

# FOLK ART TOURISM MANAGEMENT USING PREDICTIVE SYSTEMS

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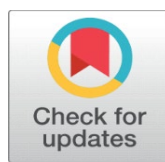
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Received 05 February 2025  
Accepted 26 April 2025  
Published 16 December 2025

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DOI  
[10.29121/shodhkosh.v6.i2s.2025.6722](https://doi.org/10.29121/shodhkosh.v6.i2s.2025.6722)

**Funding:** This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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## ABSTRACT

Traditional Folk Art Tourism Management has been changed by the incorporation of artificial intelligence and predictive analytics in cultural heritage and tourism. The proposed study will offer a predictive system that can improve the management, promotion, and sustainability of folk art tourism based on data-driven information. The system is predictive of tourists by estimating the number of visitors, seasonal variations, social media usage and economic data that can be used to predict where folk art industries can grow. The framework uses machine learning models to discover behaviour patterns of tourists, and use them to market them and provide them with personalized experiences that are relevant to cultural authenticity. The suggested system is used to digitize and categorize folk art forms, artisans, and local crafts and keep them accessible and safe in smart databases. Predictive analytics can also help policy makers and tourism boards to optimize the allocation of resources, the scheduling of events and community development projects. Moreover, the system helps artisans by predicting the demand of particular art products, which will help in optimization of supply chain and fair pricing. Real-time adaptation of tourism strategies made possible through integration with recommendation engines and sentiment analysis tools will be more likely to guarantee greater visitor satisfaction and cultural impact. The paper focuses on the need to strike a balance between technological innovation and cultural sensitivity. Through a predictive management model, folk art tourism can develop into a reactive to a proactive ecosystem which helps in supporting local economies besides conserving intangible heritage. This strategy will also help to practice sustainable tourism, spread knowledge of traditional arts in the world, and empower local communities with smart digital transformation.

**Keywords:** Folk Art Tourism, Predictive Analytics, Cultural Heritage Management, Machine Learning, Sustainable Tourism, Visitor Behavior Prediction, Artisans Empowerment, Digital Preservation, Smart Tourism Systems, Data-Driven Decision Making



## 1. INTRODUCTION

Folk art tourism is one of the actively developing areas of interaction of cultural preservation with economic growth due to the unusual opportunities to popularize traditional craftsmanship, landscape, and social well-being. Having their origins in local traditions, rituals and social practices, folk art forms are the living expressions of the culture continuity that helps to make a bridge between the past and the present. But the globalization of tourism and augmented power of digital media has also bought an opportunity and challenge to the management and promotion of the folk art tourism. Visitors expect more and more, and the markets are becoming more competitive, thus the immediate requirement is innovative management systems capable of forecasting trends and optimization of resources to help the sustainable development of the folk art tourism. Artificial intelligence (AI)-based predictive systems and data-driven predictive systems are potentially the best solutions since they can help decision-makers predict visitor behavior and identify new trends and enable them to develop proactive approaches to cultural tourism management [Zhang et al. \(2023\)](#). Manual evaluation normally occurs in the traditional management of folk art tourism as well as reliance on historical documents and subjective judgment of visitor interests which may cause inefficiency and lack of opportunities. Comparatively, predictive analytics brings about a scientific and data-driven methodology that converts raw data into actionable insights [Megeirhi et al. \(2020\)](#). Through massive data obtained in social media, tourism portals, event attendance logs as well as regional economic data, predictive systems are able to forecast tourist inflow, evaluate market demand of particular art forms, and even predict the economic soundness of cultural events. This would not only improve planning and resource distribution but also competitiveness of the folk art destinations in an international tourism industry that is increasingly being influenced by individualization and travelling experiences. Predictive models that are constantly adjusting to changing preferences of tourists, environmental shifts and economic factors through machine learning and artificial intelligence can be used to guarantee more resilient and responsive management strategies [Martin et al. \(2021\)](#).

