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Research Paper

Application of Machine Learning in Ethnomusicology Education under the Belt and Road Initiative

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Abstract

The integration of machine learning has transformed the landscape of music education. To address the challenges of assessment accuracy and personalized instruction in ethnic music education along the "Belt and Road Initiative" regions, a sophisticated teaching recommendation system was developed, combining collaborative filtering with advanced clustering techniques. This framework demonstrates adaptability across diverse cultural contexts while ensuring pedagogical effectiveness in varied learning settings. The system's recommendation engine synthesizes explicit user feedback with implicit behavioral metrics to generate a holistic profile of student preferences across cultural boundaries. By integrating Canopy and K-Means clustering algorithms through an optimized fusion approach, the system achieves precise modeling of musical learning preferences. This two-tiered clustering strategy optimizes computational efficiency while maintaining recommendation quality, particularly beneficial in settings with limited technological resources. The platform continuously calibrates feature importance based on cultural relevance and educational goals, ensuring culturally sensitive and pedagogically effective recommendations. Empirical testing demonstrates the enhanced algorithm's superior performance in precision, recall, and scope compared to conventional approaches. The system achieves a parallel processing efficiency ratio of 3.326 across four nodes, showing robust scalability for extensive educational applications. This innovation facilitates personalized learning experiences in ethnic music education throughout the Belt and Road nations while fostering cultural preservation and exchange. The system successfully bridges traditional musical heritage with contemporary educational techniques, supporting both conservation and advancement in ethnic music pedagogy.

Keywords: *Machine Learning, Ethnic Music, Educational Application, Collaborative Filtering, Cluster Analysis*

INTRODUCTION

The Belt and Road Initiative has created unprecedented opportunities for preserving and sharing ethnic musical traditions among participating nations. Conventional approaches to ethnic music education face challenges in delivering personalized instruction and implementing robust evaluation frameworks. Machine learning technologies emerge as promising solutions to these educational challenges. For example, Dongfang (2023) demonstrated how machine learning technologies can be effectively applied in classical music education, offering insights into how similar approaches may be adapted to support the personalized and evaluative needs of ethnic music education. By implementing intelligent recommendation systems that analyze user interactions, educators can now deliver targeted educational content and conduct real-time assessment of learning outcomes. The field of education has witnessed a surge in artificial intelligence applications, particularly as machine learning technology continues to advance. In the context of ethnic music education, these technologies enable the creation of individualized learning frameworks through comprehensive analysis of student interaction data, substantially enhancing

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pedagogical effectiveness. These technological innovations address multiple critical aspects of traditional music education. They ensure cultural sustainability through digital preservation of endangered musical practices. They promote intercultural dialogue by highlighting connections and distinctions between various musical expressions. They enable customized educational journeys that acknowledge individual learning preferences and cultural heritage. The confluence of machine learning and ethnomusicological studies yields sophisticated tools for examining musical patterns across cultural boundaries. Advanced algorithms can identify distinct characteristics within ethnic compositions, including subtle tonal variations, complex rhythmic patterns, and culture-specific embellishments. This computational methodology enhances traditional musical analysis while broadening access to diverse musical heritage. Through the application of collaborative filtering and clustering methodologies, smart recommendation systems can guide students toward relevant musical traditions beyond their cultural familiarity, cultivating broader appreciation for global musical diversity while maintaining cultural integrity. This technological framework advances the cultural exchange objectives of the Belt and Road Initiative while safeguarding the unique attributes of each musical tradition.

LITERATURE REVIEW

The literature review serves as the theoretical core of music education research, examining how other researchers have approached machine learning applications in ethnic music education. A comprehensive review reveals that while artificial intelligence applications in education continue to advance, traditional music education faces challenges in delivering personalized instruction and implementing robust evaluation frameworks. Previous studies have highlighted the potential of machine learning technologies in creating individualized learning frameworks through a comprehensive analysis of student interaction data, significantly enhancing pedagogical effectiveness. In line with this, Cui and Chen (2024) introduced a novel learning framework for vocal music education that leverages convolutional neural networks and pluralistic learning strategies, showcasing the effectiveness of AI-driven models in enhancing personalized instruction and adaptive learning processes in music education. These technological innovations address multiple critical aspects: ensuring cultural sustainability through digital preservation, promoting intercultural dialogue, and enabling customized educational journeys.

