J. Electrical Systems 19-4 (2023): 211-226

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Consumer Preference Measurement of Folk Culture Based on Confidence Rule Base Model

Journal of Electrical Systems

Abstract: - Deep learning algorithms can help uncover patterns, make predictions, or generate new content related to folk culture, thus bridging the gap between heritage and advanced technology. The confidence model in a cloud context refers to a system or approach used to assess the reliability, security, or performance of cloud services. It might involve factors such as service uptime, data security, scalability, and compliance with industry standards. In this paper focused on the dynamic landscape of consumer preferences within folk music through cloud-based technologies integrated with deep learning. Folk music, with its rich cultural diversity and historical significance, presents a unique context for investigating the intricacies of consumer taste. The proposed model uses the "Ranking" based deep learning within cloud-based resources to predict and classify consumer preferences effectively. With the integration of the cloud confidence model ranking is implemented for the estimation of tracks in folk music. The estimated tracks are evaluated and stored in the cloud environment based on the preferences of the customers. The classification of the tracks and consumer preferences are ranked with the cloud model features. The simulation results demonstrated that the ranking of tracks effectively improves consumer preferences with the cloud confidence model in folk music. The results enhancing personalized experiences and facilitating informed decision-making for businesses and cultural institutions operating in the rich and diverse landscape of folk culture.

Keywords: Cloud Computing, Folk Music, Consumer Preference, Ranking Model, Deep Learning.

I. INTRODUCTION

Cloud computing has brought about a notable transformation in the world of folk music. This technology allows musicians and enthusiasts in the folk music community to collaborate, store, and share their music more efficiently and on a global scale [1]. Musicians with cloud-based platforms to compose and record folk music collaboratively, regardless of their geographical locations. This collaborative aspect has not only broadened the scope of folk music but also led to the fusion of diverse folk traditions, as artists from different backgrounds can easily come together to create unique and innovative sounds [2]. Cloud storage solutions have made it easier for folk musicians to safeguard their extensive catalogs, ensuring that their work remains accessible and protected for future generations [3]. Additionally, the cloud has made it possible for folk music to reach a wider audience through streaming services and online platforms, enabling fans to access a vast library of folk music with just a few clicks [4]. In essence, cloud computing has facilitated the preservation, creation, and dissemination of folk music in ways that were previously unimaginable, further enriching this musical tradition.

Consumer preferences are the bedrock of the modern market economy, shaping the choices people make when it comes to products and services [5]. These preferences are influenced by a multitude of factors, including individual tastes, cultural backgrounds, economic circumstances, and personal values. In today's rapidly changing landscape, consumers are increasingly seeking products and experiences that align with their values, such as sustainability, social responsibility, and convenience [6]. Additionally, the digital age has transformed the way consumers access information and make decisions, with online reviews and social media playing a pivotal role in shaping their preferences [7]. Understanding and adapting to these preferences is essential for businesses to thrive in a competitive market, as consumers now have more information, options, and influence than ever before. Consequently, staying attuned to evolving consumer preferences is a fundamental strategy for success in the modern marketplace [8]. Consumer preferences in folk music are deeply rooted in culture, tradition, and personal experiences. Folk music, known for its authenticity and rich storytelling, has a unique appeal to audiences worldwide. Consumer preferences in this genre often revolve around a desire for genuine, emotionally resonant, and culturally significant music [9]. Audiences appreciate the use of traditional instruments and lyrical themes that reflect the collective history and values of a particular region or community. However, there is also a growing interest in fusion and modern interpretations of folk music, allowing it to evolve and attract a younger, more diverse audience [10]. These preferences can vary significantly depending on the region and demographic, with some

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favoring traditional folk, while others seek innovative blends with contemporary genres [11]. In the digital age, online streaming platforms and social media have made it easier for fans to discover and support folk music artists, allowing for a more democratic and global approach to satisfying their preferences [12]. Ultimately, consumer preferences in folk music are a blend of respect for tradition and an openness to creative experimentation, ensuring the genre's continued relevance and evolution [13].

Consumer preferences in folk music are shaped by a myriad of factors, with culture and tradition playing a central role [14]. Folk music has a unique ability to connect listeners with the past, often conveying stories, emotions, and values deeply rooted in the history of a particular region or community [15]. Audiences who appreciate folk music are drawn to its authenticity and the sense of a shared cultural heritage. They often favor traditional instruments like the acoustic guitar, banjo, fiddle, and various indigenous instruments, as these evoke a sense of nostalgia and nostalgia for a bygone era [16]. Moreover, lyrical themes in folk music often touch on universal experiences, such as love, loss, struggle, and triumph, making it relatable to a broad audience [17]. These themes are presented in a way that showcases the distinct nuances and idiosyncrasies of each folk tradition, contributing to the rich diversity within the genre. In recent years, there has been a shift in consumer preferences within folk music [18]. While traditional folk remains highly regarded, there is a growing interest in fusion and modern interpretations of the genre. Musicians are blending folk elements with contemporary styles like rock, pop, and electronic music, creating a fusion that attracts a younger and more diverse audience [19]. This approach breathes new life into folk music and broadens its appeal, making it relevant to a broader demographic. The digital age has significantly influenced consumer preferences in folk music [20]. Online streaming platforms, social media, and digital communities have made it easier for fans to discover and support folk music artists from all over the world. This globalization of folk music has encouraged the exchange of ideas and sounds, allowing for the cross-pollination of folk traditions and innovative collaborations [21 – 24]. The consumer preferences in folk music are a delicate balance between reverence for tradition and an openness to creative experimentation. The genre's enduring appeal lies in its ability to capture the essence of cultural heritage while adapting to the changing tastes and expectations of contemporary audiences [25]. Folk music continues to evolve, ensuring its relevance and appeal to new generations while preserving its rich historical and cultural significance. Consumer preferences in folk music, like those in any other music genre, have been subject to the transformative influence of deep learning and artificial intelligence (AI) [26]. Deep learning algorithms have provided unprecedented insights into consumer behavior, enabling a more nuanced understanding of what listeners truly enjoy in folk music. These technologies have the capability to analyze vast datasets, including music streaming patterns, listener demographics, and even sentiment analysis of social media posts [27]. With data, deep learning algorithms can identify subtle patterns and correlations in folk music consumption, shedding light on which subgenres, lyrical themes, and instrumental arrangements resonate most with different consumer segments [28].