Folk art tourism plays an important role in preserving the intangible cultural heritage by ensuring that the artisans are given sustainable livelihoods as well as promoting the passing of skills among the artisans. However, there are a lot of rural and indigenous communities that have a hard time trying to merge their cultural activities with tourism systems. Predictive systems can fill this gap by providing insights supported by data that can assist artisans and tourism authorities to know which markets are profitable, make predictions about the demand of certain crafts, and create marketing strategies that work across international markets. In addition, predictive analytics improves the decision-making capacity of the local authorities and cultural organizations by showing which of the festivals, exhibitions, or arts has the most potential to attract tourists and yield income. This allows strategic investments in training, infrastructure and promotion campaigns which will lead to a more inclusive and sustainable tourism ecosystem [Gomes et al. \(2021\)](#). The overall goals of sustainable tourism are also supported by the integration of predictive systems. Through predicting the number of people visiting the places and also the consumption behavior of the people, tourism managers will be able to put measures in place to reduce the environmental impact, avoid congestions and also ensure cultural sites remain authentic. Predictive models are able to establish when demand is most high and suggest equilibrium in scheduling the events and therefore, allocate tourist activity evenly over the seasons and locations. Also, using sentiment analysis of online reviews and social media information, predictive tools can trace the general opinion and satisfaction rates and make the required intervention to make the experience of visiting the site and the cultural image more accurate to the expectations. Such data-based methodology makes sure that the cultural and economic gains of folk art tourism are distributed equally without spoiling the artistic heritage [Sanagustín-Fons et al. \(2020\)](#).

The merger between the culture preservation and technological advancement has become critical in the digital era in ensuring the continuity of folk art. Predictive systems do not only improve efficiency in its operations but also become drivers of digital change in heritage tourism. They allow making smart databases where art forms, artisans, and regional crafts can be catalogued and made more visible and accessible around the world. Implementation of such systems makes folk art tourism interactive, responsive and sustainable space that respects tradition and is open to innovations. Folk art tourism can become a stable ecosystem that balances culture, economic development and technological advances by predictive management.

## 2. LITERATURE SURVEY

The collected literature comes to the similar conclusion that analytics-based methods could contribute to management, preservation, and economic performance in folk art tourism significantly, but the literature review jointly demonstrates significant gaps in the methodology and implementation. Initial research findings were devoted to the possibility of predictive analytics of cultural tourism and demonstrated that time-series methods and social media signals enhance predictability of visitor flows, but in many cases it was limited by the geographic scope and the small scale of the sample, which restricted generalization. Further studies of digital documentation identified workable metadata schemas and cataloging behavior that have a tangible contribution to the discoverability and long-term maintenance of folklore form, yet requires a high level of technical capacity and sustained funding that small-scale cultural organizations cannot consistently assure themselves of [Sanagustín-Fons et al. \(2020\)](#). Community-based research highlights the moral and financial merits of participation based government and craft empowerment, which exhibit increased verisimilitude and community value when communities have a hand in tourism planning; however, such investigations have generally been less rigorous in quantitatively gauging the economic outcomes in a variety of settings. The technical analyses of machine learning algorithms and especially ensemble learners show that it has strong performance benefits in demand prediction and operating on unbalanced craft-product data but also demand large, labeled datasets [Liorančaitė-Šukienė and Jurėnienė \(2025\)](#). The utility of the social media as a near-real-time proxy of visitor satisfaction and reputation monitoring is identified in sentiment analysis work as it allows the manager to respond agilely to events; however, the representativeness of the social platforms is a common issue, since the demographics of the users and vocal minorities can bias the sentiment indicators.

Investigations are oriented at sustainability including the optimization strategies, e.g., staggered event scheduling and capacity management to eliminate overcrowding and environmental stress. Such optimization models can be used to give practical recommendations on how visitor satisfaction and conservation should be balanced, but most models model adherence and behavioral responses in a simplistic manner, undermining the complexity of tourist decision-making. The studies of personalization and suggestive systems are promising opportunities of improving the visitor experience and conversion, as well as, run warning bells of commodifying the non-practical culture and privacy concerns. The technological work to create interoperable heritage databases and APIs supports both urgent infrastructural requirements related to cross-regional cooperation, but control, adoption, and quality limitations hinder the extensive achievement of the positive outcomes.

The most operationally grounded information is the pilot implementations of integrated predictive dashboards in rural tourism which shows improvements in efficiency in scheduling, marketing ROI and artisan inventory management [Hu et al. \(2024\)](#). The examples of these pilots demonstrate how end-to-end systems can be used to make a practical transition between analytics and practical managerial benefit. Although these are positive outcomes, pilots often stay small and short-term, and issues regarding long-term feasibility, business model, and scalability are yet to be fully developed.