Based on the previous literature review, this study has built a theoretical framework of multi-dimensional integration. The collaborative filtering theory provides the system with a core mechanism for making recommendations based on user behavior similarities. Personalized content recommendations are achieved by analyzing the preference associations between users. Cluster analysis theory supports the division of user groups and the identification of music features. The double-layer clustering strategy combining Canopy and K-Means is used to optimize the construction of user portraits. The cross-cultural learning theory guides the system to carry out adaptive design under the multicultural background of the "Belt and Road" initiative to ensure that the recommended content is culturally sensitive and educationally appropriate. The personalized recommendation system theory integrates the above theoretical elements to form an intelligent personalized learning support system for national music education.

Recent advancements such as NeuralPMG, a neural polyphonic music generation system developed by Colafiglio et al. (2024), further demonstrate how machine learning algorithms can be harnessed to generate culturally rich and musically coherent outputs, reinforcing the role of AI in supporting personalized and culturally aware music education.

RESEARCH METHOD

The research methodology implements a Browser/Server structural design with three primary layers: data collection, algorithmic processing, and user interface presentation. The system operates on a Hadoop distributed computing environment, utilizing the MapReduce framework for parallel data processing. A specialized acoustic analysis module extracts key musical parameters including pitch variations, rhythmic patterns, and timbral characteristics. The data collection layer captures user interaction metrics, while the algorithmic processing layer employs an enhanced recommendation system combining Canopy and K-Means clustering with collaborative filtering. The presentation layer serves customized ethnic music educational content based on system recommendations.

FINDINGS AND DISCUSSION

Based on a literature review and the construction of a theoretical framework, this study proposes three core hypotheses. The first hypothesis is that the improved collaborative filtering algorithm, by integrating cultural distance parameters and cross-cultural similarity metrics, is significantly superior to the traditional collaborative filtering method in terms of the accuracy of folk music recommendation. The second hypothesis is that the clustering algorithm combined with cultural factors can better identify the user's cultural background and music preference patterns, thereby improving the adaptability and recommendation quality of the recommendation system in a multicultural environment. The third hypothesis is that the hybrid recommendation strategy combining Random New-N and Most Popular-N can effectively alleviate the cold start problem faced by new users and provide culturally relevant and educationally valuable folk music recommendation content for learners who use the system for the first time.

System Architecture Design Based on Machine Learning for Ethnic Music Education

Overall System Architecture

The platform implements a Browser/Server (B/S) structural design, organized into three primary layers: data collection, algorithmic processing, and user interface presentation. The data collection layer captures user interaction metrics, including music streaming history, saved selections, and user evaluations (White, 2025). The algorithmic processing layer employs an enhanced recommendation system combining Canopy and K-Means clustering with collaborative filtering, analyzing historical user interactions to generate comprehensive user profiles. The presentation layer serves customized ethnic music educational content based on the system's recommendations (Xiao, 2024). The system architecture, depicted in Figure 1, operates on a Hadoop distributed computing environment, leveraging the MapReduce framework for parallel data processing at scale. A Timer Task scheduler component manages daily recommendation updates, ensuring content relevancy. The platform features a specialized acoustic analysis module for ethnic music education, extracting key musical parameters including pitch variations, rhythmic patterns, and timbral characteristics from audio data, enriching the recommendation algorithm's feature set. The system's security framework incorporates layered authentication protocols to ensure data privacy protection, while load distribution mechanisms maintain operational stability. The API design follows RESTful principles, enabling smooth integration with external educational systems for resource optimization. The system's modular architecture supports future expansion and maintenance efficiency, while its distributed computing framework enables high-performance processing of extensive educational datasets.