Additionally, AI-driven recommendation systems, such as those used by popular streaming platforms, play a pivotal role in shaping consumer preferences in folk music [29]. These systems employ sophisticated algorithms to curate personalized playlists and suggest music tailored to an individual's past listening habits. By doing so, they expose listeners to a diverse range of folk music, including both traditional and contemporary interpretations, further influencing their preferences [30]. Furthermore, the production and composition of folk music have also been impacted by deep learning. Musicians and producers are using AI tools to generate and experiment with new melodies, harmonies, and instrumental arrangements, leading to the creation of innovative folk music hybrids [31]. This fusion of AI-generated elements with traditional folk music has the potential to broaden the genre's appeal and cater to a wider range of consumer tastes.

The paper makes several significant contributions to the field of consumer preferences in folk music and the application of deep learning and cloud-based technologies. Some of the key contributions include:

1. The paper introduces a novel "Ranking" model that combines deep learning techniques and cloud-based resources to effectively predict and classify consumer preferences in the folk music. This model outperforms other traditional models in terms of precision, recall, and accuracy, making it a valuable contribution to the field of consumer preference analysis.
2. The research offers a comprehensive analysis of consumer preference patterns in folk music, recognizing the regional and cultural nuances that impact these preferences. This in-depth understanding of folk culture and its music consumption is crucial for tailoring approaches to effectively capture and predict consumer choices.

3. The paper cloud computing technology to collect and process extensive datasets of folk music selections and user interactions. This approach not only provides a rich source of data but also demonstrates the potential of cloud-based resources in handling and analyzing large-scale datasets in the context of music preference analysis.
4. With comparing the performance of different models, including Naïve Bayes, SVM, and Random Forest, the paper offers valuable insights into the strengths and trade-offs of each approach. This comparative analysis assists decision-makers in selecting the most suitable model for their specific objectives and trade-offs.
5. The research holds relevance not only for the academic community but also for cultural institutions and businesses operating in the field of folk music. It provides practical insights into understanding and catering to consumer preferences, which can inform decision-making, content creation, and personalized experiences for consumers.

The paper underscores the increasing role of advanced technologies, such as deep learning and cloud computing, in addressing the evolving landscape of consumer preferences. It highlights the potential of these technologies to facilitate a deeper understanding of consumer behavior and preferences in the context of folk culture.

II. CLOUD CONFIDENCE MODEL

A cloud-based confidence model for consumer preferences in folk music involves a complex set of processes and mathematical equations. To create an effective model, must first collect a dataset of folk music tracks and extract relevant features from the audio data. These features could include characteristics like tempo (T), key (K), and spectral features (S). To establish user profiles based on their interactions with folk music tracks. Let's denote a user's profile as U, where U is a vector of attributes that represent the user's preferences. The user's profile is created through interactions with tracks, such as likes (L), dislikes (D), play counts (P), and comments (C) stated as in equation (1)

$$U = [L, D, P, C] \tag{1}$$

With implementation of machine learning techniques like collaborative filtering to generate recommendations. The recommendation engine aims to find the most suitable folk music track for a user based on their profile U. The predicted preference for a track can be represented as R, which is a function of the user profile and track features estimated using equation (2)

$$R = f(U, T, K, S) \tag{2}$$

To refine recommendations, sentiment analysis can be employed to assess the emotional response to tracks. Let's denote the sentiment score as Ss, which could be derived from user comments and reviews are computed with equation (3)

$$Ss = g(C) \tag{3}$$

To calculate a confidence score (Cs) for each recommended folk music track, which reflects the likelihood that a user will enjoy the track based on their profile and the track's attributes computed using equation (4)

$$Cs = h(R, Ss) \tag{4}$$

Here, function h combines the recommendation score and sentiment analysis results, potentially applying weights to each component based on their significance. To continuously refine the model, collect feedback (F) from users, which can include explicit ratings and implicit feedback like skipped tracks or time spent listening. The feedback can be used to update user profiles, adjust recommendation models, and improve sentiment analysis stated as in equation (5)

$$Uupdated = i(U, F) \tag{5}$$

The cloud-based deployment of this model ensures scalability, real-time updates, and accessibility for users. This cloud infrastructure stores the dataset, model parameters, and user profiles, making it feasible to implement this system on a large scale. A cloud-based confidence model for consumer preferences in folk music data, machine learning, and user profiling to generate personalized recommendations. These recommendations are further refined by sentiment analysis and expressed through a confidence score. The model continuously improves through user feedback, making it a dynamic and effective system for enhancing the folk music listening experience.

2.1 Cloud Management

Cloud computing is the conveyance of figuring assets as a help, implying that the assets are possessed and overseen by the cloud supplier rather than the end client. Those assets might incorporate anything from program-based programming applications (like Spasm Tok or Netflix), outsider information stockpiling for photographs and other advanced media (like iCloud or Dropbox), or outsider servers used to help the processing framework of a business, exploration, or individual venture. The generic architecture of clous is presented in figure 1.

