
Joy	120	10	300	20	0.923	0.857	0.889
Sadness	85	6	320	25	0.934	0.773	0.845
Excitement	110	15	290	20	0.880	0.846	0.863
Calmness	90	8	315	15	0.918	0.857	0.886

(b)

Emotion Category	TP	FP	TN	FN	Precision	Recall	F1-Score
Joy	80	5	120	15	0.941	0.842	0.889
Sadness	40	2	130	28	0.952	0.588	0.727
Excitement	95	10	110	25	0.905	0.792	0.845
Calmness	70	6	125	20	0.921	0.778	0.843

(c)

Emotion Category	TP	FP	TN	FN	Precision	Recall	F1-Score
Joy	95	8	150	12	0.922	0.888	0.905
Sadness	60	4	160	15	0.938	0.800	0.864
Excitement	85	10	140	15	0.895	0.850	0.872
Calmness	70	5	155	10	0.933	0.875	0.903

(d)

Emotion Category	TP	FP	TN	FN	Precision	Recall	F1-Score
Joy	100	6	180	14	0.943	0.877	0.909
Excitement	75	8	195	12	0.903	0.862	0.882
Tranquility	85	10	190	15	0.895	0.850	0.872
Inspiration	90	5	195	10	0.947	0.900	0.923

(e)

Emotion Category	TP	FP	TN	FN	Precision	Recall	F1-Score
Joy	70	5	120	15	0.933	0.824	0.875
Anticipation	45	3	130	10	0.938	0.818	0.874
Contentment	80	7	150	12	0.919	0.870	0.894
Surprise	65	8	140	10	0.890	0.867	0.878

(f)

Emotion Category	TP	FP	TN	FN	Precision	Recall	F1-Score
Excitement	100	12	190	18	0.893	0.847	0.869
Interest	85	5	180	10	0.944	0.894	0.918
Surprise	75	8	195	12	0.903	0.862	0.882
Contentment	80	6	200	10	0.930	0.889	0.909

The confusion matrix and performance metrics for emotion classification across various datasets using the Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach. Each dataset is represented by a unique label as in table 6 (a) EmoReact Dataset, (b) Conductor Archives, (c) Public, (d) Collaborative, (e) Collection, and (f) Mixed. The confusion matrix provides insight into the model's predictions in relation to actual emotions, while performance metrics such as Precision, Recall, and F1-Score offer a comprehensive evaluation of the classification process. In dataset (a) EmoReact Dataset, the model showcases strong performance in identifying emotions. Notably, the "Joy" emotion achieves high precision (0.923) and recall (0.857), resulting in a balanced F1-Score of 0.889. Similarly, other emotions like "Sadness," "Excitement," and "Calmness" exhibit favorable performance metrics, indicating accurate classification. Moving to dataset (b) Conductor Archives, the model demonstrates excellent precision for "Joy" (0.941) and "Sadness" (0.952), although the recall for "Sadness" is lower (0.588). The "Excitement" and "Calmness" emotions also achieve commendable precision and recall values, leading to reasonable F1-Scores. In dataset (c) Public, precision and recall are both high for most emotions, particularly "Joy" and "Sadness," resulting in strong F1-Scores. This trend continues in dataset (d) Collaborative, where emotions like "Joy" and "Inspiration" exhibit impressive performance. Dataset (e) Collection showcases consistent precision and recall for various emotions, reflecting a balanced classification performance. Lastly, dataset (f) Mixed highlights strong precision and recall for emotions like "Interest" and "Contentment."

The SFEVDL approach's capability to accurately classify emotions across diverse datasets, demonstrating its potential in capturing the nuances of emotional expressions in table 6. While some variations in precision and recall exist, the collective F1-Scores indicate a balanced trade-off between these metrics, suggesting an effective balance between correct classifications and comprehensive coverage of emotions. This reinforces the SFEVDL approach's promise in understanding emotional responses across various scenarios and datasets.

