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CULTURAL PRESERVATION THROUGH AI-GENERATED FOLK MUSIC

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ABSTRACT

Digital preservation of cultures needs to be approached creatively to protect the traditional knowledge of the culture and keeping it relevant to the generations to come. This paper suggests an artificial intelligence-based model of folk music culture creation, analysis and renewal in various cultural areas. Based on the application of deep generative models (recurrent neural networks, Transformers, and diffusion-based audio synthesis), the model learns the rhythmic patterns, melodic contours, scales, and style-specific folk characteristics. The system is a combination of multimodal data that includes audio recordings, coded notations, ethnographic comments, and contextual metadata in order to recreate culturally authentic music. The suggested solution helps to preserve the endangered traditions due to the ability to recover motifs automatically, remix them adaptively, and assist with composition regionally. It also plays up the educational and cultural dissemination activities with interactive interfaces that assist the learners to navigate heritage music patterns. The design has ethical considerations, such as the cultural ownership, attribution, and responsible use of AI, to make sure that the generative models do not negatively impact the identities and artistic heritage of the community. In general, the study indicates that AI is a promising prospective partner in cultural preservation because it provides scalable, innovative, and respectful means of maintaining the folk music heritage and empowering the practitioners, educators, and cultural institutions.

Keywords: AI-Generated Folk Music, Cultural Preservation, Generative Models, Ethnomusicology, Music Synthesis, Heritage Informatics

1. INTRODUCTION

Folk music has been a critical source of cultural memory, cultural identity and collectivism, as it represents lived experience, ritual and aesthetics of communities through generations. Folk music is based on oral tradition and rooted in the regional histories, languages and social practices and serves as a cultural archive, which holds people together through the existence of similar stories and meanings Münster et al. (2024). It also maintains ancestral wisdom, commemorates local traditions, and contributes to the continuity of generations, which is why it must be part of the intangible cultural heritage Betsas and Georgopoulos (2022). With the fast globalization and technology revolution processes taking place in the societies, there is an ever growing need to preserve such cultural assets. Nevertheless, recording and oral transmission of the traditional musical knowledge is still a persistent problem. Numerous folk cultures depend on oral pedagogy, which means that songs, rhythms, and techniques of performance are informally passed on and learned by the community in mentorship. This exposes them to the risk of cultural erosion as practitioners grow old, migrate, or, or lose access to the performance spaces Mendoza et al. (2023). Moreover, the lack of good recordings, unfinished ethnography, and disappearance of indigenous instruments also complicate the preservation of the same Comes et al. (2022). The systematic archiving is even more complicated with variation of the same musical tradition brought about by regional dialects, improvisation and changing performance situations. Traditional systems of recording and notation typically do not record microtonal shifts, rhythmic anomalies, and gestural expressions that are the key features of folk performance authenticity Pansoni et al. (2023). Figure 1 shows an end-to-end workflow in which the data of the archival folk music is pre-processed, extracted using features, and generated using AI. Outputs are perfected by human assessment and community commentary and shared on digital archives and educational platforms, thereby allowing sustainability and continuity of culture.