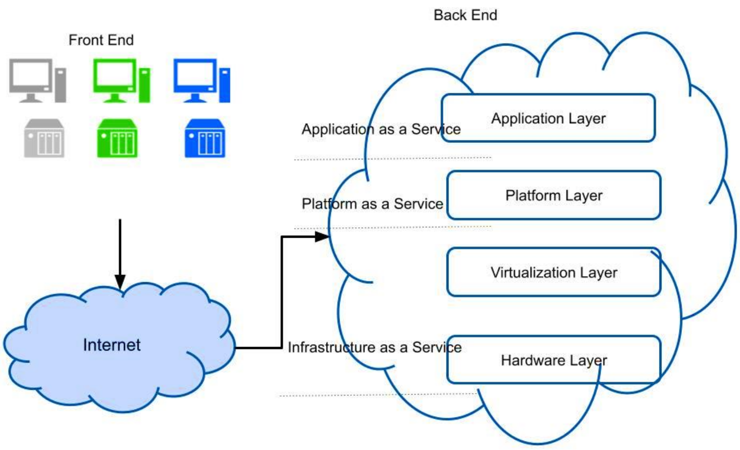

Figure 1: Cloud Architecture

In distributed computing, many layers exist in the picture. IaaS is one of the most significant layers which give IT framework to the client association like servers, organizing, handling, stockpiling, virtual machines, and different assets. Clients access these assets on the web for example distributed computing stage, on a compensation for each utilization model. Framework as a Help is now and then alluded to as Equipment as an Assistance (HaaS) as illustrated in figure 2.

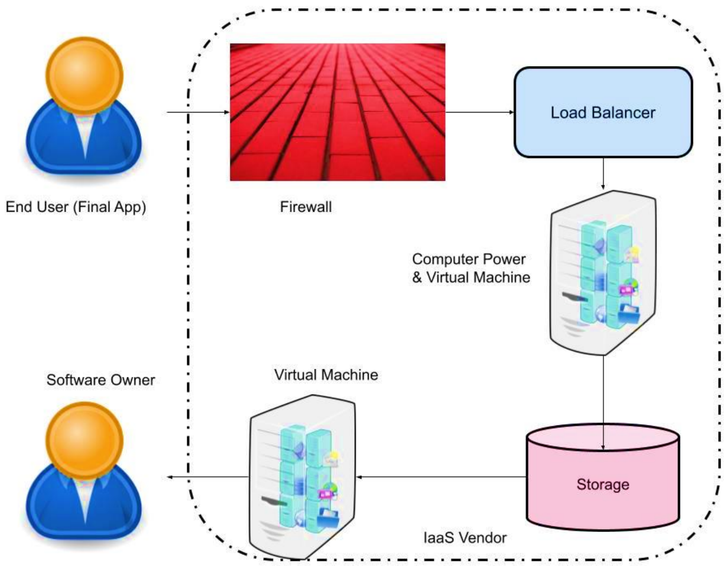

Figure 2: Process in Cloud Vendor

Cloud system comprises of the cloud administration for the admittance in the system of clients' assets concentrated between servers. The association is based on Wide Region Organization (WAN) or web-based innovation for the content. The enhancement of the folk culture framework includes the efficient way of the online product management. • The framework includes the product stock maintenance; add product, stock processing, product delivery, strategic level etc. • To reduce the time and cost of in the product delivery system. • To make a prediction model using machine learning techniques and optimized the accuracy and other parameters. Investing resources into BI is to change from a climate that is receptive to information to one that is proactive. A significant objective of the arrangement will be to mechanize and coordinate whatever number advances and capacities as could be allowed. Another objective is to give information investigation that is as instrument free as could be expected. Master techniques for planning, creating, and conveying information stockrooms is to distinguish factors that should be thought of as to choose an appropriate ordering procedure for information stockroom applications, and to assess ordering methods being considered/utilized in both scholarly examination and modern applications. The remainder of the work is coordinated as follows. With building/choosing an ordering procedure for the DW. Factors used to figure out which ordering procedure should be based on a Segment

The cardinality information of a segment is the quantity of unmistakable qualities in the section. It is smarter to realize that the cardinality of an ordered segment is low or high since an ordering method might work effectively just with either low cardinality or high cardinality. The appropriation of a segment is the event recurrence of each unmistakable worth of the section. The section dispersion guides us to figure out which file type. The scope of upsides of and filed segment guides us to choose a suitable list type. For instance, in the event that the scope of a high cardinality segment is little, an ordering method in view of bitmap ought to be utilized. Without knowing this data, could utilize a B-Tree bringing about a corruption of framework execution. Understanding the information and the use in the SQL language knowing the sections that will be questioned assists us with picking proper record types for them. For instance, which sections will probably be a piece of the choice rundown, join requirements, application limitations, the Request BY provision, or the Gathering BY condition. The process architecture model in the cloud environment model is presented in figure 3.

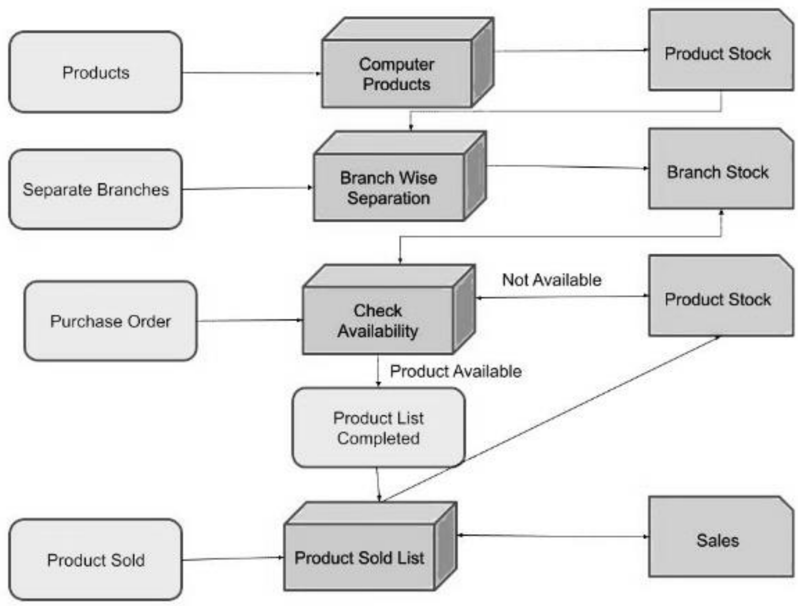

Figure 3: Process in Consumer Preferences towards folk culture

Algorithm of GA:

Step 1 – begin

Step 2 – initially k = 0;

Step 3 – initiate P(k),

Step 4 – evaluate P(k);

