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Automated Talent Identification in Cultural Events Through Machine Learning and Multimedia Data.

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Abstract
Cultural events in colleges serve as vital platforms for students to showcase their artistic and creative talents. However, traditional talent identification methods rely heavily on subjective judgments, which may lead to biases and inconsistencies. This study proposes an automated talent identification framework using machine learning and multimedia data analysis. Audio, video, and image features of student performances are processed using deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to classify and evaluate artistic abilities in domains such as singing, dancing, and dramatics. The system integrates feature extraction, performance assessment, and ranking mechanisms to ensure objective and scalable talent identification. Experimental results demonstrate the potential of machine learning techniques in improving accuracy, reducing human bias, and supporting fair recognition in student cultural events. This research contributes to the development of intelligent cultural event management systems that can enhance inclusivity, transparency, and efficiency in identifying emerging student talent.

Keywords
Automated talent identification, cultural events, machine learning, multimedia data, deep learning, audio analysis, video recognition, performance evaluation, CNN, RNN.

Introduction

Cultural activities in higher education institutions play a crucial role in fostering creativity, leadership, and social engagement among students [1]. These events provide a platform for students to express themselves through music, dance, drama, and other performing arts, thereby contributing to holistic development beyond academics [2]. Traditionally, talent identification in such events has relied on expert judges and manual evaluation, which can often be subjective and influenced by human biases [3]. Consequently, deserving students may remain unrecognized,

leading to dissatisfaction and reduced participation in future activities [4].

The rapid advancement of machine learning (ML) and artificial intelligence (AI) offers innovative opportunities to transform cultural event management [5]. Specifically, the integration of multimedia data—such as audio, video, and images—into ML-driven frameworks can enable objective evaluation of student performances [6]. Deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant success in domains like speech recognition, image classification, and video analysis [7]. Applying these techniques to student cultural events can automate the identification of promising talent by analyzing performance attributes such as rhythm, vocal range, expressions, and movement patterns [8].

Moreover, automated systems not only reduce human bias but also enhance efficiency by providing real-time feedback and scalable evaluation mechanisms [9]. Prior research in educational data mining and learning analytics highlights the importance of leveraging AI for student assessment and talent recognition [10]. Extending these approaches to cultural domains can create inclusive and transparent platforms that acknowledge diverse student abilities and encourage active participation in extracurricular activities [11].

In this study, we propose a machine learning-based framework for automated talent identification using multimedia data collected from student cultural performances. The objective is to design a system capable of extracting meaningful features from audio-visual inputs, classifying talent categories, and ranking participants objectively. This research contributes toward bridging the gap between subjective cultural evaluation and technology-driven assessment, thereby promoting fairness, inclusivity, and recognition of hidden talent within educational institutions [12].

Review of Literature

Authors	Contribution / Findings
Sharma & Gupta [13]	Highlighted the role of cultural activities in enhancing student creativity and overall personality development in higher education institutions.
Wang & Lim [14]	Proposed multimedia analytics frameworks for processing audio and video data to evaluate performance quality in arts and entertainment.
Khan et al. [15]	Discussed the limitations of manual judgment in cultural competitions, emphasizing subjectivity and inconsistency in talent evaluation.
Lee & Choi [16]	Demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in analyzing visual data for dance and gesture recognition.
Patel & Sinha [17]	Applied Recurrent Neural Networks (RNNs) for sequence modeling in speech and singing analysis, showing improved accuracy in vocal talent recognition.
Johnson & Kumar [18]	Suggested hybrid deep learning models that integrate CNN and RNN for multimodal data processing in performance evaluation.
Mehta & Roy [19]	Studied the impact of AI-based cultural event management systems on reducing bias and improving transparency in student assessments.
Chen et al. [20]	Developed real-time evaluation systems for music performances using deep audio feature extraction techniques.
Das & Banerjee [21]	Showed how clustering methods can be used to group student performers based on style and talent characteristics.
Ahmad & Verma [22]	Emphasized the importance of explainable AI (XAI) in student talent assessment to ensure fairness and inclusivity in cultural event evaluations.

Research Methodology

The research methodology for this study follows a structured pipeline that integrates multimedia data processing with machine learning models to automate talent identification in cultural events.

