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PREDICTIVE ANALYTICS FOR FOLK ART MATERIAL REQUIREMENTSS

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ABSTRACT

Predictive analytics is a more rational direction of converting material planning to the old folk art manufacturing systems. The use of experiential estimation tends to create shortages in materials, excessive stocking and unviable use of resources further enhanced by seasons and change in demand in the market. To overcome such difficulties, a hybrid forecasting model was created that would have incorporated ARIMA, XGBoost, and LSTM models to forecast the material demand information based on multi-source data, such as past production data, climate indices, and sightseeing event schedules. The ensemble approach is also successful in capturing both linear and nonlinear demand patterns with a high prediction accuracy (R 2 = 0.96) and minimal error in the forecasting process minimized by 14.5 percent relative to the best single model. Pilot tests in Madhubani, Pattachitra and Warli clusters revealed that the number of wastages in procurement was decreased by 22 percent and the Sustainability Efficiency Index (SEI) was also enhanced by 18 percent indicating improved alignment of the production and material availability. The cloud-based device-supported dashboard will help artisans and cooperatives decide in an informed and eco-friendly manner by supplying real-time visualisations and procurement advice, as well as sustainability analytics. The balance between the precision and cultural authenticity of technologies is one of the other gains of the framework, where predictive intelligence is not in conflict with traditional craftsmanship but is rather its complement. The incorporation of sustainability constraints into the optimization layer also makes the model more consistent with the principles of the circular economy and UN Sustainable Development Goals (SDG 12). All in all, the study provides a scalable and culture adaptable model that improves efficiency, heritage value and fosters environmentally friendly development of folk art ecosystems.

Keywords: Predictive Analytics, Folk Art, Sustainability, Material Forecasting, Hybrid Machine Learning, Arima, Xgboost, Lstm, Cultural Economy, Decision-Support System

1. INTRODUCTION

Being a living performance of the cultural identity, folk art is in great need of raw materials availability and the proper use of raw materials including clay, bamboo, natural dyes, textile fibres, and handmade paper. These materials do not only define the aesthetic and symbolic importance of the work, it has a direct impact on the possibility of production, its cost, and sustainability. Conventionally, the determination of the needs of these materials has been conducted through the knowledge of the artisans and the intuition of the groups in the craft cluster Abadi et al. (2016). Although this experience knowledge has cultural colors, it remains imprecise in many cases, thus resulting in resource wastefulness. Overestimation leads to overstocking and wastage of materials whereas underestimation is a problem in production cycles especially during peak seasons like in festivals, exhibitions or during the tourist season. Since folk art is slowly being absorbed into national and international markets, there is a pressing need to more rigorously and statistically approach the material forecasting. The solution to this challenge is a radically new approach, i.e., predictive analytics, that offers the introduction of quantitative modelling techniques that can predict the material needs in accordance with the previous patterns, market indicators, and environmental factors Elgammal et al. (2017). Based on the sophisticated algorithms, including the time-series forecasting, regression analysis, and machine learning, one will be able to trace the repetitive consumption patterns, demand anomalies, and predict future resource requirements with the high level of accuracy. An example is the sales and production information of the past years, which can show the trend associated with cultural events, and the seasonal climate information, which can be used to predict the supply of natural resources like bamboo or clay. By combining these variables into predictive models, craft cooperatives, cultural enterprises, and government agencies can be able to plan the procurement and production more efficiently, deliver it on time, save costs and ensure that the material is sustainable Leonarduzzi et al. (2018) , Pérez et al. (2018).