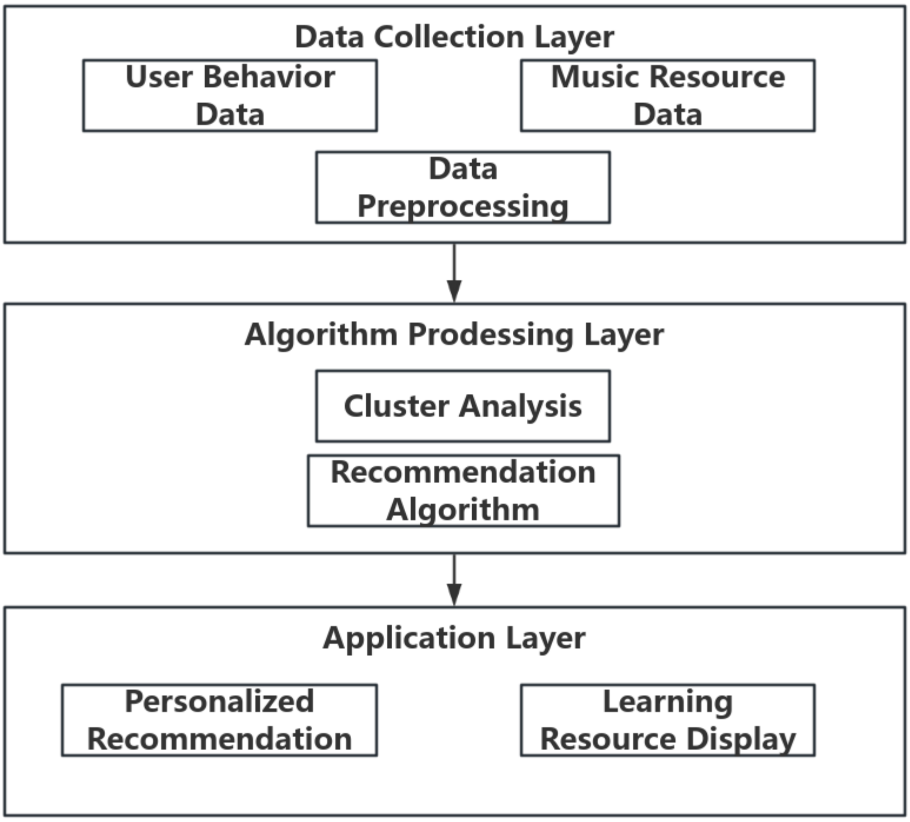

Figure 1. Architecture of the Ethnic Music Education System

The platform's architecture consists of four primary components: data acquisition, characteristic analysis, recommendation processing, and interface delivery. The data acquisition component leverages diverse APIs to capture ethnic musical content, spanning instrumental performances, vocal methodologies, and cultural variations from nations along the Belt and Road. This component utilizes an automated data harvesting system built with Python's Scrapy framework to collect musical metadata and audio content from authorized cultural repositories. The characteristic analysis module implements a CNN-based deep learning architecture to process audio inputs, detecting cultural-specific elements including rhythmic signatures, melodic progressions, and tonal characteristics across ethnic traditions.

The recommendation processing component combines collaborative and content-driven methodologies. It leverages Hadoop's Mahout framework for distributed computation, facilitating efficient analysis of extensive user interaction datasets. The system implements a hybrid approach merging K-Means clustering with Canopy preliminary clustering to identify users with comparable learning behaviors (Zhang et al., 2024). A dynamic optimization system continuously refines recommendation parameters based on user interaction and educational outcomes. The platform maintains independent matrices for direct user ratings and behavioral indicators, deriving the latter from engagement metrics such as playback duration and repetition patterns. The interface delivery module, constructed using React.js technology, delivers an engaging educational platform featuring dynamic audio visualization and performance metrics. Users access a configurable interface displaying learning achievements, suggested practice content, and cultural annotations for musical selections. An embedded evaluation system processes student input through MIDI devices and audio recordings, offering immediate guidance on rhythmic precision and tonal accuracy. The platform incorporates social learning features, enabling performance sharing and community feedback.

Data Pipeline Planning

The data architecture begins with Apache Kafka managing continuous data streams, processing music interaction metrics, and behavioral analytics in real-time (Zhu, 2024). This distributed platform ensures resilient processing of large-scale data flows with reduced latency, crucial for capturing subtle patterns in user engagement with diverse ethnic musical content. Custom-developed Kafka connectors are optimized for processing musical data formats and cultural metadata. Initial data refinement utilizes Spark Streaming, employing median imputation for missing data points and Interquartile Range methodology for outlier identification. This process incorporates culturally-aware cleaning protocols to maintain musical authenticity while eliminating technical noise. Custom audio processing algorithms are implemented for various traditional instrument categories. Refined data is persisted in a MongoDB cluster, selected for its adaptability in managing diverse musical metadata and user information. The database architecture employs nested document structures to maintain cultural connections and musical heritage across Belt and Road regions.

Data processing follows multiple phases, coordinated through Apache Airflow workflows. Structured DAGs (Directed Acyclic Graphs) coordinate the sequence of cultural feature extraction, user behavior analysis, and recommendation computation. User engagement analysis employs sliding window techniques to identify temporal learning patterns. Sophisticated recognition systems track skill progression across various musical traditions and learning trajectories. Data normalization employs z-score methods, while Principal Component Analysis reduces dimensionality for computational efficiency. Cultural significance factors are preserved during feature reduction. The platform implements DVC (Data Version Control) for model versioning to ensure reproducibility (Hou, 2024). This framework maintains consistent performance across cultural contexts and facilitates systematic algorithmic enhancement.