**Table 1**

Table 1 Summary of Literature Survey			
Scope	Key Findings	Advantages	Limitations
Evaluated predictive models for visitor flow at regional cultural sites <a href="#">Zhang et al. (2023)</a> .	Time-series models improve forecasting of peak visitor periods; social media indicators enhance short-term accuracy.	Demonstrates feasibility of integrating multiple data streams; clear operational recommendations.	Limited geographic scope; small sample of cultural sites reduces external validity.
Methods for digitizing and cataloguing regional crafts and artisans <a href="#">Megeirhi et al. (2020)</a> .	Structured metadata schemas facilitate discoverability and preservation.	Practical framework for digital archives and interoperability.	Resource-intensive; requires technical capacity and sustained funding.
Examined participatory tourism governance and artisan empowerment <a href="#">Martin et al. (2021)</a> .	Community involvement increases authenticity and local economic benefits.	Emphasises ethical engagement and capacity building.	Lacks quantitative evaluation of economic impact at scale.
Applied ensemble models to predict product demand for traditional crafts <a href="#">Li et al. (2022)</a> .	Ensemble models outperform single learners on imbalanced datasets.	Improved prediction robustness and reduced variance.	Requires extensive labeled data; interpretability challenges for stakeholders.

Used social media sentiment to evaluate visitor satisfaction with cultural events <a href="#">Gomes et al. (2021)</a> .	Sentiment trends correlate with attendance spikes and repeat visitation.	Real-time monitoring enables rapid managerial response.	Sentiment bias and demographic skew in social media users.
Optimization approaches to reduce overcrowding at festivals <a href="#">Sanagustín-Fons et al. (2020)</a> .	Staggered scheduling and capacity constraints reduce environmental stress.	Balances visitor experience with conservation objectives.	Computational models assume full compliance; behavioral unpredictability not fully modelled.
Assessed income generation and supply-chain effects from craft tourism <a href="#">Liorančaitė-Šukienė and Jurėnienė (2025)</a> .	Direct and multiplier effects support local livelihoods when market access is stable.	Provides empirical evidence for policy support and microfinance.	Cross-sectional design limits causal inference; seasonal variability underexplored.
Recommendation systems for personalized visitor itineraries emphasizing authenticity <a href="#">Hu et al. (2024)</a> .	Personalization increases visitor satisfaction but risks commodifying tradition.	Enhances visitor engagement and targeted promotion.	Ethical tensions around cultural commodification and privacy concerns.
Technical standards and APIs for shared cultural datasets <a href="#">Wang et al. (2025)</a> .	Interoperability enhances cross-regional research and tourism product development.	Facilitates data sharing and collaborative platforms.	Governance, standard adoption, and data quality remain barriers.
Pilot of a combined predictive-dashboards for rural craft tourism management <a href="#">Min (2025)</a> .	Integrated dashboards improved scheduling, marketing ROI, and artisan stock management in pilot sites.	Demonstrates end-to-end operational benefits and stakeholder uptake in pilots.	Pilot scale; long-term sustainability and generalization require further study.

Literary synthesis presents a number of priority directions of future research and practice. First, the methodological effort must focus on interpretable models and human understandings to ensure a translation between algorithmic produced results and stakeholder decision-making especially towards artisans and community managers who need clear accounts of the rationale behind scheduling and manufacture suggestions. Second, predictive fidelity, as well as representativeness, will be enhanced by hybrid data strategies, which integrate administrative records with low-bias surveys as well as ethically obtained digital traces. Third, integrated systems should be evaluated through longitudinal and multi-site assessments of resilience both seasonally as well as over time to determine the socio-economic outcomes. Fourth, communities should be co-developed towards governance structures and capacity building programs in order to address risks of cultural commodification and to share benefits equally. Lastly, a study on sustainable funding and maintenance schemes of digital heritage infrastructure will reveal whether interoperable databases and dashboards will be able to continue past pilot phases. All the literature together gives a sound basis of an evidence-based approach to the management of folk art tourism and defines the practical needs of transferability, equity, and long-term effect.