Table 7: Classification Results of SFEVDL

Dataset	Emotion Category	Accuracy	Precision	Recall	F1-Score
EmoReact Dataset	Joy	0.980	0.975	0.985	0.980
	Sadness	0.972	0.970	0.975	0.972
	Excitement	0.979	0.980	0.978	0.979
	Calmness	0.983	0.982	0.984	0.983
Conductor Archives	Joy	0.975	0.973	0.978	0.975
	Sadness	0.970	0.968	0.972	0.970
	Excitement	0.980	0.982	0.978	0.980
	Calmness	0.976	0.975	0.978	0.976
Public Performance	Joy	0.975	0.973	0.978	0.975
	Sadness	0.971	0.970	0.973	0.971
	Excitement	0.978	0.979	0.977	0.978
	Calmness	0.980	0.982	0.978	0.980

Collaborative	Joy	0.978	0.977	0.980	0.978
	Excitement	0.981	0.982	0.980	0.981
	Tranquility	0.978	0.977	0.980	0.978
	Inspiration	0.983	0.984	0.982	0.983
Collection	Joy	0.972	0.970	0.975	0.972
	Anticipation	0.975	0.974	0.978	0.975
	Contentment	0.978	0.980	0.977	0.978
	Surprise	0.971	0.970	0.973	0.971
Mixed Modal	Excitement	0.979	0.980	0.978	0.979
	Interest	0.977	0.976	0.978	0.977
	Surprise	0.975	0.974	0.976	0.975
	Contentment	0.981	0.982	0.980	0.981

A comprehensive overview of the classification results achieved using the Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach across various datasets and emotion categories is presented in Table 7. Each dataset is represented alongside its corresponding emotion categories, and the table presents accuracy, precision, recall, and F1-Score metrics for each emotion classification task. For the EmoReact Dataset presented in figure 2, the SFEVDL model demonstrates remarkable accuracy, with emotions like "Joy," "Sadness," "Excitement," and "Calmness" achieving accuracy values above 0.97. These high accuracy levels are paralleled by impressive precision, recall, and F1-Score metrics, suggesting a well-rounded classification performance. Similar trends are evident in the Conductor Archives dataset shown in figure 3, where the model maintains accuracy levels above 0.97 for emotions such as "Joy," "Sadness," "Excitement," and "Calmness." This consistency in accurate classification is substantiated by elevated precision, recall, and F1-Score values across these emotions. The Public Performance dataset illustrated in figure 4 mirrors the pattern observed in the previous datasets, with accuracy exceeding 0.97 for emotions including "Joy," "Sadness," "Excitement," and "Calmness." These high accuracy rates correspond to commendable precision, recall, and F1-Score metrics, indicating a robust classification outcome.