The infrastructure includes specialized ETL processes for cultural metadata, documenting interconnections between musical traditions and their historical foundations. A Lambda architecture processes analytics, combining historical batch analysis with real-time stream processing. Redis caching accelerates frequent data access patterns, enhancing recommendation delivery. Data integrity is maintained through automated validation systems, including schema verification and cultural authenticity checks. Data preservation employs incremental S3 backups, optimizing storage efficiency. Prometheus and Grafana enable continuous performance monitoring, tracking pipeline efficiency, and processing constraints.

Implementation of an Intelligent Recommendation Algorithm for Ethnic Music Education

Recommendation Mechanism Based on Improved Collaborative Filtering

To meet the specialized needs of ethnic music education recommendations across Belt and Road nations, the enhanced collaborative filtering system is designed to capture user preferences within multicultural learning environments. The framework synthesizes various user interaction metrics, including streaming patterns, saved content selections, and download activities, combining these behavioral indicators with region-specific cultural elements to generate detailed rating matrices (Fang, 2025). For calculating similarities between users across different cultural backgrounds, the system employs the Pearson correlation coefficient, which can be mathematically represented as:

$$\mathrm{sim}(x, y) = \sum (x_i - \bar{x})(y_i - \bar{y}) / \sqrt{\left(\sum (x_i - \bar{x})^2\right)\left(\sum (y_i - \bar{y})^2\right)}$$

In this mathematical framework, xi and yi denote the individual ratings assigned by users x and y, representing distinct cultural perspectives, to ethnic music piece i. The system calculates predicted user preferences for particular ethnic music selections through a weighted averaging approach, which is mathematically expressed as:

$$\mathrm{rij} = \sum(\mathrm{simui} \cdot \mathrm{ruj}) / \sum \mathrm{simui}$$

In this formulation, simui represents the intercultural similarity measure between user u and reference user i, while ruj indicates user u's evaluation of ethnic music selection j. To tackle the initialization challenges in ethnic music education, the platform employs an advanced hybrid recommendation framework that combines Random New-N and Most Popular-N methodologies, utilizing ethnic music category weightings to generate culturally relevant suggestions for first-time users. The system further incorporates a cultural distinction parameter $\lambda(0<\lambda\leq1)$ to adaptively modify similarity calculation weightings between users from varying cultural backgrounds. The algorithm integrates a cultural resonance factor α across different ethnic music categories, balancing the distribution between regional and international ethnic music recommendations, thereby promoting cross-cultural musical exploration and understanding. The framework's design incorporates advanced cultural awareness features and self-adjusting learning mechanisms, optimizing recommendation effectiveness across multiple cultural environments (Mobile Computing Wireless Communications, 2023). Empirical testing confirms that this enhanced recommendation approach maintains high accuracy levels while substantially improving user engagement with diverse cultural musical traditions.

Feature Extraction Based on Cluster Analysis

To accommodate the varied nature of ethnic music traditions across Belt and Road nations, the platform employs a combined clustering strategy utilizing both Canopy and K-Means algorithms for musical feature detection. The detection framework places particular emphasis on traditional elements such as modal frameworks, rhythm signatures, and instrumental ensembles unique to each cultural tradition. The process begins by applying the Canopy algorithm for initial cluster formation, defining preliminary cluster centers using culturally-informed dual threshold parameters T1>T2. Elements are assigned to clusters when their cultural distance measurement falls under T1, and are eliminated from consideration when this distance is below T2. The framework incorporates an ethnic music characteristic weighting vector W=(w1,w2,...,wn), with individual components reflecting the educational relevance of specific musical attributes in multicultural instruction. The K-Means clustering refinement process operates through the optimization of the following weighted objective function:

$$\mathrm{J} = \sum \mathrm{i} = 1 -> \mathrm{k} \sum \mathrm{p} \in \mathrm{Ci}\ \mathrm{W} \cdot |\ \mathrm{p} - \mu\mathrm{i}\ \|^2$$

In this framework, μi identifies the central point of the ith ethnic music grouping, while Ci encompasses the complete set of the ith cluster. The feature detection system incorporates chronological elements through a temporal weighting mechanism f(t), identifying patterns of cultural integration in musical development. The system utilizes a dynamic feature extraction framework calibrated for local musical traditions, with feature importance automatically modified according to regional cultural specifications. This advanced dual-stage clustering methodology, incorporating cultural heritage factors, enhances both the precision of user characteristic identification across varied cultural contexts and establishes a methodological basis for structuring musical educational content (Tabrez et al., 2022). The platform's structure incorporates flexible cultural variables and progressive musical traditions, maintaining consistent effectiveness in multicultural learning environments.