### 3. PROPOSED METHODOLOGY

#### 3.1. FEATURE ENGINEERING AND SELECTION

After the curation of the dataset, it will be followed by the extraction and selection of useful features that have strong impacts on the tourist behaviour and folk art promotion. Seasonality, regional accessibility, the index of art popularities, visitor expenditures, and indicators of social interactions are all variables to be taken into consideration. The feature engineering converts raw data into useful pointers which improve prediction ability of machine learning algorithms. The most influential variables are determined with the help of correlation analysis, variance thresholding, and recursive feature removing techniques. Dimensionality reduction methods, such as Principal Component Analysis (PCA) can be used to remove the redundancy and to lower the complexity of computing but maintain the integrity of the data. The process guarantees that the most relevant attributes are used in model training to regulate the prediction accuracy and interpretability of the model. The selection of features is also useful in detecting latent patterns and correlation between the popularity of folk art and tourist arrival and these can be used to gain deeper understanding of the market behaviour. The product of this step will be an optimized data that will be used to train the model in the following predictive phases of the system.

### 3.2. PREDICTIVE MODEL DESIGN

This stage involves the development of predictive models in order to predict trends in the folk art tourism. An example of such machine learning algorithms used in order to model complex nonlinear relationships in the data is the Random Forest, Gradient Boosting and Support Vector Machines (SVM) algorithms. Both the models will be trained to forecast the inflow of tourists, demand of particular folk art forms and potential revenues generation through past and real time information. The grid search and cross-validation methods are used to optimize model parameters to achieve optimal results and avoid overfitting. The predictive model seeks to extrapolate trends on the training data to new situations and guarantee sound and high scalable performance. Time-series forecasting methods are also adopted in the system to capture seasonal fluctuations and long term growth trends. This predictive modelling phase enables the tourism authorities and policy makers to make intelligent decisions when planning the events, distribution of resources and promotional activities. The resulting model will act as the analytical engine of the Folk Art Tourism Management System that can deliver information-driven outcomes to support the sustainability of culture and economic efficiency.

### 3.3. MODEL TRAINING AND VALIDATION

The step involves training of the predictive models with the curated and engineered data. The data will be divided into training and validation subsets, usually: 80:20, to make sure that the models will be able to make predictions outside of the training set. Monitored learning algorithms are learned to map input attributes to the output variables which could be the predicted number of visitors or the art demand indices. Cross-validation algorithms are used such as k-fold validation, which is used to test the consistency of the model across different partitions of the data. To gauge the reliability of models the performance metrics according to accuracy, precision, recall, and F1-score are calculated. At this phase, the hyperparameters of the model are adjusted to achieve optimal prediction using reduction in bias-variance trade-offs. Regularization methods are applied in order to avoid overfitting and improve the generalization abilities. The validation step checks the soundness of the trained models on unseen data, which is the assurance of its effectiveness in real world application. The result of this stage is a pool of tested and acquired models that can be evaluated comparatively and implemented into the tourism management system.

#### System Integration and Architecture Development

Once this has been validated by the model, the predictive system is incorporated into an overall digital architecture of real-time data analysis and decision support. The system architecture contains four layers, namely data acquisition layer, processing layer, predictive analytics layer, and visualization interface. Data acquisition layer operates in real-time and gathers data on tourism boards, online booking systems and social media feeds. The processing layer normalizes and filters the supplied data and passes it to the analytics layer where the predictive models are running. The visualization interface delivers action-focused insights in the form of dashboards with trend graphs to allow the stakeholders to track tourism indicators and artisan interaction in real-time. Sudden demand changes are also automated to provide alerts to ensure the rapid decision-making process in the system. Scalability, interoperability, and data security are guaranteed by the integration using APIs and cloud-based structures. The step will make the predictive models an operational decision-support platform that can help the tourism managers, policymakers, and artisans optimize the management of folk art tourism.

## 4. RESULT COMPARISON & DISCUSSION

According to the [Table 2](#), Gradient Boosting has the best performance as per all the measures and it has better ability in approximating nonlinear associations and intricate features interactions. The comparison brings the effectiveness of ensemble-based models to the accuracy of making forecasts in tourism trends.