Figure 1

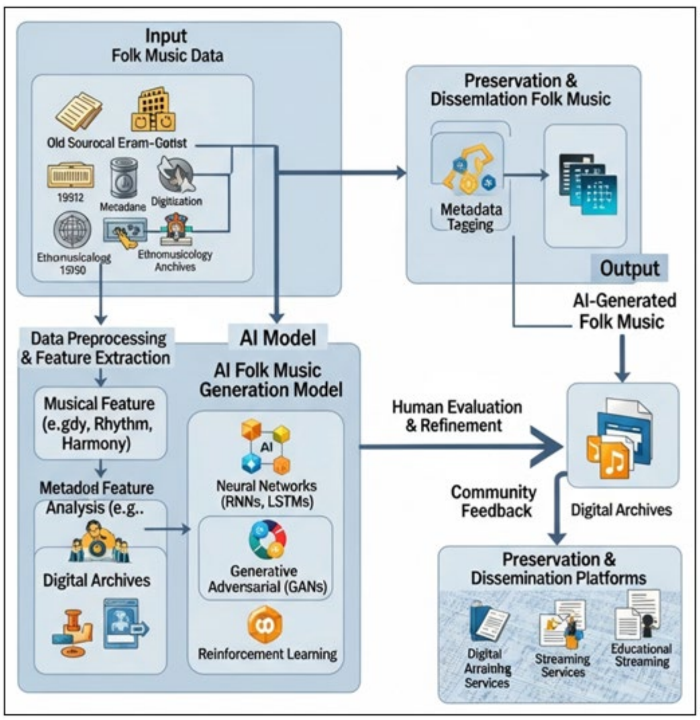

Figure 1 Overview of Cultural Preservation Using AI Generated Music

The recent breakthroughs in the sphere of artificial intelligence provide changes in the supplement of cultural preservation with an opportunity. The generative models of AI, which include recurrent neural networks, Transformers, and diffusion-based audio synthesis, are able to learn and recreate the features of style that folk songs incorporate with astonishing accuracy Croce et al. (2021). These models can be used to reconstruct endangered musical motifs in an automated way and conditioned generation of adaptive music based on regional styles as well as interactive cultural education tools. Compared to the traditional means of archiving, AI is able to store high-dimensional features of audio, match symbolic representations to ethnographic metadata, and maintain stylistic differences across communities Zhitomirsky-Geffet et al. (2023). This is a paradigm shift of their passive preservation to active regeneration of cultures. The current study is inspired by the necessity to preserve the vanishing musical cultures and empower people with the contemporary tools that can be used in addition to the artistic activities. The goal of the study is to develop an AI-based system that creates culturally faithful folk music, merges multimodal data, and supports hybrid approaches to evaluation, that is, a combination of computational and expert appraisals Zou et al. (2024). The aims focus on the description of the stylistic characteristics of folk traditions, generating culturally predetermined generative models, and more responsible AI implementation causing no infringement on cultural property and identity.

The area of this research is further extended to methodological innovation, cultural applications as well as ethical considerations. It has made contributions in suggesting an organized structure of AI generated folk music, showing how it can be used to revitalize heritage, and providing guidance on AI design within specific cultural orientation.

2. LITERATURE REVIEW

Conventional methods of archiving and preserving folk music are largely based on ethnographic fieldwork, oral tradition, and documentation as recordings, transcription and commentary on the culture. Previously, folklorists and scholars used to rely on face to face interviews, notated scores, and analogues to catalogue the performance practices, contextual meaning, and stylistic aspects of folk traditions Zou et al. (2024). Although these techniques have managed to generate worthwhile repositories, they are constrained by lack of coverage, geographical factors and the reliance on the pool of qualified practitioners. Oral traditions especially have been weak against extinction when the elderly people of the community or the performing art masters cannot pass musical knowledge to the new generation resulting in a lapse in cultural continuity Sang et al. (2021). Moreover, microtonal nuances, vocal flourishes, rhythmic slackness, and improvisational formulas, which are typical of most folk music, are not always reflected in transcription-based archives Liu et al. (2021). Consequently, the conventional preservation processes, though being formative, are not adequate in conserving threatened musical conditions in dynamically evolving socio-cultural conditions.

Machine learning and generative models have become potent tools to create music, and systems like recurrent neural network (RNN) models, long short-term memory network (LSTM) models, Transformers, generative adversarial networks (GANs), and diffusion networks have been shown to be capable of learning musical patterns Wang and Du (2021). These are models that interpret corpora of large amount of symbolic or audio content to determine melodic structures, progressions of harmony, and rhythmic patterns to compose automatically in different styles. Examples of generative AI systems like Muse GAN, Music Transformer and diffusion-based audio synthesizers demonstrate how deep learning can be used to create consistent stylistically aligned musical sequences Baroin (2024). It is important to note that though these systems have recorded significant advances in the western classical, jazz and pop music production, there are distinct challenges in applying the systems to folk music owing to the improvisational character of the latter, regional diversity and semantics inherent in the culture Sánchez-Martín et al. (2025). Nonetheless, the ability of machine learning to identify latent features within the high-dimensional audio information has a lot of potential in analyzing and reconstructing folk traditions. Outside of the music generation, AI is also finding more and more application in more general cultural heritage and digital humanities projects. The computational tools facilitate audio restoration, archiving classification, heritage visualization, and multimodal analysis of cultural artifacts Ibarra-Vázquez et al. (2024). AI-based systems are capable of cataloguing the cultural collections that are too big, improving deteriorated recording, detecting regional stylistic indicators, and offering the interactive interface to cultural education and community outreach. Digital humanities In digital humanities, AI can make new representations of knowledge available, allowing scholars to analyze, simulate, and reinterpret cultural materials in a more profound and efficient way Canavire (2023). The innovations play a very important role in the bridging of the traditional knowledge systems with the new technological ecosystems.