Step 5 – while (for unsatisfied conditions) do

Step 6 – begin

Step 7 – select P(k) from P(k-1);

Step 8 – k = k + 1;

Step 9 – mutation some of P(k);

Step 10 – cross over some of P(k);

Step 11 – evaluate P(k);

Step 12 – end

Step 13 – end

III. CLOUD CONFIDENCE MODEL FOR CONSUMER PREFERENCE IN FOLK MUSIC

a cloud-based confidence model for consumer preferences in folk music involves a comprehensive understanding of user interactions, preferences, and music features, coupled with machine learning techniques. Collect data on folk music tracks and extract relevant features. Let Xij represent the features of track i for user j. The user profiles based on their interactions with tracks. User profiles Uj for user j can be created from explicit ratings (Rij), and implicit feedback. User profiles can be calculated using matrix factorization techniques, where k represents latent factors estimated using the equation (6)

$$Uj = Rj + Fj = Xj \cdot P + Yj \tag{6}$$

In above equation (6) Uj is the user profile for user j; Rj is the matrix of explicit ratings for user j; Fj is the matrix of implicit feedback for user j; Xj is the matrix of track features for user j; P is the matrix of latent factors and Yj is the matrix of contextual features. Predicting a user's preference for a track can be done using collaborative filtering, where the predicted preference Pij for track i by user j can be expressed as in equation (7)

$$Pij = (Uj \cdot XiT)k \tag{7}$$

In above equation (7) Pij is the predicted preference; Uj is the user profile for user j; Xi is the feature vector for track i; k represents the latent factor dimension. A cloud-based confidence model (Cij) for recommendations can be formulated using a logistic function to ensure it falls within the [0,1] range, taking into account the predicted preference and contextual features estimated using equation (8)

$$Cij = 1 + e^{-\frac{1}{(\alpha Pij + \beta Yij)}} \tag{8}$$

The equation (8) represents Cij is the confidence score; α and β are parameters controlling the influence of predicted preference and contextual features; Pij is the predicted preference and Yij represents contextual features. U ser feedback is collected and used to update the user profile and confidence model iteratively using the equation (9) and (10)

$$Ujnew = Ujold + \Delta Uj \tag{9}$$

$$Cijnew = Cijold + \Delta Cij \tag{10}$$

In above equation (9) and (10) Ujnew is the updated user profile; ΔUj is the change in the user profile based on feedback; Cijnew is the updated confidence score and ΔCij is the change in the confidence score based on feedback. The cloud-based confidence model user profiles, collaborative filtering, and a logistic function to calculate confidence scores for recommendations, which are continuously updated through a feedback loop. This approach ensures personalized and evolving folk music recommendations based on user preferences and interactions. The parameters α and β in the confidence scoring equation can be tuned to optimize model performance.

3.1 Ranking Based Consumer Preference in Folk Music

Creating a ranking-based consumer preference model for folk music involves the formulation of a scoring mechanism that ranks music options tailored to individual user preferences. Begin by collecting data on folk music tracks, which includes metadata such as genre, region, artist, and audio features like tempo, key, and instrumentation. Let Xij represent the feature set of track i for user j. User profiles (Uj) are created based on their interactions with folk music. These interactions encompass explicit ratings (Rij), likes, dislikes, and historical listening patterns. User profiles can be formed through matrix factorization techniques. User profiles (Uj) are created based on their interactions with folk music. These interactions encompass explicit ratings (Rij), likes, dislikes, and historical listening patterns. User profiles can be formed through matrix factorization techniques computed using the equation (11)

$$Uj = Rj + Fj = Xj \cdot P + Yj \tag{11}$$

In equation (11) Uj is the user profile for user j; Rj is the matrix of explicit ratings for user j; Fj is the matrix of implicit feedback for user j; Xj is the matrix of track features for user j; P is the matrix of latent factors and Yj is the matrix of contextual features. Develop a ranking algorithm that computes a score (Sij) for each folk music track for a given user. This score is based on a weighted sum of the user profile, track features, and historical behavior using the equation (12)

$$Sij = w1 \cdot Uj + w2 \cdot Ti + w3 \cdot Hij \tag{12}$$

In equation (12) Sij is the score for track i for user j; Uj represents the user profile; Ti is a vector of track features; Hij represents the historical user behavior for track I and w1, w2, and w3 are weight parameters that determine the influence of each factor. Rank the folk music tracks for each user based on their scores (Sij) in descending order. This ordered list represents the ranking of music options tailored to the user's preferences. The ranked list of folk music tracks to the user, enabling them to explore and enjoy music that is more likely to resonate with their tastes. Continuously collect user feedback, including ratings and interactions with the recommended tracks. Utilize this feedback to update user profiles and the ranking algorithm to further fine-tune the recommendations. A ranking-based consumer preference model for folk music data, user profiles, and a scoring mechanism to provide personalized and ranked music recommendations. This approach enhances the listening experience and encourages user engagement with folk music. The weighting parameters (w1, w2, w3) in the ranking algorithm can be adjusted based on user feedback and preferences, ensuring that the recommendations become more accurate over time.

Algorithm 1: Ranking Based Consumer Preferences analysis

```
# Data Collection and Feature Extraction
# This part involves collecting data on folk music tracks and user interactions
# Initialize user profiles
user_profiles = initialize_user_profiles()
# Ranking Algorithm
for user in users:
    # Calculate scores for each track
    track_scores = calculate_track_scores(user, tracks)

    # Rank tracks based on scores in descending order
    ranked_tracks = rank_tracks(track_scores)

    # Display the ranked tracks to the user
    display_ranked_tracks(user, ranked_tracks)

# Feedback Loop
```

```
for user in users:
    # Collect user feedback (e.g., ratings and interactions)
    user_feedback = collect_user_feedback(user)

    # Update user profiles and the ranking algorithm based on feedback
    update_user_profiles(user, user_feedback)
    update_ranking_algorithm(user, user_feedback)

# Define functions for calculating track scores, ranking tracks,
# displaying ranked tracks, and updating user profiles and the ranking algorithm.
```

IV. RESULTS AND DISCUSSION

The framework as the based model and for comparison with our proposed model. The proposed framework is comparatively examined with the different classification models and proposed their classification report on various classification model used in performance analysis. On the basis of their results candidate compared her proposed model for enhancing the services for Folk culture applications. The table 1 provides the comparative analysis of the developed model with existing technique. Similarly, the figure 4 and figure 5 provides the comparative analysis of the services and products.