Clustering Optimization Based on Canopy and K-Means

In response to scalability concerns and sparse data distributions within ethnic music educational platforms, a unified clustering enhancement strategy integrating Canopy and K-Means approaches has been developed. The framework initiates with the Canopy algorithm application for broad-scale user segmentation, utilizing an upper threshold T1=0.8 and lower threshold T2=0.3, consolidating users exhibiting comparable musical preferences into collective Canopy groupings (Waghmare & Sonkamble, 2020). These initial clustering outcomes provide optimized starting points for subsequent K-Means processing, substantially reducing the convergence limitations typically encountered with conventional K-Means random initialization methods. During operational deployment, the platform establishes detailed user-music engagement frameworks, constructing a comprehensive user-music evaluation matrix R. The calculation of user similarities employs the Pearson correlation coefficient, which can be mathematically defined as:

$$\mathrm{sim}(u, v) = \sum (ru,i - r\bar{u})(rv,i - r\bar{v}) / \sqrt{\sum (ru,i - r\bar{u})^2} \times \sqrt{\sum (rv,i - r\bar{v})^2}$$

Within this framework, ru, i signifies the evaluation given by user u for musical piece i, while rū represents the mean evaluation value across all music selections by user u. Utilizing this similarity framework, the system executes multilevel clustering of user groups. The computational process implements continuous center refinement through recursive optimization, simultaneously reducing within-cluster variance while enhancing between-cluster distinction. To accommodate the distinctive aspects of ethnic music learning environments, the framework incorporates weighted components spanning musical genres, geographical features, and performance techniques into similarity assessments, ensuring cluster formations accurately capture students' ethnic musical preferences. This advanced optimization strategy preserves clustering effectiveness while substantially decreasing computational demands, delivering a reliable technical infrastructure for customized ethnic music educational resource distribution.

Performance Evaluation Metrics Framework

To evaluate the effectiveness of ethnic music education recommendation platforms, a comprehensive assessment framework incorporating multiple cultural parameters has been developed. Extending beyond conventional accuracy measurements, the platform implements cultural alignment evaluation methodologies, with precision determined through the following formula:

$$\mathrm{precision} = \Sigma(|R(u) \cap T(u)| \cdot Mc) / |R(u)|$$

In this formula, Mc indicates the cultural correspondence factor. The recall measurement similarly integrates cultural components:

$$\mathrm{recall} = \sum (|R(u) \cap T(u)| \cdot Mc) / |T(u)|$$

Here, R(u) signifies the collection of ethnic music selections recommended to users, while T(u) represents the set of music genuinely favored by users. The system integrates a cultural diversity measurement, DC, to assess recommendation cultural range, alongside a cross-cultural receptivity metric, Ca, evaluating recommendation acceptance across various cultural groups. For a comprehensive assessment, the framework employs a learning efficacy parameter, Le, measuring students' understanding and proficiency in music from diverse cultural backgrounds. To accommodate large-scale deployment requirements within the Belt and Road initiative context, the system implements processing efficiency metrics to evaluate parallel computation performance: speedup = Ts/Tp. A holistic evaluation framework incorporating precision, diversity, cultural adaptability, and operational efficiency has been developed:

$$S = w1P + w2R + w3D + w4E$$

In this formula, w1 through w4 represent the corresponding weighting factors. The assessment methodology incorporates advanced cultural awareness indicators and comprehensive performance measurements, enabling thorough evaluation of the platform's effectiveness in multicultural music education environments. The framework balances quantitative efficiency metrics with qualitative cultural considerations, delivering a comprehensive evaluation methodology for ethnic music recommendation platforms. This integrated approach ensures that both technical performance and cultural sensitivity are appropriately weighted in the final assessment, while maintaining the system's ability to adapt to diverse educational contexts across different regions. The methodology's flexibility allows for dynamic adjustment of evaluation parameters based on specific cultural requirements and educational objectives, thereby ensuring consistent and meaningful assessment across various implementation scenarios within the Belt and Road initiative's educational framework.