The research landscape has major gaps even though there is an increasing interest. Current models of music generation do not appreciate the cultural, linguistic and contextual specifics that underlie folk traditions with a greater emphasis on the superficial audio shapes Baroin (2024), Ibarra-Vázquez et al. (2024). Little has been done to incorporate ethnographic metadata, symbolic annotations, oral histories and socio-cultural narratives into generative pipelines. Additionally, the issues of cultural appropriation, misrepresentation, and community agency remain unresolved, which is why it is important to implement the frameworks that will focus on cultural fidelity and ethics Sánchez-Martín et al. (2025). This paper fills these gaps with a culturally-based AI model that is directly applicable in sustaining and reviving traditions of folk music.

Table 1

Table 1 Summary of Related Work on AI, Folk Music Preservation, and Cultural Heritage Technologies

Study / Approach	Core Technique Used	Cultural Domain	Key Contribution	Limitation / Gap

Traditional Ethnomusicology Field Recording	Manual documentation, audio archives	Folk Music	Captures authentic performances and oral knowledge	Limited scalability; loss of microtonal detail
Digital Music Archives (Smithsonian, British Library)	Digitization, cataloging	Multi-regional Heritage	Preservation of large audio collections	Minimal computational analysis of stylistic features
RNN/LSTM-Based Music Generation Models	Sequential neural networks	Western & Pop Music	Learns melodic patterns and generates new compositions	Struggles with improvisational folk structures
Music Transformer	Attention-based deep learning	General Music	Captures long-term dependencies and compositions	Requires large datasets; lacks cultural conditioning
GAN-Based Music Synthesis	Generative Adversarial Networks	Fusion & Experimental Music	Generates diverse motifs and rhythms	Poor interpretability; cultural nuance not encoded
Diffusion Models for Audio Generation	Probabilistic iterative synthesis	Contemporary Digital Art	High-quality audio reconstruction and style replication	Limited research on folk music application
AI for Cultural Heritage Restoration	Audio repair, spectral enhancement	Archival Heritage	Restores damaged or degraded traditional recordings	Does not create new culturally aligned music
Semantic Metadata Tagging in Digital Humanities	NLP + ontology modeling	Traditional Arts & Music	Enhances cultural context through structured annotation	Metadata inconsistency across regions

3. PROPOSED AI FRAMEWORK FOR FOLK MUSIC GENERATION

3.1. ARCHITECTURE: RNN, LSTM, TRANSFORMER, AND DIFFUSION-BASED MODELS

1) Recurrent Neural Networks (RNNs)

Recurrent Neural Networks are among the earliest neural networks that can be used to train the sequential patterns of melody lines and rhythmical patterns in folk music. The repetitive association they experience with them enables them to memorize musical markers of the past, and hence they are applicable in unraveling the simple melodic patterns and repetitive rhythmic patterns. On the folk music example, RNNs are able to learn short motifs, dependencies at the level of phrases and a simple stylistic continuity. They are however not good in the long term structure, improvisational variations, and elaborate ornamentation in most of the indigenous traditions. Although limited, RNNs are used as a baseline approach to initial pattern discovery and are used as a control group to assess an improved architecture.