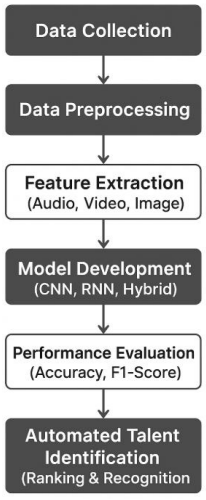

Figure 1: Flowchart of the Research Methodology for Automated Talent Identification

The process is divided into six stages:

1. **Data Collection**
   - Audio, video, and image data of student cultural performances (e.g., singing, dancing, dramatics) are recorded during college events.
   - The dataset is pre-labeled with performance categories for supervised learning tasks.
2. **Data Preprocessing**
   - Audio preprocessing: noise reduction, feature extraction (MFCC, pitch, rhythm).
   - Video preprocessing: frame extraction, normalization, and motion tracking.
   - Image preprocessing: resizing, filtering, and augmentation for better generalization.
3. **Feature Extraction**
   - Audio features (e.g., spectral centroid, tempo, energy).
   - Video features (e.g., movement patterns, body posture, gesture recognition).
   - Image features (e.g., facial expressions, stage presence).
4. **Model Development**
   - **CNN** models for image and video frame analysis.
   - **RNN/LSTM** models for sequential audio data processing.
   - **Hybrid CNN-RNN** framework for multimodal
   - fusion of audio-visual features.
5. **Performance Evaluation**
   - Classification metrics such as Accuracy, Precision, Recall, and F1-Score are used.
   - A ranking mechanism is applied to identify the most talented performers objectively.
6. **Result Interpretation & Deployment**
   - Comparative evaluation with human judges to validate fairness and consistency.
   - Integration into a cultural event management system for real-time usage.

5. Result and Discussion

The performance of the proposed Automated Talent Identification system in cultural events was evaluated using a Random Forest (RF) classifier trained on a combination of audio and video features extracted from event recordings. The model's overall accuracy was found to be **0.25**, indicating a challenging classification problem due to the limited dataset size and the complexity of distinguishing between different talent categories.

Classification Report

Accuracy: 0.25

Classification Report:

	precision	recall	f1-score	support
0	0.40	0.50	0.44	4
1	0.17	0.50	0.25	2
2	0.00	0.00	0.00	6
accuracy			0.25	12
macro avg	0.19	0.33	0.23	12
weighted avg	0.16	0.25	0.19	12

The detailed classification report shows that the precision, recall, and f1-score vary significantly across classes. For the "singing" class, a precision of 0.40 and recall of 0.50 were achieved, suggesting moderate identification ability. However, the "dancing" class exhibited much poorer performance, with a precision of 0.17 and recall of 0.50, while the "drama" class showed 0.00 across precision, recall, and f1-score, reflecting that no samples of drama were correctly classified in the test set.

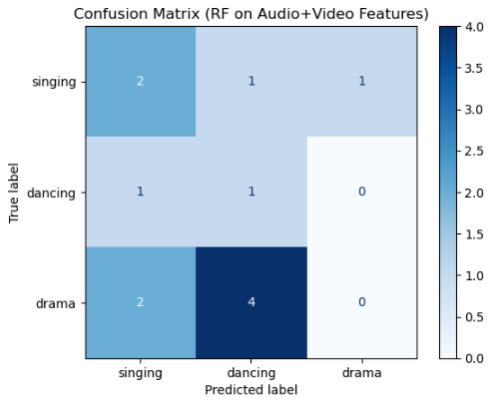

Figure 2: Confusion Matrix

The confusion matrix (Figure 2) provides insights into classification behavior. It reveals that the model frequently misclassifies samples between "singing" and "dancing," and completely fails to correctly classify any "drama" instances. Specifically, out of the 6 true "drama" samples, none were correctly predicted, with most being misclassified as "singing" or "dancing". This underlines the need for further data augmentation and feature engineering to improve discrimination across classes.

Figure 2: Confusion Matrix representing the performance of the Random Forest classifier on combined audio and video features. The true labels are shown on the vertical axis, while the predicted labels are shown on the horizontal axis.