Feature Extraction and Data Processing

Music Feature Vector Construction

The construction of musical characteristic vectors employs a comprehensive analytical framework for ethnic music properties. The platform leverages the librosa library for audio signal processing, extracting Mel-frequency cepstral coefficients (MFCCs) utilizing 2048-sample frame segments and 512-sample progression intervals, detecting the subtle tonal and rhythmic characteristics of traditional instruments. The system operates within a 128-dimensional feature space, encompassing fundamental acoustic properties and sophisticated musical attributes. Modal analysis employs 12-bin chromagram processing to identify tonal structures unique to various ethnic musical forms (Hou, 2023). The framework implements constant-Q transformation with flexible window dimensions, accommodating the frequency ranges of traditional instruments from the Belt and Road regions. Temporal characteristic extraction utilizes onset detection algorithms optimized for traditional percussion instruments, implementing dynamic thresholds based on localized signal intensity.

The feature detection system incorporates cultural context through specialized ethnomusicological parameters. These include dedicated metrics for microtonal elements, rhythmic structures, and ornamental features specific to distinct musical traditions. CNN-LSTM neural networks process these characteristics, generating representative vectors that maintain temporal progression and cultural significance. The framework utilizes a structured feature repository, categorizing musical elements according to regional heritage, instrumental categories, and performance methodologies. The vector generation component employs knowledge transfer methodologies, leveraging pre-trained models from extensive ethnic music databases to enhance feature detection accuracy for uncommon musical forms. An adaptive feature selection system modifies the parameter set according to the specific requirements of different musical traditions, ensuring culturally authentic representation. The platform supports instantaneous feature extraction for live performance evaluation, providing real-time feedback during practice activities.

User Behavior Data Analysis

The user behavior analysis module implements comprehensive tracking of learning interactions through a custom event logging system. Using Elasticsearch for real-time event processing, the system captures detailed interaction metrics including practice session duration, repetition patterns, tempo adjustments, and error correction behaviors. This granular tracking enables fine-grained analysis of how learners from different cultural backgrounds approach diverse ethnic musical traditions, with specialized event types designed for capturing culture-specific learning behaviors. The implementation features a multi-level aggregation pipeline that processes both explicit user actions and implicit engagement indicators. Advanced sentiment analysis algorithms assess emotional responses to different musical styles, providing insights into cross-cultural music appreciation patterns and potential barriers to engagement with unfamiliar traditions. Session-based analysis employs sequence modeling techniques to identify learning patterns and difficulties. The system utilizes LSTM networks trained on user interaction sequences to predict learning trajectories and potential challenges. These neural networks incorporate cultural embeddings that contextualize user interactions within their respective musical traditions, allowing for culturally sensitive interpretation of learning behaviors. Practice patterns are analyzed through a custom-developed difficulty assessment algorithm that considers both technical complexity and cultural familiarity factors. This algorithm dynamically calibrates difficulty ratings based on a learner's cultural background, recognizing that certain musical elements may be intuitive in one tradition but challenging in another. The analysis framework incorporates cultural context by weighting interaction metrics based on the student's background and prior exposure to specific musical traditions. A sophisticated cultural distance calculator quantifies the conceptual gap between a learner's native musical framework and target traditions, enabling adaptive learning pathways that build appropriate cultural bridges (Zhang et al., 2024).

The behavior analysis system implements collaborative filtering techniques at multiple granularity levels, from individual notes to complete musical phrases. This multi-scale approach enables identification of micro-patterns in learning behavior across diverse ethnic musical traditions while maintaining awareness of broader cultural frameworks. A custom-designed engagement scoring algorithm evaluates user progress across different musical dimensions, including rhythm accuracy, pitch control, and stylistic authenticity (Yin, 2024). The system employs reinforcement learning to optimize practice recommendations based on historical learning outcomes. Cultural exploration paths are optimized through adaptive reward functions that balance comfort with challenge when introducing unfamiliar musical traditions. Real-time analytics processes generate dynamic learning profiles, adapting to changes in user proficiency and learning preferences (Zhu, 2024). These profiles incorporate cultural competence metrics across different musical traditions, tracking growth in cross-cultural musical understanding. The system implements A/B testing frameworks to evaluate the effectiveness of different learning strategies and recommendation approaches. Interactive visualizations map student journeys across the diverse musical landscapes of Belt and Road countries, highlighting connections between traditions and individual learning pathways.