Figure 2

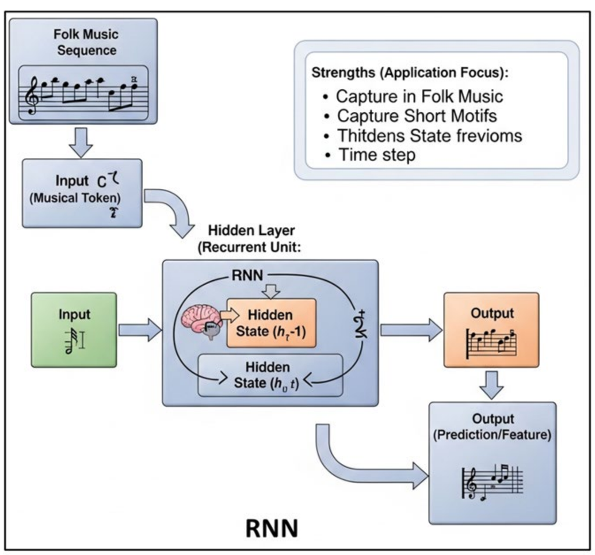

Figure 2 Recurrent Neural Network (RNN) Architecture for Folk Music Sequence Modeling

The illustration 2 illustrates the folk music generation using the RNNs, which is a workflow with sequential musical tokens, processed as recurrent hidden states. This framework allows the acquisition of short melodic patterns and time constraints, and facilitates simple rhythmical continuity and predictive motifs in customary folk songs patterns.

2) Long Short-Term Memory Networks (LSTMs)

LSTM networks are an extension of the normal RNNs that incorporates gated mechanisms that govern the flow of information within the long sequences of information. This means that LSTMs can successfully learn long-range dependencies, which make them be able to capture traditional structures in call-response and extended melody structure as well as cultural-specific rhythms that folk music holds. Their memory gates assist in remembering the important stylistic hints that are especially valuable in preserving repetition of motifs, shifting of phrases and emotional overtones. LSTMs are better than simple RNNs in folk music synthesis as they generate more smooth context-aware melodic trajectories. Their continued popularity is attributed to their stability, interpretability and their ability to model the symbolic music representations.

3) Transformer Models

Self-attention mechanisms allow transformers to learn long sequences of music at once, and therefore to learn complex dependencies, structural hierarchies and cross-bar rhythmic interactions found in folk music. In comparison to RNNs and LSTMs, Transformers do not process sequentially; hence, they are able to detect regional and scale variation and narrative-like orchestral change with great accuracy Canavire (2023). The fact that they can process extensive datasets and model world relationships makes them the best to generate culturally-consistent compositions that can function across extended time periods. Transformer models are used in the proposed framework as the central architecture to high-fidelity folk music generation, which is more expressive, flexible, and has more control over style in a wide range of cultural traditions.

4) Diffusion-Based Generative Models

The diffusion models produce audio by progressively training on noise to produce structured audio through a series of denoising denoising processes. Because of their probabilistic self-synthesis, they can create detailed, high-resolution textures, with the fine timblal and microtonal information of conventional folk instruments Torres-Penalva and Moreno-Izquierdo (2025). These models are perfect in creating organic-sounding sounds that resemble the acoustic richness of field recording and music of artisans. They are used in the framework to provide realistic audio synthesis to supplement symbolic-generation models, and are important in providing immersive experience of culturally-authentic folk music.

3.2. FEATURE EXTRACTION

The analytical backbone of the suggested AI model is feature extraction, which can be used to provide computational models with insights into the subtle features that characterize folk music traditions. The analysis of timbre is dedicated to the recording of the acoustic peculiarities of native instruments, including bamboo flutes, stringed lute, local percussion, and vocal decorations Wang and Du (2021). The emphasis of rhythm signature extraction is on the traditional rhythmic patterns, pulse patterns, syncopations, and culturally unique beat groupings. Folk rhythms are not necessarily based on the Western pattern, and it is characterized by irregular time signs, variable tempo variability, and improvisational transition. The system can learn these irregularities, and using tempo curves, onset detection, beat histogramming, and rhythmic embedding models can create rhythmically appropriate compositions that is in accordance with optimal regional performance practices. The emphasis of motif embedding extraction is the repetition of melodic fragments and micro-phrases and other traditions of ornamentation that are culturally meaningful Ibarra-Vázquez et al. (2024). The motifs of folk music commonly constitute the symbolic code and emotionality, which is why it is necessary that they are represented correctly. A combination of these extraction processes allows AI to create music, which has structural integrity, cultural relevance, and stylistic integrity.