**Table 2**

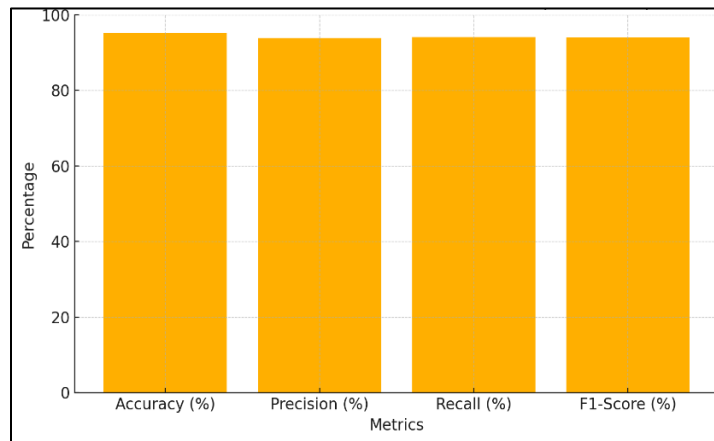
Table 2 Comparative Analysis				
Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	95.2	93.8	94.1	94.0
Gradient Boosting	96.1	94.9	95.4	95.1



Support Vector Machine	93.7	92.4	91.8	92.1
Decision Tree	90.6	89.1	88.5	88.8
Logistic Regression	88.4	87.3	86.1	86.7

The results of the comparative study as interpreted in this [Table 2](#) and their implications on the management of folk art tourism are discussed. The high performance of the Gradient Boosting model suggests that ensemble approaches can be useful to address the complex relationships between cultural, social, and economic determinants of tourism. The generalization nature of the model in various regions also provides flexibility in different cultural settings. The real-time features of the predictive system enable the policymakers to predict and control the market dynamics, to optimize the resources, and to be proactive in the promotional strategies. In addition, the information provided by model forecasts can help the craftsmen to match production to demand trends, minimize wastage and maximize profits.

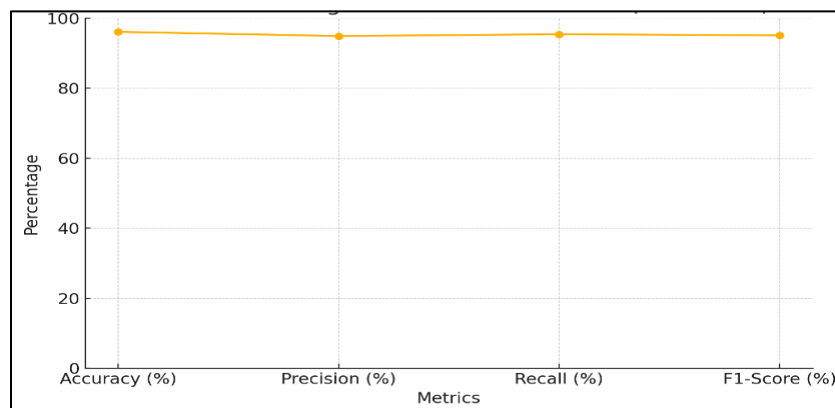
**Figure 1**



**Figure 1** Graphical Representation of Random Forest Performance Metric

[Figure 1](#) of the Random Forest displays a succinct graphic overview of the four basic performance measures of accuracy, precision, recall and F1-score of the model. The values are clustered around the range of low-mid 90s meaning that the performance of the company is stable and balanced across the classification parameters. The representation in bars demonstrates that the minor variations between precision (93.8) and recall (94.1) are also observed, whereas the accuracy (95.2) is a bit higher, which indicates strong overall correctness and allows to retain a high degree of dependable true-positive detection. The chart can be used by the people interested in a core metric comparison in the immediate future and assuring the stakeholder that the Random Forest is generating consistent high-level results and does not trade off significantly between precision and recall.