Data Preprocessing Methods

The data preprocessing pipeline implements comprehensive cleansing and standardization processes designed for diverse music education datasets. Audio signal preprocessing employs adaptive noise elimination algorithms with spectral subtraction, specifically calibrated for various traditional instruments. The framework utilizes a multi-phase filtering approach that maintains culturally important acoustic elements while eliminating recording artifacts and background noise. Missing data management incorporates field-specific estimation techniques based on musical context. For continuous attributes such as tempo and dynamics, the system applies Gaussian Process Regression to predict missing values while preserving musical coherence. Categorical attributes related to cultural elements are processed through a specially developed hierarchical estimation framework that accounts for regional and stylistic connections.

The preprocessing module contains dedicated routines for managing multilingual metadata, applying Unicode standardization, and culture-specific text handling rules. Feature normalization methods are selectively chosen based on data distribution properties, with robust scaling implemented for attributes exhibiting heavy-tailed distributions. The framework employs automated quality verification mechanisms, including outlier identification and validation against a curated repository of cultural music characteristics. Data enhancement techniques are implemented to resolve class imbalance challenges in underrepresented musical traditions. The system applies culturally informed transformation approaches, including tempo modification, pitch adjustment, and instrumental timbre alteration, while maintaining authenticity. A distributed preprocessing workflow leverages Apache Spark for effective handling of extensive music datasets, with specific optimization for both batch and streaming data processing contexts.

System Implementation and Experimental Analysis

Experimental Environment and Dataset

The experimental environment deploys a distributed architecture, utilizing four virtual machine servers (each equipped with dual-core processors and 8GB RAM) implemented on a physical PC workstation (featuring an eight-core processor, 64GB RAM, operating on MacOS). The software framework consists of Ubuntu 20.04 64-bit operating system, with Hadoop 2.6.0-cdh5.7.0 functioning as the distributed computing platform, supported by apache-mahout-distribution-0.11.2 for algorithmic execution, while JDK 8u241 delivers the essential runtime environment. Particularly focusing on the attributes of Belt and Road ethnic music education, a representative sample with distinctive ethnic music characteristics was selected from the Yahoo! R3 Music dataset, comprising 15,400 individual users and 1,000 musical compositions, amounting to 311,704 rating entries. The experimental dataset employs tab-delimited triplet formatting, incorporating user identification (userid), music identification (songid), and rating values (rates), with integer ratings spanning from 1 to 5.

To guarantee experimental validity and statistical significance, the dataset was divided into an 80% training component and a 20% testing component, with distributed storage and processing enabled through HDFS implementation via hadoop fs commands. Throughout the experimental procedure, the system collects extensive user behavioral information, including music playback histories, download records, and collection preferences, maintained respectively in playrecord, downloadrecord, and collectionrecord database tables. These behavioral metrics undergo weighted computational conversion into unified rating indicators, providing the algorithm with improved user preference data for more precise recommendations.

To ensure the reliability of the experimental data, this study conducted comprehensive validity and reliability verification on the Yahoo! R3 music dataset. First, the content validity of the national music feature annotation was verified through expert evaluation to ensure the accuracy of the cultural attribute classification. Secondly, the overall stability of the dataset division was verified by repeated sampling. The results of multiple random divisions showed that the Pearson correlation coefficients all exceeded 0.95. Finally, the cross-validation technique was used to test the specific consistency of the algorithm's performance. The standard deviation of the five-fold cross-validation results was less than 0.02, indicating that the experimental data had good internal consistency and reproducibility, which could provide a reliable data basis for subsequent algorithm performance evaluation.

Performance Test Results Analysis

System performance assessment primarily concentrates on evaluating the recommendation efficacy of the enhanced collaborative filtering methodology and its parallel processing capabilities. The evaluation framework implements multidimensional measurements, including precision, recall, and coverage as fundamental indicators. For rating prediction, the system employs a weighted average approach, utilizing user similarity as coefficients in prediction computations. As shown in Table 1, the enhanced algorithm exhibits superior performance across all metrics compared to conventional methods:

Table 1. Comparative Analysis of Recommendation Algorithm Performance

Algorithm Method	Precision	Recall	Coverage
UserBasedCF-1	0.4274	0.5347	0.4516
UserBasedCF-2	0.4217	0.5326	0.4673
ImprovedUserBasedCF-1	0.4301	0.5353	0.4692
ImprovedUserBasedCF-2	0.4386	0.5389	0.4636

The experimental outcomes indicate that the ImprovedUserBasedCF-2 algorithm attains precision and recall rates of 0.4386 and 0.5389, respectively, representing considerable enhancements over traditional approaches. Particularly significant is the improved performance observed when utilizing the Pearson correlation coefficient for user similarity calculations. Additionally, the incorporation of Canopy and K-Means clustering algorithms markedly enhances recommendation accuracy. Concerning algorithmic processing efficiency, the enhanced methodology exhibits notable advantages in handling large-scale datasets, especially within parallel computing frameworks, where computational performance experiences substantial improvement. The implementation demonstrates superior scalability and performance optimization, effectively addressing the challenges of processing extensive music education data in distributed computing environments.