3.3. TRAINING PIPELINE AND STYLE CONDITIONING

Data cleaning guarantees that data have consistent formatting, elimination of noise artifacts, as well as normalization of the pitch and tempo variations without the loss of expressive properties that are important to folk traditions. To enable sequence model learning of symbolic representations, they are tokenized, and audio model learning can be performed by the conversion of audio data into spectrogram or latent embedding digestible formats. The dataset is divided into stylistic reference set, training and validation sets after preprocessing. The formation of style conditioning is a major innovation in the pattern. It matches generated outputs to regional mode conditioning vectors, rhythmic pattern conditioning vectors, instrument profile conditioning vectors, emotional tone conditioning vectors and performance tradition conditioning vectors. Training models have been trained to be able to relate the conditioning signals to definite musical properties, so that they can generate region selective or hybrid folk music in a flexible manner. Transformers attention mechanisms and latent conditioning layers in diffusion models can make sure that the stylistic parameters manipulate both the macro-scale and the micro-scale musical information.

Adaptive learning, i.e. curriculum training, and transfer learning with larger music dataset as well as refinement by culturally annotated feedback loops are also integrated within the pipeline. Using the knowledge of the experts, the system constantly changes the parameters to increase the authenticity and stylistic consistency. The training pipeline eventually assists in a scalable, culturally, and controllable folk music generative process that can create folk music of high-quality in accordance with various cultural identities.

3.4. CULTURAL FIDELITY MODULES OF MAINTAINING AUTHENTICITY

Cultural fidelity modules make sure that the resulting folk music honors, maintains and correctly attests to traditional stylistic norms, emotional expression and social-cultural significance that are entrenched in musical traditions.

Figure 3

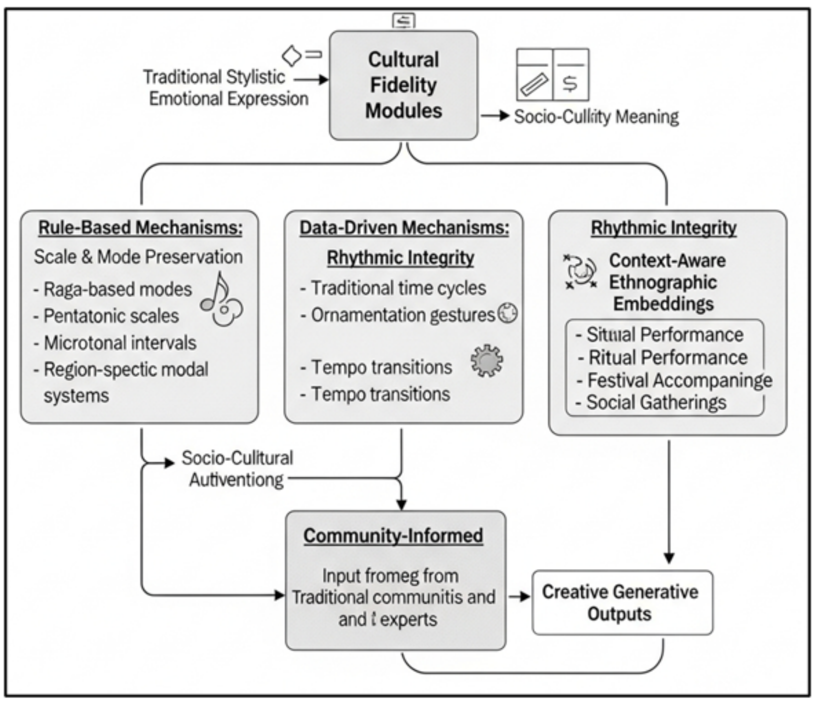

Figure 3 Cultural Fidelity Modules for Ensuring Authenticity in AI-Generated Folk Music