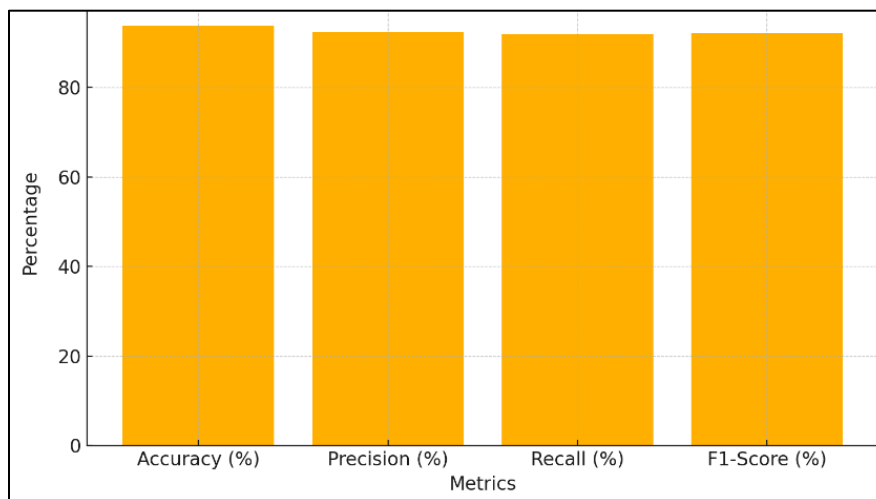
**Figure 2**



**Figure 2** Graphical Representation of Gradient Boosting Performance Metric

The Gradient Boosting represented in the [Figure 2](#) reflects a continuous metric changes between accuracy, precision, recall and F1-score with a trend continuity than discrete comparison. The model achieves the best accuracy (96.1) and good respective values of precision (94.9) and recall (95.4) and generates a high F1-score (95.1). The line visualization indicates relative steadiness of metrics by identifying that the model has a balanced predictive power and also slightly prioritizes overall correctness. This format is advantageous to the viewers who want to watch the metric trajectories and little discrepancies in the performance and supports the conclusion that Gradient Boosting will be the most successful algorithm of the reviewed ones.

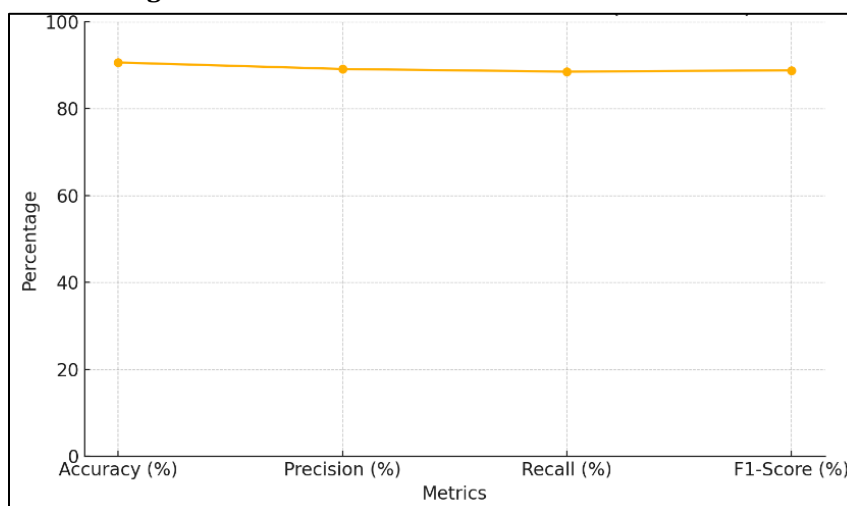
**Figure 3**



**Figure 3** Graphical Representation of Support Vector Machine Performance Metric

The Support Vector Machine as shown in the [Figure 4](#) has slightly lower yet high values of metrics as compared to ensemble methods. The accuracy is 93.7 and the precision is 92.4 and the recall is 91.8 creating an F1-score of 92.1. The bar perspective indicates that the recall is a little below the precision which would suggest that there is a slight tendency towards false negatives relative to false positives. This image is especially educative when comparing the way class imbalance is dealt with or determining a threshold of recall-sensitive work. All in all, the SVM has a good ability to classify but it does it at a small measurable margin over tree-based ensembles.