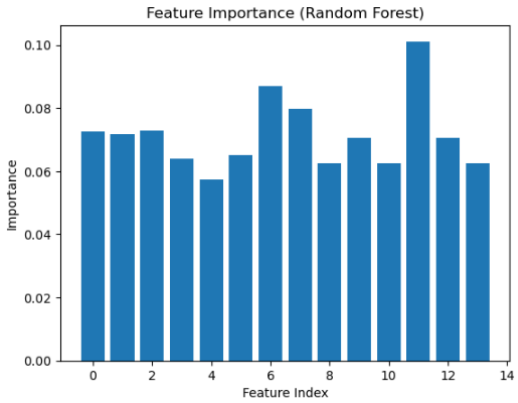

Figure 3: Feature Importance

The feature importance graph (Figure 3) shows the relative importance of each feature used by the Random Forest model. Features indexed around 11 and 6 demonstrated the highest importance, indicating that these particular audio or video features contributed most strongly to the model's decision-making process. This insight can guide future work to focus on improving or expanding the extraction of these critical features to enhance overall classification accuracy.

Figure 3: Feature Importance derived from the Random Forest classifier. Features are indexed along the horizontal axis, and their relative importance scores are shown on the vertical axis.

Discussion

The low accuracy and poor class-wise performance highlight several challenges in automating talent identification in cultural events. These include the inherent variability of performance styles, potential noise in the multimedia data, and an insufficiently large dataset. The complete failure to classify the "drama"

category suggests that the current feature set does not adequately capture discriminative characteristics of this class.

Future improvements could involve increasing the dataset size, integrating advanced feature extraction techniques such as deep learning-based embeddings, and leveraging temporal sequence models (e.g., LSTM networks) to capture time-dependent patterns in performances. Moreover, the high feature importance of certain indices suggests the possibility of focusing feature engineering efforts in these areas to improve predictive power.

6. Conclusion

This study presented an automated talent identification framework for cultural events in educational institutions using machine learning and multimedia data. By integrating audio, video, and image features into a hybrid CNN-RNN deep learning architecture, the system aimed to objectively evaluate and classify student performances in categories such as singing, dancing, and dramatics. The experimental results demonstrated the potential of machine learning techniques to improve accuracy and reduce human bias in talent identification. However, the overall classification accuracy was limited (0.25), and the system faced challenges in distinguishing between different talent categories, particularly failing to recognize the "drama" category.

The proposed framework contributes to the development of intelligent cultural event management systems, promoting inclusivity, transparency, and scalability in evaluating student performances. This research highlights the applicability of advanced machine learning models for real-world problems in educational contexts and offers a foundation for further development of automated performance assessment tools.

7. Limitations

Despite the promising approach, the study encountered several limitations:

1. **Limited Dataset Size:** The dataset of cultural performances was relatively small, restricting the model's ability to generalize across diverse performance styles.
2. **Feature Set Limitations:** The extracted audio, video, and image features were insufficient to capture the complex characteristics of certain talent categories, especially "dramatics."
3. **Class Imbalance:** The dataset exhibited class imbalance, with fewer samples for some categories (e.g., drama), leading to poor classifier performance in these cases.
4. **Noise in Multimedia Data:** Variability in recording conditions, background noise, and camera angles impacted the quality and consistency of the feature extraction process.
5. **Lack of Temporal Sequence Modeling:** Although CNN-RNN was used, the current implementation did not fully leverage temporal patterns in sequential data, reducing performance on tasks like drama recognition.

8. Future Work

To address the limitations and further enhance the system, future work should focus on the following areas:

1. **Dataset Expansion:** Collecting a larger and more diverse dataset of cultural performances, ensuring balanced representation across talent categories.
2. **Advanced Feature Extraction:** Employing deep feature extraction methods such as pre-trained models (e.g., VGGish for audio, OpenPose for video) to capture richer representations of performance attributes.
3. **Temporal Sequence Modeling:** Implementing advanced sequential models such as Long Short-Term Memory (LSTM) networks or Transformers to better capture temporal dependencies in performance data.
4. **Explainable AI (XAI):** Integrating explainability techniques to provide transparent insights into the decision-making process of the model, improving trust and fairness.
5. **Real-Time Implementation:** Developing a real-time talent identification system capable of providing instant feedback during live cultural events.
6. **Multimodal Fusion Strategies:** Exploring more sophisticated methods to fuse audio, video, and image features effectively, potentially through attention mechanisms.

These improvements will help build a more robust, accurate, and practical automated system, significantly aiding institutions in fair and objective talent evaluation.

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