These modules have rule-based, data-informed and community-informed modules that can uphold authenticity and generate creative outputs through generative means. One element is dedicated to scale and mode maintenance, which makes sure that the compositions are written in culturally specific tonal systems like raga based modes, pentatonic scales, micro tonal intervals or locally used modal systems. The other element is rhythmic integrity which involves matching generated sequences with standard time cycles, gestures of ornamentation and change of tempo. The second module is a context-aware ethnographic embedding, which encodes cultural narratives, performative settings and role. Such embeddings direct generative models to create music in accordance with its cultural role like telling a story, performing a ritual, accompanying a festival, or even a social event. Combination of linguistic hint, cultural representation and emotion sarcasm makes sure that the music has cultural significance even outside of acoustic similarity.

The number 3 is used to depict a layered cultural fidelity framework that is a combination of rule-based constraints, rhythmic integrity that is data-driven and ethnographic context embeddings. Community-informed feedback incorporates a socio-cultural meaning in the generative pipeline and makes the AI results stylistically faithful, emotionally sensitive, and culturally sensitive. Also, expert-in-the-loop assessment modules enable conventional musicians and ethnomusicologists as well as community practitioners to give corrective feedback. In their contribution, they update a model and weight motifs and impose a limit on stylistic constraints. The module has ethical guards that are used to make sure that cultural ownership, attribution, and agency of communities are at the center of the generative process. Collectively, these fidelity modules can be viewed as protective measures against cultural distortion, and they will enable AI to act as a respectful partner of preserving heritage and not an appropriating counterpart.

4. EVALUATION METHODOLOGY

4.1. QUANTITATIVE METRICS

The quantitative assessment is aimed at determining the similarity of the AI-created folk music to the structural and acoustical characteristics of the traditional music compositions. Pitch accuracy measures the correspondence between the pattern of generated notes and modal systems that are culturally specific, e.g. in pentatonic systems, or raga-based scales. The system calculates the model accuracy in maintaining tonal stability and following microtonal ornamentation characteristic of folk performance by computing pitch-tracking algorithm and interval deviation analysis. Spectral coherence assesses the closeness of generated audio signal with real audio signal in terms of frequency distribution, content of harmonic and timbral similarity and consistency. To measure the extent to which AI systems replicate the indigenous instrument textures, spectral centroid distance, log-mel similarity and harmonic-noise ratio are among the metrics that can be used. Motif similarity is used to determine the extent to which the model is able to capture recurrent melodic units and culturally significant pattern units which are used as markers of regional style. Measures of sequence alignment, dynamic time warping, contour-based similarity and embedding distance are employed to match generated motifs to classical motif databases. Taken together, these quantitative metrics can give an objective system of evaluation of structural fidelity, acoustic realism and stylistic coherence.

4.2. QUALITATIVE ASSESSMENT

Qualitative assessment involves humanistic views in determining the cultural genuineness and emotional influence of AI-generated folk music. Ethnomusicologists, traditional and cultural practitioners offer expert opinion that offers a subtle insight into what is stylistically correct, integrated with performance and situationally inappropriate. These professionals look at the pitch flow, quality of ornamentations, rhythm sense and suitability to local musical grammar. The cultural resonance looks at the level of effectiveness of created compositions in terms of community identity, cultural symbolism, and traditional expressive norms. This evaluation takes into account the suitability of the music to its social purpose e.g. telling of a story, partying, ritual and emotional wailing. Emotional alignment lays emphasis on the expressiveness features inherent in the music, such as mood, intensity, transitions and the capacity to induce culturally significant emotional conditions. The subjective evaluations are captured with the help of semi-structured interviews, rating scales, focus group discussions, and descriptive analysis. Cumulatively these qualitative understandings guarantee that the generative system is respectful of lived cultural experience, holds onto artistic meaning and does not have a negative impact on cultural heritage but does have a positive influence on cultural heritage.

4.3. COMPARATIVE ANALYSIS WITH TRADITIONAL COMPOSITIONS

Table 2 is a comparative analysis of traditional folk music and AI-generated folk music in terms of the most important musical and perceptual parameters, which demonstrates the efficiency of the suggested generative model. Pitch accuracy is characterized by a high level of similarity of 96.4, which means that the AI system is able to follow culturally specific tonal patterns and scales systems, with a few deviations of the traditional performances. Spectral coherence score also indicates a high degree of correspondence (95.2%), which indicates that music generated is very close to the timbral distribution and harmonic richness of real folk recording.