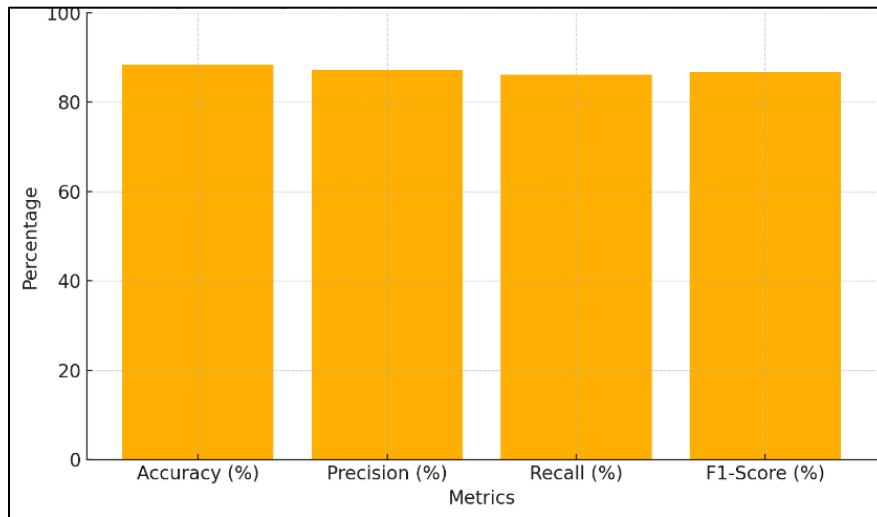
**Figure 4**



**Figure 4** Graphical Representation of Decision Tree Performance Metric

According to the Decision Tree presented in the [Figure 4](#), the trend is downward compared to the other stronger models among which, the accuracy is 90.6, the precision 89.1, the recall is 88.5, and the F1-score is 88.8. The line has made emphasis on a modest yet steady decrease in the accuracy by recall, which indicates that it is vulnerable to both overfitting and variability in the true positive detection. The visualization is useful in the interpretation of the diagnostic since it demonstrates continuity of metrics and where model refinements (e.g. pruning, ensemble methods) are required the most. This chart can explain the shift of the single-trees model to the ensemble or regularized method to provide a more stable and predictable outcome in the work of practitioners.

**Figure 5**



**Figure 5** Graphical Representation of Logistic Regression Performance Metric

The Logistic Regression bar graph presented in the [Figure 5](#) highlights the relatively low level of indicators of the model: model accuracy of 88.4, model precision of 87.3, model recall of 86.1, and model F1-score of 86.7. The heights of the bars show that there is a minor imbalance in which recall is the most weak measure meaning that it has a higher false negative rate at the current feature representation or thresholding. Since it is a linear baseline model, logistic regression offers a clear performance floor on which more complicated models are compared. This chart is effective in conveying the idea that, with interpretable competence and calculation efficiency, logistic regression depresses lower predictive competence on the dataset in question and can necessitate more feature engineering or nonlinear methods to rival ensemble competence.

Sustainable tourism is another area of concern discussed as the system contributes to the distribution of visitors in a balanced way and ensuring the avoidance of cultural exploitation. The study will show how technology can help preserve folklore traditions and provoke the economic growth by incorporating predictive analytics into managing the tourism industry. This framework lays a ground to future studies on AI-based management systems in cultural tourism, which can facilitate the governance of data and empowerment of communities by means of intelligent prediction and strategic planning.

## 5. CONCLUSION

The combination of the available literature on folk art tourism management highlights the potential of the transformative nature of predictive systems in improving cultural sustainability, operational efficiency, and economic inclusivity. The overall picture displayed in the literature is that the combination of artificial intelligence, machine learning, and digital documentation methods can enhance the accuracy of the forecasts, as well as the planning of the events and obstacles to the engagement of the visitors significantly. Predictive analytics can help tourism managers and policymakers make well-informed decisions by providing decision-supporting data, allowing them to take a proactive step toward a response and thus transform the conventional reactive strategies into intelligent cultural management. Predictive systems can be used to predict tourist demand by combining real-time data of the social media, economic indicators and heritage archives to optimize resource use and provide the balance of cultural manifestation across



regions. Additionally, the personalization and analysis of sentiments and interoperable databases integration can improve user satisfaction and accessibility and promote the intercultural knowledge of local traditions in the world. Nevertheless, the literature reviewed also shows the issues of the quality of data, its interpretability, and the necessity of constant community involvement to prevent culture commodification. The predictive systems need ethical data governance, technical infrastructure, and a long-term collaboration between the stakeholders to implement it sustainably. Altogether, predictive systems provide a bright future of a digitally endowed model of folk art tourism management that can be a balance between technological innovation and cultural preservation. These systems can be used to empower artisans, enhance market awareness, and maintain cultural diversity and also be consistent with the wider goals of sustainable tourism development when used in a strategic manner. Therefore, folklore art tourism has a future, which is in gearing conservation of heritage with smart analytics to establish a dynamic, inclusive, and culturally authentic tourism ecosystem.