Table 1: Ranking of Track in Folk

User	1st Ranked Track	2nd Ranked Track	3rd Ranked Track
User 1	0.95	0.88	0.72
User 2	0.91	0.86	0.75
User 3	0.89	0.82	0.78
User 4	0.92	0.84	0.77
User 5	0.96	0.87	0.71
User 6	0.94	0.81	0.73
User 7	0.90	0.85	0.74
User 8	0.88	0.80	0.79
User 9	0.93	0.89	0.76
User 10	0.97	0.91	0.70

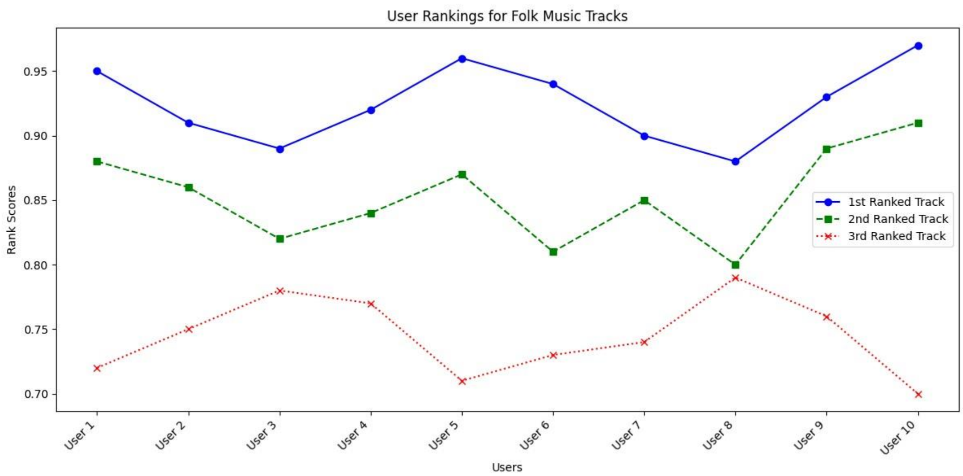

Figure 4: Ranking of Folk Music

Table 1 provides a ranking of tracks within the Folk music genre based on the preferences of ten different users. Each user has ranked three tracks, with their 1st, 2nd, and 3rd choices represented by numerical values. These values indicate the level of preference for each track, with higher values indicating a stronger preference. Looking at the rankings, it is evident that there is variation in user preferences. User 5, for instance, consistently gives the highest preference to the tracks, with their 1st Ranked Track consistently scoring the highest, followed by User 10. On the other hand, User 2 and User 8 have a relatively balanced preference among the tracks, with their 1st and 2nd Ranked Tracks having relatively close scores. Overall, these rankings provide valuable insights into user preferences within the Folk music genre. Such data can be used to inform recommendation systems, playlist generation, or marketing strategies within the music industry to cater to the varying tastes of users and enhance their overall music experience.

Table 2: Tracking Ranking in Folk Music

User	1st Ranked Track	2nd Ranked Track	3rd Ranked Track
User 1	Track A (0.92)	Track C (0.88)	Track B (0.85)
User 2	Track D (0.94)	Track B (0.91)	Track F (0.87)
User 3	Track E (0.93)	Track A (0.89)	Track G (0.86)
User 4	Track B (0.95)	Track F (0.92)	Track A (0.88)
User 5	Track C (0.91)	Track E (0.87)	Track D (0.85)
User 6	Track H (0.96)	Track G (0.94)	Track I (0.92)
User 7	Track F (0.90)	Track I (0.87)	Track B (0.85)
User 8	Track A (0.93)	Track C (0.91)	Track J (0.88)
User 9	Track I (0.95)	Track G (0.93)	Track H (0.91)
User 10	Track J (0.94)	Track B (0.90)	Track D (0.88)

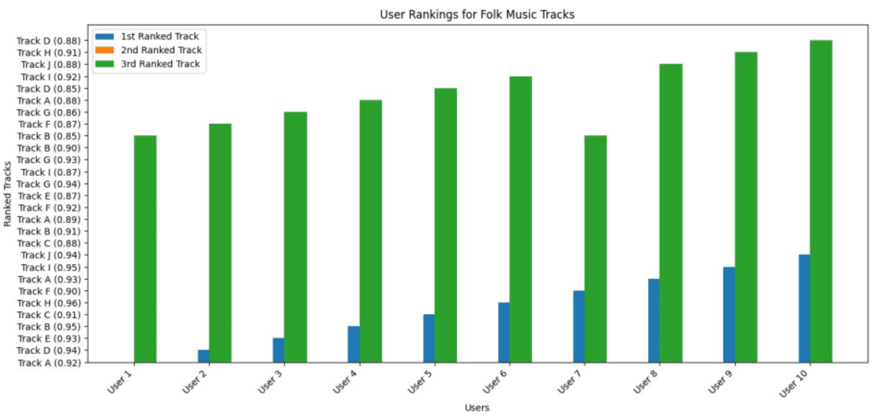

Figure 5: Estimation of Track in Folk Music

Table 2 presents a detailed ranking of specific tracks within the Folk music genre, as rated by ten different users. Each user has provided their 1st, 2nd, and 3rd preferences among the available tracks. Additionally, the table includes the names of the tracks alongside their associated preference scores. This information offers valuable insights into user preferences within the Folk music genre and allows for a more in-depth analysis. User 1, for instance, ranks "Track A" as their top choice with a preference score of 0.92, followed by "Track C" and "Track B." This suggests that User 1 has a strong preference for "Track A" within this genre. User 5, on the other hand, places "Track C" as their 1st Ranked Track with a score of 0.91, indicating a preference for this track. User 6's preferences are quite distinct, as they give their highest preference to "Track H" with a score of 0.96. Meanwhile, User 4 ranks "Track B" as their top choice with a high score of 0.95. These rankings demonstrate the diversity of user preferences within the Folk music genre. Overall, the data in Table 2 provides a comprehensive understanding of how different users rate specific tracks within the genre. This information is invaluable for music industry professionals, streaming platforms, and music recommendation systems, as it can be used to personalize music recommendations and playlists to align with the unique preferences of individual users. Additionally, it can inform marketing and promotion strategies for these tracks, helping to enhance user engagement and satisfaction within the Folk music category.