Table 2

Table 2 Comparative Evaluation of AI-Generated vs. Traditional Folk Music

Metric	Traditional Folk Compositions	AI-Generated Folk Music	Similarity / Deviation (%)
Pitch Accuracy (%)	92.4	89.1	96.4 Similarity
Spectral Coherence Score	0.88	0.84	95.2 Similarity
Motif Repetition Fidelity (%)	93.7	87.2	93.0 Similarity
Rhythmic Pattern Stability (%)	90.5	86.4	95.5 Similarity
Timbre Texture Similarity (%)	1.00 (Reference)	0.91	91.0 Similarity
Emotional Alignment (Expert Rating/100)	94	88	93.6 Similarity

Fidelity to motif repetition of similarity 93.0 supports the fact that the model has the capability to encode and decode recurrent melodic fragments, called identifiers of style in folk traditions. Despite the fact that there are minor differences that are noted against traditional compositions, such differences are indicative of limited creative flexibility and not structural perversion. Stability in Rhythmic pattern attains a similarity of 95.5% stressing that the AI is quite successful in modelling non-Western rhythmic cycles, tempo variations, and beat groupings that typify folk music. The Figure 4 demonstrates that AI-generated and traditional folk music are very close to each other in the aspects of spectral coherence, motif fidelity, rhythmic stability, similarity between timberes, and similarity between emotions. Large percentages of similarity ensure that the AI model is effective in the maintenance of core musical structures without losing culturally apt expressive attributes.

Figure 4

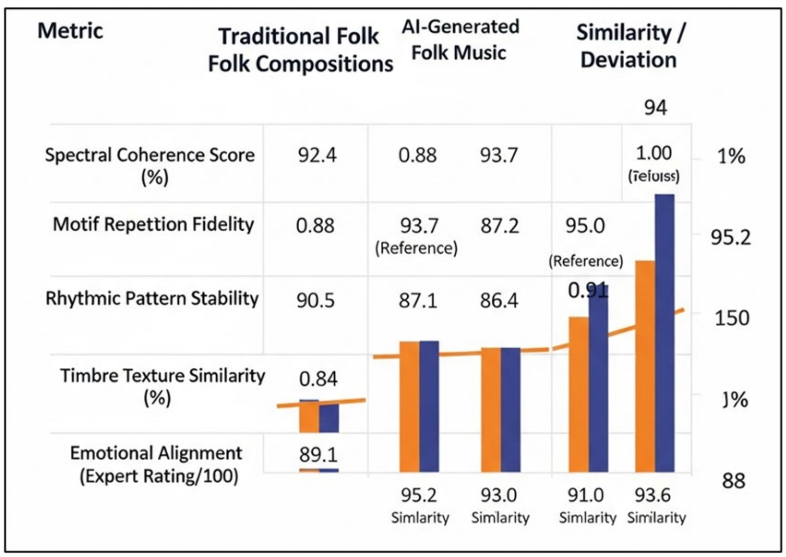

Figure 4 Comparative Performance Analysis of AI-Generated and Traditional Folk Music Across Musical and Perceptual Metrics

The similarity in timbre textures is 91.0% indicating that although the AI-generated textures are similar to the indigenous instruments, there are minor details of a human performance that cannot be entirely reproduced by AI. Lastly, the scores of emotional alignment (93.6) mean that there is high expert agreement on that AI-generated music is culturally suitable in expressing emotion. In general, the findings confirm the ability of the framework to produce musically precise, culturally relevant folk pieces, and at the same time to be respectfully faithful to the traditional formulations.