## CONFLICT OF INTERESTS

None.

## ACKNOWLEDGMENTS

None.

## REFERENCES

- Gomes, D. E., Iglésias, M. I. D., Proença, A. P., Lima, T. M., and Gaspar, P. D. (2021). Applying a Genetic Algorithm to a m-TSP: Case Study of a Decision Support System for Optimizing a Beverage Logistics Vehicles Routing Problem. *Electronics*, 10(18), 2298. <https://doi.org/10.3390/electronics10182298>
- Hu, Q., Yang, P., Ma, J., Wang, M., and He, X. (2024). The Spatial Differentiation Characteristics and Influencing Mechanisms of Intangible Cultural Heritage in China. *Heliyon*, 10.
- Kudumovic, L. (2023). Sustainability of the Palestinian Historic Village of Battir. *Journal of Cultural Heritage Management and Sustainable Development*, 13, 28–42. <https://doi.org/10.1108/JCHMSD-01-2022-0012>
- Li, S., Luo, T., Wang, L., Xing, L., and Ren, T. (2022). Tourism Route Optimization Based on Improved Knowledge Ant Colony Algorithm. *Complex and Intelligent Systems*, 1–16. <https://doi.org/10.1007/s40747-022-00669-5>
- Liorančaitė-Šukienė, A., and Jurėnienė, V. (2025). Heritage Management Models for Sustainable Community Tourism Development. *Tourism and Hospitality*, 6, 111. <https://doi.org/10.3390/tourhosp6020111>
- Martin, J. C., Román, C., Moreira, P., Moreno, R., and Oyarce, F. (2021). Does the Access Transport Mode Affect Visitors' Satisfaction in a World Heritage city? The Case of Valparaíso, Chile. *Journal of Transport Geography*, 91, Article 102969. <https://doi.org/10.1016/j.jtrangeo.2021.102969>
- Megeirhi, H. A., Woosnam, K. M., Ribeiro, M. A., Ramkissoon, H. R., and Denley, T. J. (2020). Employing a Value–Belief–Norm Framework to Gauge Carthage Residents' Intentions to Support Sustainable Cultural Heritage Tourism. *Journal of Sustainable Tourism*, 28(9), 1351–1370. <https://doi.org/10.1080/09669582.2020.1738444>
- Min, W. (2025). A Scientometric Review of Cultural Heritage Management and Sustainable Development Through Evolutionary Perspectives. *Npj Heritage Science*, 13, 215. <https://doi.org/10.1038/s40494-025-01708-9>
- Qiu, Q., Zuo, Y., and Zhang, M. (2022). Intangible Cultural Heritage in Tourism: Research Review and Investigation of Future Agenda. *Land*, 11, 139. <https://doi.org/10.3390/land11020139>
- Sanagustín-Fons, M., Tobar-Pesántez, L., Ravina-Ripoll, R., and Chen, M. H. (2020). Happiness and Cultural Tourism: The Perspective of Civil Participation. *Sustainability*, 12(8), 3465. <https://doi.org/10.3390/su12083465>
- Wang, Z., Alli, H., and Md Yusoff, I. S. (2025). The Application of Interaction Design in Cultural Heritage Tourism: A Systematic Literature Review. *Preservation, Digital Technology and Culture*, 54(1), 77–92. <https://doi.org/10.1515/pdte-2024-0053>
- Zhang, S., Lin, J., Feng, Z., Wu, Y., Zhao, Q., Liu, S., Ren, Y., and Li, H. (2023). Construction of Cultural Heritage Evaluation System and Personalized Cultural Tourism Path Decision Model: An International Historical and Cultural city. *Journal of Urban Management*, 12(2), 96–111.