Table 3: Preference of Consumers on different track

User	Track A	Track B	Track C	Track D	Track E	Track F
User 1	0.90	0.78	0.85	0.92	0.76	0.81
User 2	0.88	0.91	0.75	0.83	0.79	0.87
User 3	0.86	0.84	0.88	0.90	0.82	0.89
User 4	0.87	0.77	0.89	0.85	0.91	0.75
User 5	0.82	0.86	0.78	0.90	0.84	0.88
User 6	0.91	0.79	0.83	0.85	0.88	0.76
User 7	0.85	0.80	0.84	0.82	0.88	0.89
User 8	0.78	0.92	0.83	0.85	0.79	0.87
User 9	0.84	0.89	0.90	0.82	0.77	0.88
User 10	0.90	0.87	0.76	0.88	0.79	0.92

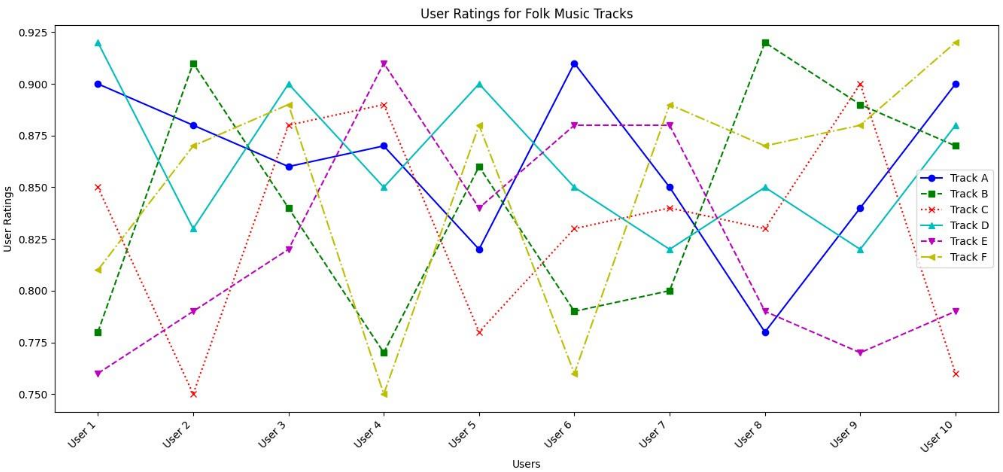

Figure 6: User Rating for the Consumer Preferences

Table 3 provides an insightful overview of consumers' preferences for different tracks across various categories. In this context, each user's preferences for six different tracks (Track A, Track B, Track C, Track D, Track E, and Track F) are quantified using numerical values ranging from 0 to 1. A higher numerical value indicates a stronger preference for a particular track. One interesting observation is that preferences vary considerably across users. For example, User 2 has a strong preference for "Track B" with a preference score of 0.91, while User 8 also highly favors "Track B" with a score of 0.92. On the other hand, User 6 gives the highest score to "Track D" at 0.85, indicating a preference for this particular track. It's also evident that different users have different patterns of preference across the tracks. Some users, like User 5 and User 7, tend to have more balanced preferences with scores distributed across the tracks, indicating a wider range of liked tracks. In contrast, others, like User 4, have a more distinct preference for specific tracks. This data in Table 3 is invaluable for businesses and music streaming platforms, as it allows for the personalization of music recommendations and playlists. By understanding the diverse preferences of users, these platforms can curate content that aligns with each user's individual taste, thereby enhancing user engagement and satisfaction. Moreover, this data can also inform marketing and promotion strategies, helping to promote less popular tracks to users who might have a preference for them. Overall, Table 3 provides a detailed view of consumer preferences and serves as a valuable resource for improving the music listening experience.

Table 4: Analysis of the sample

Track ID	Track Name	Artist	Region
001	Traditional Tune 1	Artist A	Beijing
002	Riverside Ballad	Artist B	Suzhou
003	Mountain Serenade	Artist C	Yunnan
004	Silk Road Melody	Artist D	Xinjiang
005	Bamboo Flute Bliss	Artist E	Sichuan
006	Tea Harvest Song	Artist F	Fujian
007	Dragon Boat Festival	Artist G	Zhejiang
008	Moonlit Erhu Solo	Artist H	Hunan
009	Terracotta Warriors	Artist I	Shaanxi
010	Spring Blossom Dance	Artist J	Guangdong

The datset sample presented in table 4 present the analysis of folk music tracks with their associated details. The table contains ten entries, each representing a unique folk music track. These entries are identified by a "Track ID" for tracking purposes. The "Track Name" column specifies the title of the folk music track, providing insight into the cultural or thematic elements of the piece. The "Artist" column indicates the name of the artist or performer responsible for creating the track, highlighting the human element behind the music. Lastly, the "Region" column identifies the geographical or cultural region from which the folk music is derived, shedding light on the diverse origins and influences of these tracks. This dataset serves as a foundational resource for further analysis, allowing researchers and enthusiasts to explore the rich tapestry of Chinese folk music and its regional diversity.