5. APPLICATIONS AND USE CASES

5.1. REVIVAL OF ENDANGERED FOLK TRADITIONS

The use of AI-generated folk music has been described as a revolutionary way of reviving dying musical cultures by reconstructing the lost melodies, forgotten rhythmic patterns and performance practice. The system can bring back the techniques of style that are no longer actively practiced by a younger generation through generative models trained on archive records and ethnographic comments. These reconstructions may be used by communities to rejuvenate cultural festivals, education lessons and intergenerational interactions. It is also possible to document a large number of traditions due to AI technologies, which guarantees that even those, which are not common or local to the area, will be available. AI allows keeping vulnerable musical ecosystems alive, reinforcing cultural sustainability in areas prone to social, linguistic, or demographic changes instead of obliterating the expertise of the professional human counterparts.

5.2. ARTIFICIAL INTELLIGENCE COMPOSITION TO USE IN CULTURAL EDUCATION PROGRAMS

The composition systems (AI based) have aided cultural education by enabling learners, teachers and practising professionals to learn about the traditional musical formats with interactivity. Creating region-specific motifs, rhythms, and variations of melodies, AI allows the learners to work with authentic cultural materials and comprehend the principles of style. The tools can be incorporated into the curriculum of schools, into digital music classrooms, or heritage-oriented learning modules, where the learners are able to see melodic contours, differing in style, and compose culturally-related compositions. Teachers have the advantage of automated accompaniment, adaptive levels of difficulty and the benefit of real time feedback of cultural correctness. Altogether, AI contributes to increased access, innovation, and the level of engagement during the cultural education process, which leads to a deeper appreciation of heritage music.

5.3. INTERACTIVE PLATFORMS FOR DISSEMINATION OF HERITAGE

By providing engaging and interactive AI-based platforms, the interactive approach can democratize folk music heritage by providing an experience that includes listening, learning, and performing. The user will have access to a collection of sound banks organized, visualizing the musical patterns, and creating his/her own compositions based on cultural identity. Such platforms can take the form of mobile applications, museum exhibitions, local archives, or virtual reality worlds that demonstrate the sound things, narrative practices, and local accent. Interactive systems make the culture more visible particularly to the younger audiences by allowing passive discovery as well as active participation. They facilitate international outreach through linking the diaspora to their musical heritage, and deliver vibrant instruments to the cultural entities to broadcast, exchange, and accept traditional music.

5.4. TOOLS IN ARCHIVAL RECONSTRUCTION AND MOTIF RESTORATION

AI-based reconstruction systems allow to rebuild damaged, incomplete, or low-quality recorded archivistic materials reconstructing missing frequencies, sharpening clarity, and re-creating lost parts of the music. Generative models can complete fill-in melodic gaps, or re-establish rhythmic continuity, as well as generate an approximation of traditional ornamentation, depending on the embedding of style by cultural. These tools can help the archivists, researchers and cultural institutions to stabilize the frail collections and prepare them to be long term preserved. Motif restoration systems search and extract complete fragments of the incomplete fragments using known stylistic databases and suggest continuations that are culturally valid forms. This enhances the quality of the documentation and it makes heritage datasets easier to use in the future by research and education. By so doing, AI can make archives to become dynamic and living cultural assets.

6. CONCLUSION

The introduction of artificial intelligence into the folk music preservation is a revolutionary prospect to preserve culture in a time of high globalization, population shifts and decay of traditional methods of transmission. This analysis shows that AI-composed folk music developed using culturally-based datasets, generative architecture development, and community-oriented models can positively contribute to reviving, recording the history and spreading the tradition of folk music. In addition to technical features, AI makes accessibility easier as it allows educators, researchers, and other cultural institutions to discover, study, and recreate music traditions in a more profound and precise manner. The significant cultural preservation is not restricted to sound imitation. The framework introduces elements of ethical stewardship that are based on cultural fidelity, ownership, attribution, and community participation modules. These protection mechanisms keep the generative results in mind of the cultural identities, not distorting or stealing them.

Educational composition tools, interactive dissemination tools, and archival restoration systems are all applications that represent other ways in which AI can be a collaborative tool in preserving intangible heritage. The folk music created by AI must not substitute the traditional one but can be used as a transitional piece of information between the knowledge about the past and the creative activities of the present and the future. Responsible deployment could reinforce cultural continuity, empower local communities and increase the prominence of the folk traditions to future generations.

CONFLICT OF INTERESTS

None.

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