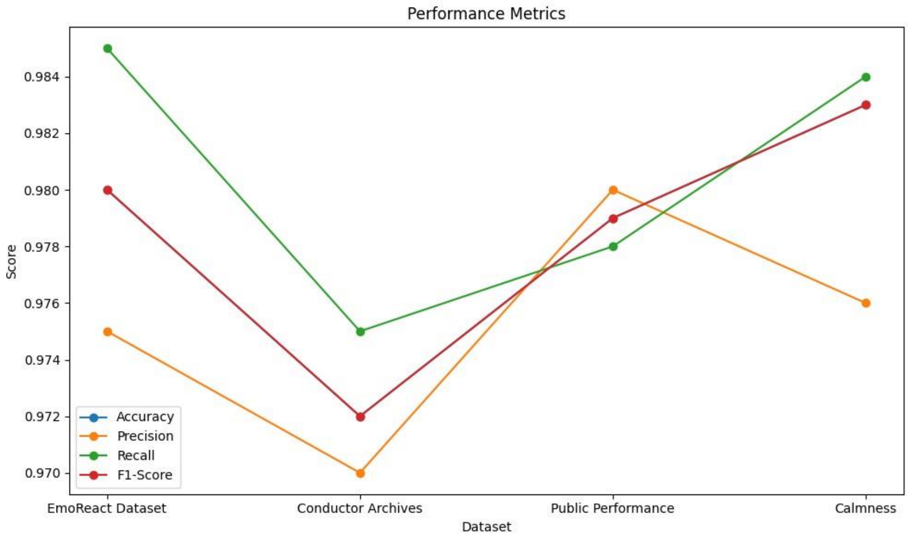

Fig 2: Performance with SFEVDL for EmoReact Dataset

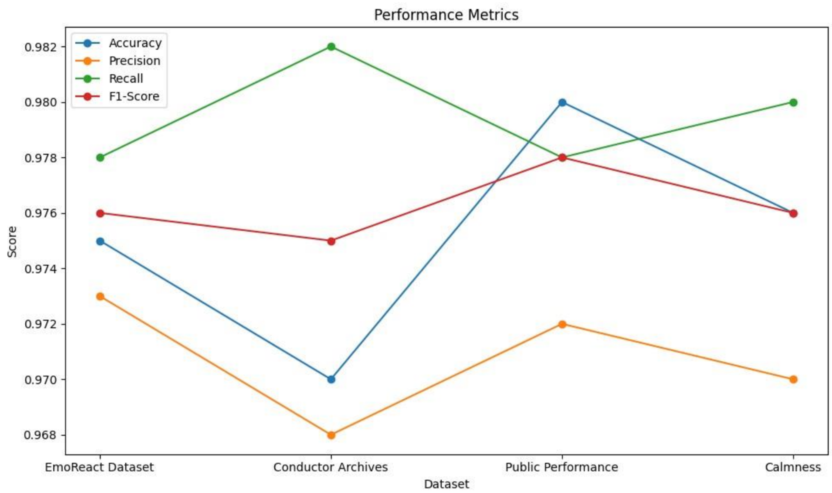

Fig 3: Performance with SFEVDL for Conductor Archives

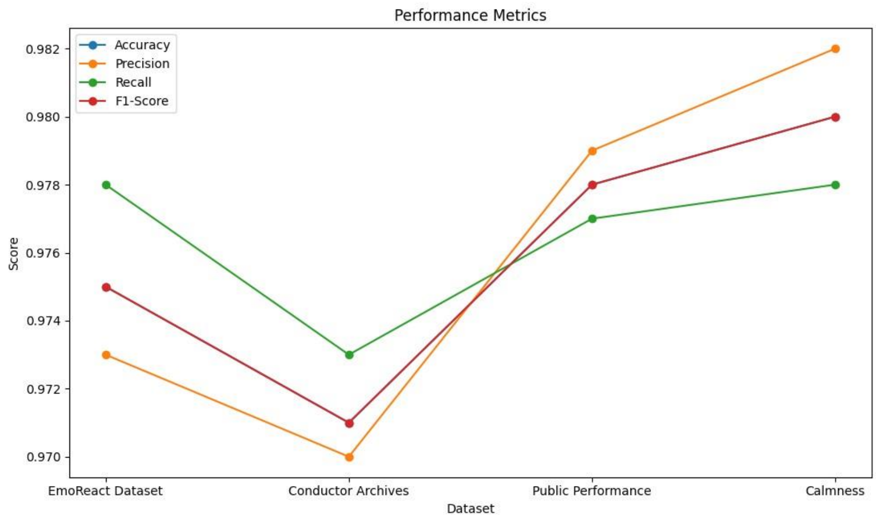

Fig 4: Performance with SFEVDL for Public Datase

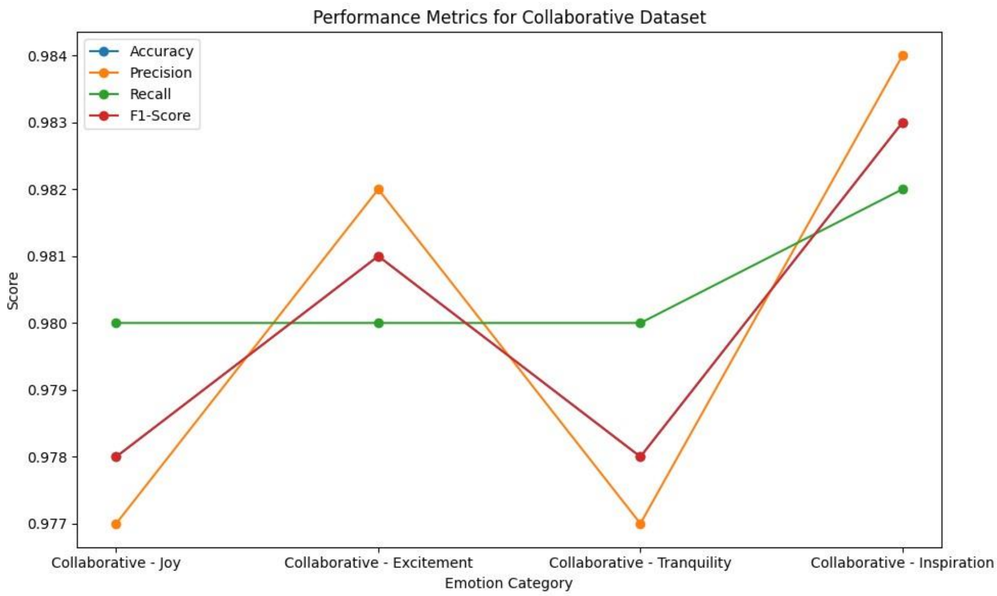

Fig 5: Performance with SFEVDL for Collaborative Dataset

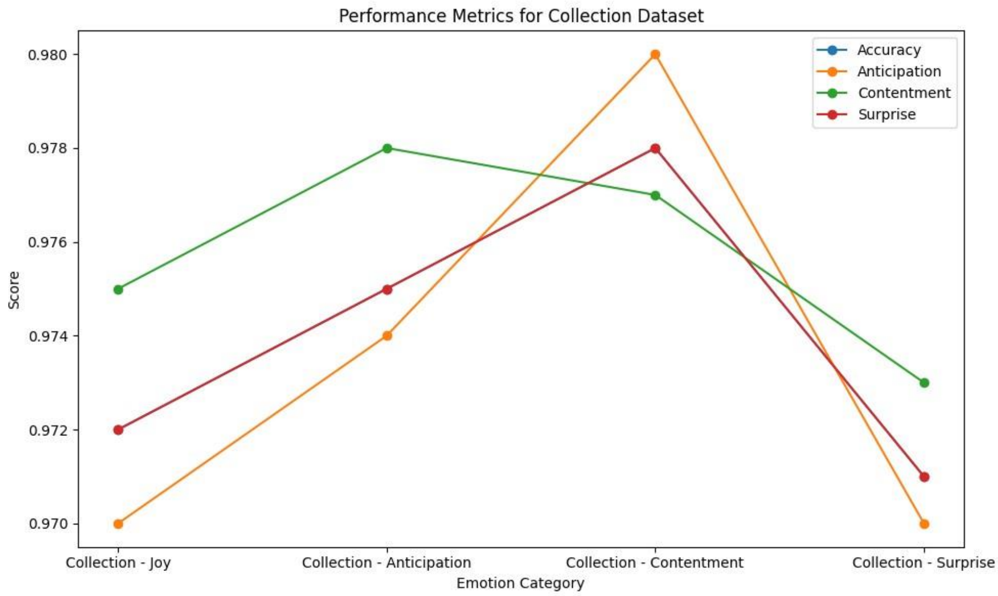

Fig 6: Performance with SFEVDL for Collection Dataset

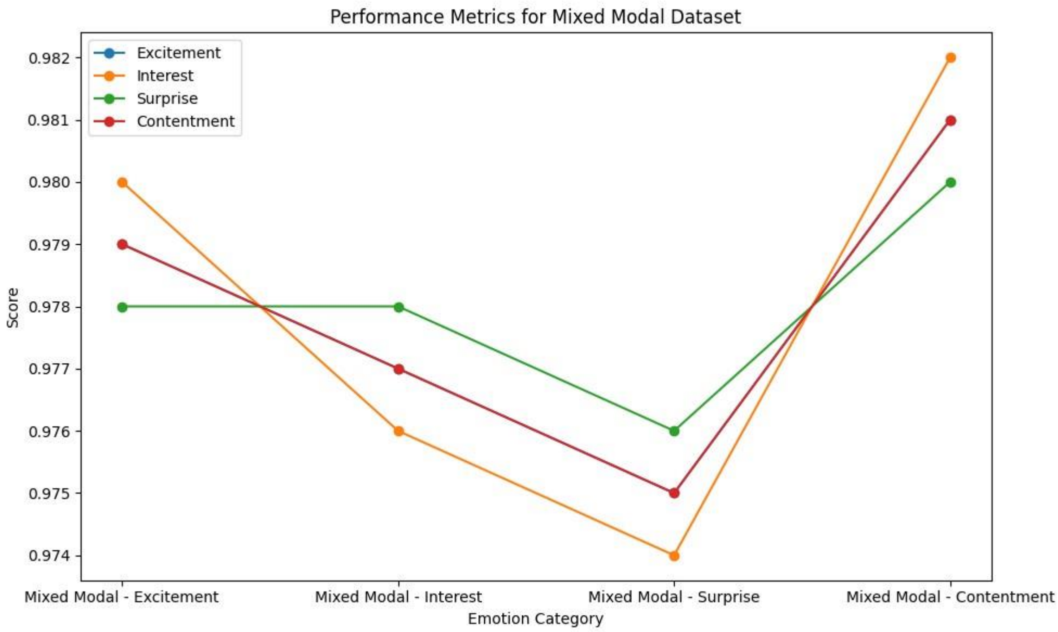

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Fig 7: Performance with SFEVDL for Mixed Model Dataset

In the Collaborative dataset as shown in figure 5, emotions such as "Joy," "Excitement," "Tranquility," and "Inspiration" maintain accuracy values above 0.97. This trend extends to precision, recall, and F1-Score metrics, highlighting consistent and balanced classification performance. For