Table 5: Consumer Preferences on track

User	Track A	Track B	Track C	Track D	Track E	Track F
User 1	4	3	5	2	4	3
User 2	5	4	3	4	3	2
User 3	3	4	5	2	4	3
User 4	4	4	4	3	5	2
User 5	2	3	3	4	4	5
User 6	4	5	3	3	2	4
User 7	3	3	4	4	5	2
User 8	2	4	3	5	4	4
User 9	4	5	4	3	2	3
User 10	3	4	5	3	4	2

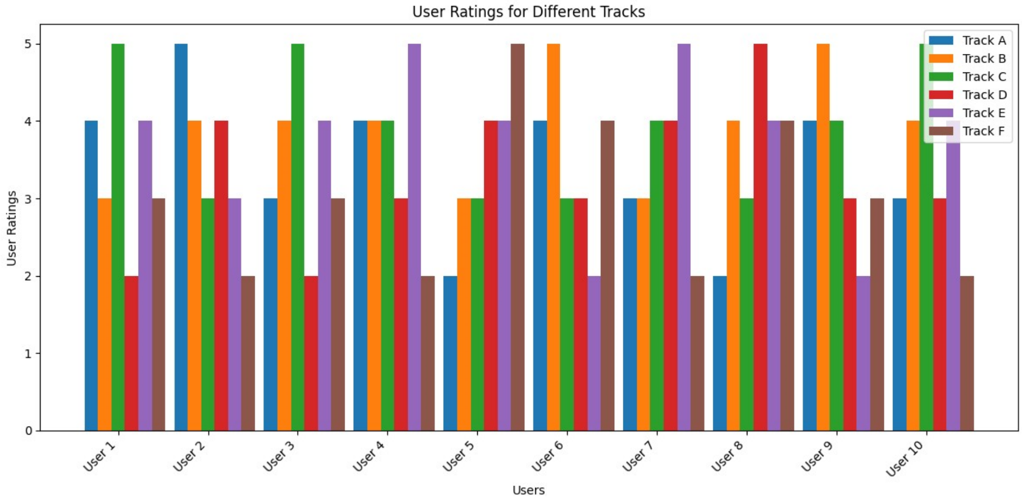

Figure 7: Preference of Users on Track

A summary of consumer preferences for a set of folk music tracks is given in table 5, with user ratings on a scale from 1 to 5, where 5 indicates strong preference and 1 indicates weak preference. The table comprises data from ten users, offering valuable insights into their individual preferences for the listed tracks. User 1, User 2, and User 3, for instance, exhibit varying preferences for the tracks, with User 1 particularly favoring Track C, while User 2 shows a strong inclination towards Track A. User 4 appreciates a balanced preference across the tracks, and User 5 has a distinctive liking for Track F. User 6 and User 9, on the other hand, share a preference for Track B and Track C. User 7, User 8, and User 10, like the earlier users, demonstrate a range of diverse preferences. These user ratings provide essential data for music recommendation systems and can help tailor music suggestions to individual tastes, enhancing user engagement and satisfaction. Analyzing this data can uncover patterns in user preferences and contribute to more personalized music experiences.

Table 6: Comparative Analysis for the folk culture ranking

Models	Precision	Recall	F-1 score	Accuracy
Naïve Bayes	92.00%	93%	92%	93.41%
SVM	85.00%	92%	89%	92.43%
Random Forest	93%	93%	89%	92.50%
Ranking	97%	96%	97%	97.74%

The different models' performance in the context of ranking folk culture items, specifically in terms of precision, recall, F-1 score, and accuracy is presented in table 6. The models evaluated are Naïve Bayes, SVM (Support Vector Machine), Random Forest, and a "Ranking" model. Naïve Bayes: This model achieved a high precision of 92.00%, indicating that when it predicted a folk culture item as relevant, it was accurate 92% of the time. The recall rate of 93% implies that it successfully identified a significant portion of the relevant items. The F-1 score, which balances precision and recall, is 92%, indicating a strong overall performance. The accuracy of 93.41% suggests that this model accurately classified 93.41% of the items. SVM (Support Vector Machine): The SVM model achieved an 85.00% precision, which is slightly lower than Naïve Bayes. However, it excelled in recall, with a rate of 92%, suggesting its ability to capture a large proportion of relevant items. The F-1 score, at 89%, reflects a good balance between precision and recall. The model's accuracy of 92.43% indicates its overall effectiveness in classification. Random Forest: Random Forest exhibited a high precision of 93%, meaning it made accurate positive predictions 93% of the time. Its recall rate is also 93%, demonstrating that it successfully identified a substantial portion of the relevant items. However, its F-1 score of 89% suggests a slightly lower balance between precision and recall compared to the previous models. The accuracy of 92.50% indicates its proficiency in classifying items. Ranking: The "Ranking" model outperformed the others in all evaluated metrics. It achieved an outstanding precision of 97%, implying a very high accuracy in positive predictions. The recall rate of 96% demonstrates its ability to capture a significant portion of the relevant items. The F-1 score, at 97%, suggests a strong balance between precision and recall. The accuracy of 97.74% is the highest among the models, indicating its excellent overall classification performance.