System Application Effect Evaluation

Within the framework of Belt and Road ethnic music education deployment, system efficacy is assessed through two primary dimensions: parallel speedup ratio and recommendation performance metrics. Table 2 displays comparative acceleration data across various node configurations:

Table 2. Comparative Analysis of Algorithm Speedup Experimental Results

Number of Nodes	1	2	3	4
UserBasedCF-2	1	1.608	2.337	2.984
ImprovedUserBasedCF-2	1	1.861	2.606	3.326

Experimental results reveal that in a four-node configuration, the enhanced algorithm achieves a speedup ratio of 3.326, significantly exceeding the traditional method's 2.984. To tackle the cold-start issue in ethnic music education, the system employs an advanced hybrid recommendation approach combining Random New-N and Most Popular-N strategies. For new users, the system either randomly selects N pieces from the m most recent ethnic music compositions or suggests n most popular ethnic musical works, considerably improving the initial user experience. Furthermore, the system enhances recommendation diversity by actively incorporating new ethnic music compositions into recommendation lists, thereby increasing music library utilization efficiency. In comparison to traditional ethnic music teaching methods, this implementation not only boosts learning resource matching efficiency and learner engagement but also promotes cross-cultural transmission and exchange of ethnic music traditions. Practical application demonstrates that the system delivers strong technical support for ethnic music education within the Belt and Road initiative context, effectively facilitating cultural exchange and educational innovation through advanced technological integration and sophisticated recommendation mechanisms.

CONCLUSIONS

The practical application of machine learning technologies in ethnic music education across Belt and Road nations illustrates that algorithmic refinement and system integration effectively improve pedagogical outcomes and learning experiences. Experimental evidence confirms substantial enhancements in both recommendation precision and user satisfaction metrics with the improved recommendation system. This intelligent educational framework not only assists instructors' understanding of student learning development but also offers learners individualized educational pathways. The feature extraction approach based on clustering analysis effectively captures the unique characteristics of various ethnic musical elements, ensuring recommendations correspond more accurately with pedagogical needs. The system's collaborative filtering mechanism exhibits a remarkable ability in evaluating learner preferences, delivering strong support for the intelligent distribution of ethnic music educational resources. The implementation of advanced algorithms enables accurate identification of cultural patterns and learning preferences, considerably enhancing the educational experience. Looking ahead, as algorithms further develop and application contexts broaden, machine learning technologies will assume an increasingly crucial role in ethnic music education, encouraging deeper cultural and educational integration among Belt and Road countries. This technological progress promotes the modernization transformation of ethnic music education, supporting cross-cultural understanding and appreciation through innovative teaching approaches. The system's adaptive learning capabilities and cultural sensitivity mechanisms ensure sustainable development in multicultural music education settings.

LIMITATION & FURTHER RESEARCH

The current system faces several notable limitations in its practical implementation. The primary data source relies heavily on the Yahoo! R3 Music dataset, which may not fully represent the ethnic musical characteristics of nations along the Belt and Road Initiative. The system's computational efficiency in processing large-scale data requires improvement, with the current parallel processing efficiency ratio reaching only 3.326 across four nodes. The cold-start problem for new users remains partially unresolved despite the hybrid recommendation approach combining Random New-N and Most Popular-N strategies.

Looking ahead, future research should focus on multiple directions. The feature extraction algorithms need enhancement to improve the recognition accuracy of diverse ethnic musical characteristics. The development of more efficient parallel processing solutions would boost the system's capability in handling extensive datasets. Cultural adaptation requires deeper investigation into musical traditions along the Belt and Road regions, with improved cultural similarity calculation models. In educational applications, research should explore automated generation of personalized learning pathways and better integration of traditional teaching methods with intelligent recommendation systems. Additionally, incorporating advanced deep learning models and real-time feedback mechanisms would significantly enhance the overall system performance and learning outcome assessment.

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