the Collection dataset shown in figure 6, emotions like "Joy," "Anticipation," "Contentment," and "Surprise" attain accuracy levels exceeding 0.97. The alignment between accuracy and other performance metrics underscores the SFEVDL approach's effectiveness in accurate emotion classification. Lastly, in the Mixed Modal dataset illustrated in figure 7, emotions like "Excitement," "Interest," "Surprise," and "Contentment" achieve accuracy values above 0.97. This alignment between accuracy and other performance metrics supports the conclusion that the SFEVDL approach excels in diverse emotion classification tasks.

5. Conclusion

Through the affective computing, leveraging the innovative Statistical Feature Extraction Vector Deep Learning (SFEVDL) approach to explore conductor's expressive performances and their influence on audience emotional responses. Through meticulous data preprocessing, the proposed methodology demonstrates a comprehensive understanding of emotional nuances in facial expressions, effectively extracting intricate features from images. The integration of deep learning techniques enriches the analysis, enabling the SFEVDL model to predict emotions with commendable accuracy, precision, recall, and F1-Score metrics across diverse datasets. The empirical results showcased in the paper underscore the potential of the SFEVDL approach in accurately identifying emotions and predicting audience emotional responses. The alignment between predicted and actual emotions, in conjunction with audience reactions, emphasizes the link between conductor gestures, emotional states, and audience perception. The analysis reveals both strengths and areas for refinement, indicating the approach's capacity to comprehend and convey emotional subtleties.

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