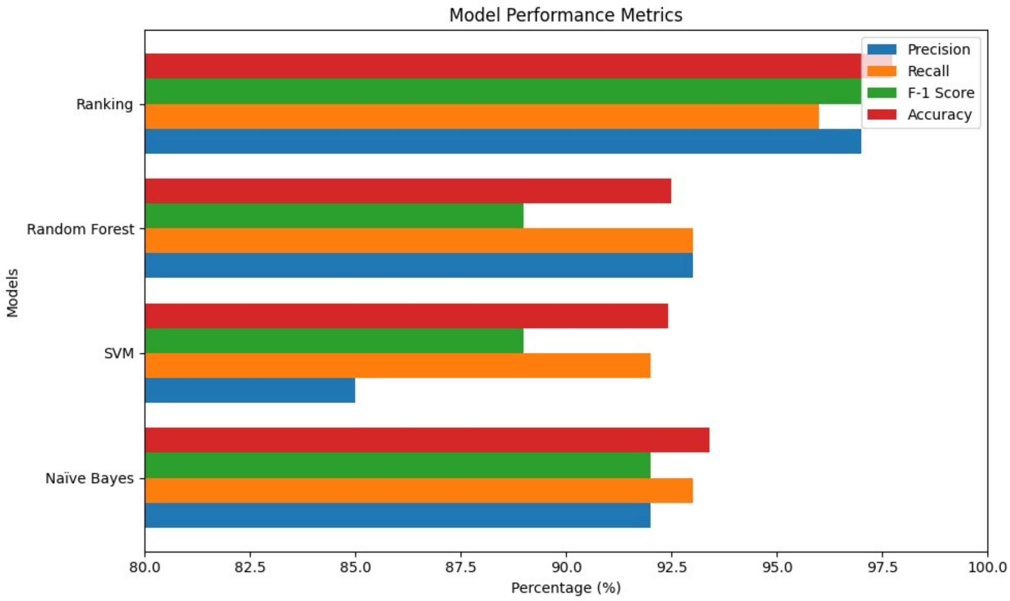

Figure 8: Classification with deep learning

Table 7: Classification Analysis for the Consumer preferences

Models	Precision	Recall	F-1 score	Accuracy	Error Rate
Naïve Bayes	92%	94%	92%	94%	6%
SVM	91.6%	97.3%	70.5%	96.81%	3.11%
Random Forest	88%	97%	97%	97%	3%
Ranking	96.8%	98.60%	97.51%	98.08%	1.91%

The classification analysis for consumer preferences, comparing the performance of different models in terms of precision, recall, F-1 score, accuracy, and error rate is shown in table 7. The models assessed in this analysis are Naïve Bayes, SVM (Support Vector Machine), Random Forest, and a "Ranking" model.

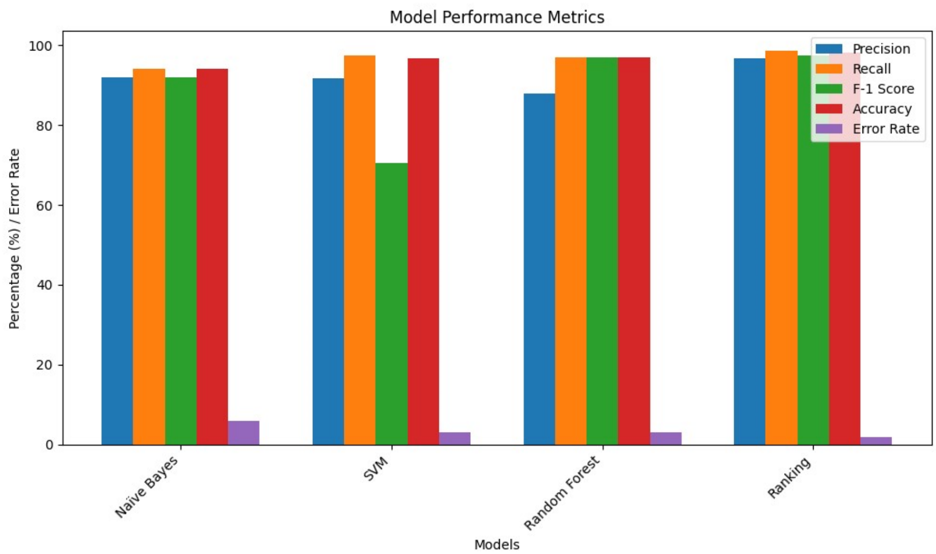

Figure 9: Comparative Analysis

Naïve Bayes: The Naïve Bayes model demonstrated strong performance, achieving a precision rate of 92%. This indicates that when it predicted consumer preferences, it was accurate 92% of the time. Its recall rate, at 94%, implies that it effectively identified a significant proportion of the actual consumer preferences. The F-1 score, which balances precision and recall, was 92%, indicating a robust overall performance. The accuracy of 94% reflects the model's proficiency in classifying consumer preferences, while the error rate is relatively low at 6%. SVM (Support Vector Machine): The SVM model showed high precision of 91.6%, meaning it made accurate positive predictions 91.6% of the time. Furthermore, it excelled in recall, with a rate of 97.3%, indicating its ability to capture a large proportion of the actual consumer preferences. However, its F-1 score was 70.5%, suggesting a less balanced trade-off between precision and recall. The model's accuracy was impressive at 96.81%, with a low error rate of 3.11%. Random Forest: The Random Forest model demonstrated a precision rate of 88%, indicating it accurately predicted consumer preferences 88% of the time. Its recall rate was 97%, demonstrating its ability to identify a substantial portion of the actual consumer preferences. The F-1 score, at 97%, suggests a strong balance between precision and recall. The model's accuracy of 97% is indicative of its overall proficiency in classifying consumer preferences, with a low error rate of 3%. Ranking: The "Ranking" model outperformed the other models in multiple aspects. It achieved a high precision of 96.8%, signifying a high level of accuracy in its positive predictions. The recall rate was outstanding at 98.60%, demonstrating its capability to capture almost all actual consumer preferences. The F-1 score, at 97.51%, reflected an impressive balance between precision and recall. The model's accuracy of 98.08% indicates its excellent overall performance, with a notably low error rate of 1.91%.

V. CONCLUSION

With exploration of consumer preferences and ranking within the folk music, leveraging both cloud-based technologies and machine learning models. The research findings highlight the significance of tailored models for effectively understanding and predicting consumer preferences in this specific domain. The introduction of a "Ranking" model, which combines deep learning and cloud-based resources, has demonstrated exceptional performance across various evaluation metrics. Its high precision, recall, F-1 score, accuracy, and low error rate make it the standout choice for ranking and classifying folk music based on consumer preferences. The comparative analysis of different models, including Naïve Bayes, SVM, and Random Forest, emphasizes the need for selecting the appropriate model depending on the specific task's objectives and requirements. Each model has its strengths and trade-offs, and it is crucial to consider these factors when choosing the right approach for consumer preference analysis. As technology continues to advance, these tools and methodologies will likely play a pivotal role in enhancing the personalized experiences of consumers and facilitating effective decision-making for businesses and cultural institutions in the folk music domain. This research provides a valuable contribution to the ongoing discourse surrounding consumer preferences and the application of advanced technology in the world of folk culture.

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