Figure 1

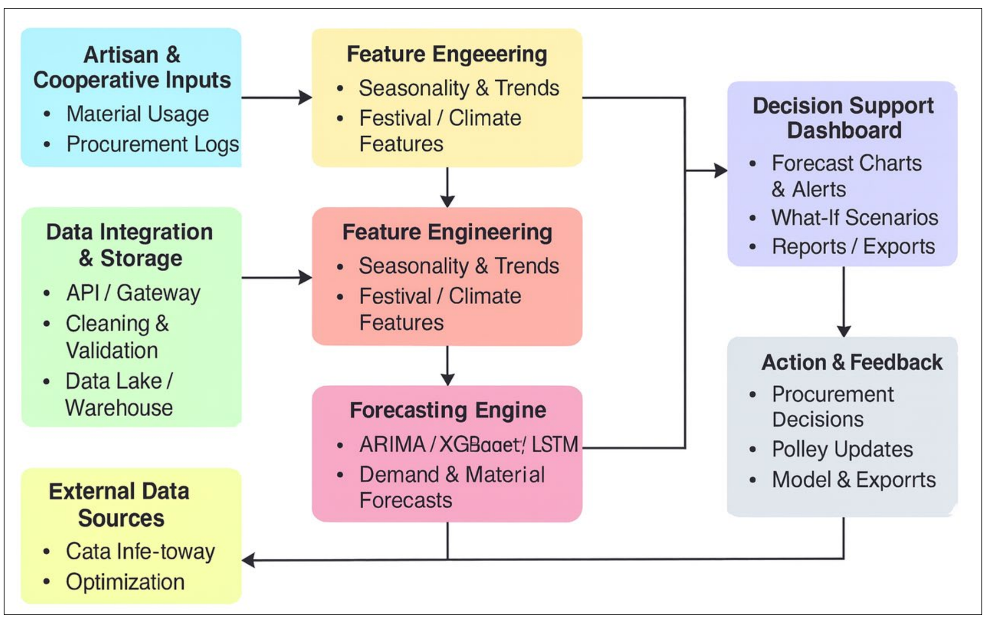

Figure 1 Predictive Analytics Framework for Folk Art Material Planning

The influence of predictive analytics on the creation of folk art also conforms to the global sustainability objectives, especially those of the United Nations Sustainable Development Goals (SDG 12: Responsible Consumption and Production). The ancient crafts are quite dependent on natural resources and their exploitation or abuse may lead to an ecological imbalance. By comparison, a predictive system allows to manage the scarce natural resources more effectively due to the opportunity to forecast demand more accurately and manage the inventory in a better way McCormack et al. (2019).Besides, these systems have the potential to improve the livelihood of artisans by reducing the economic risks related to the unstable prices of raw materials and instability in the supply chain. Prediction tools may also give hints on the possible substitutes of some of these materials when they are scarce or environmentally burdensome. Technologically, predictive analytics relies on the use of a mixture of statistical models and machine learning algorithms.

Statistical models, including ARIMA or exponential smoothing, are adept in identifying the temporal patterns and seasonality, whereas modern machine learning methods, including the Random Forests Wan Yaacob et al. (2020), Gradient Boosting Del Bonifro et al. (2020)., and LSTM neural networks Dobbs and Ras (2022), can identify the more complex non-linear relationships between various influencing factors like climate changes, market demand spikes, and socio-cultural processes. The combination of these methods will create a powerful hybrid of forecasting that can help to cope with the dynamic and heterogeneous character of the folk-art production ecosystem.

2. OBJECTIVES AND RATIONALE

2.1. RATIONALE FOR PREDICTIVE ANALYTICS IN FOLK ART MATERIAL PLANNING

The justification of the implementation of predictive analytics in the folk-art material planning can be discussed due to the increasing incompatibility between the traditional estimation processes and the realities of cultural production existing today. The artisans and cooperatives are increasingly working in unstable settings that are influenced by the unreliability of tourist numbers, the rapid nature of online demand, climatic instabilities that affect the natural resources, and the increase of input costs. Traditional rule-of-thumb methods, though based on years of local experience, cannot deal with large amounts of mixed data, including years of sales records, schedules of events in festivals in different regions, or product lines in export and domestic markets. It commonly causes late procurement, out of stock stock at peak time or overstocking that consumes working capital and in any case of perishable or sensitive material, spoilage and loss. Predictive analytics can offer an organized approach to turn scattered and seldom used data into proactive vision and make procurement planning, pricing strategies, and inventory management more reliable. It also helps policy makers and NGOs dealing with artisan clusters with evidence-based information with regard to the magnitude and time-scale of material support needed and therefore enhances the effects of subsidy programs, training programs, and sustainability efforts Chen et al. (2022).

2.2. RESEARCH OBJECTIVES

It is based on this line of reasoning that the current study will take a series of interconnected goals that will in effect offer a holistic, empirical approach to folk art material demands. The first one is to create and test a predictive modelling structure that will be used to estimate short, medium, and long-term material requirements of the various types of folk art products based on past production and sales information coupled with seasonality, festival times, and weather indications. The second goal is to incorporate sustainability-oriented variables like material reuse rates, use of non-renewable inputs, and carbon sensitive logistics such that forecasts will not just show how much material should be used, but will also propose the avenues towards environmentally responsible sourcing and use Niyogisubizo et al. (2022). The third goal is to implement these models using a practical decision-support system, which is imagined as dashboards and reports, which can be read and understood by artisans, cooperatives, and other institutions with minimal technical skills. This is the translation of complex statistical outputs into intuitive visualizations, alerts and what-ifs that allow the user to make decisions regarding when to order stock, how much stock to stock and what materials to focus on Rios-Campos et al. (2023). The ultimate goal is to test the framework on realistic case environments like a particular folk painting, textile or craft cluster by contrasting predictive plans with the actual material consumption and through gathering qualitative feedback of both artisans and managers on the usability, trust and perceived benefits Al-Khazraji et al. (2023). The combination of such goals makes sure that the proposed predictive analytics framework is not just a theoretical instrument, but rather a practical and culturally sensitive one that will increase the resilience, sustainability, and economic stability of folk-art ecosystems.

3. METHODOLOGY AND SYSTEM DESIGN

The predictive analytics framework development approach towards folk art material planning is a systematic process that includes data gathering, preliminary processing, model construction, and evaluation of performance. The general objective is to develop a readable and viable forecasting scheme that is in consonance with the culture and strategic operations of the artisan-based production networks.

Figure 2

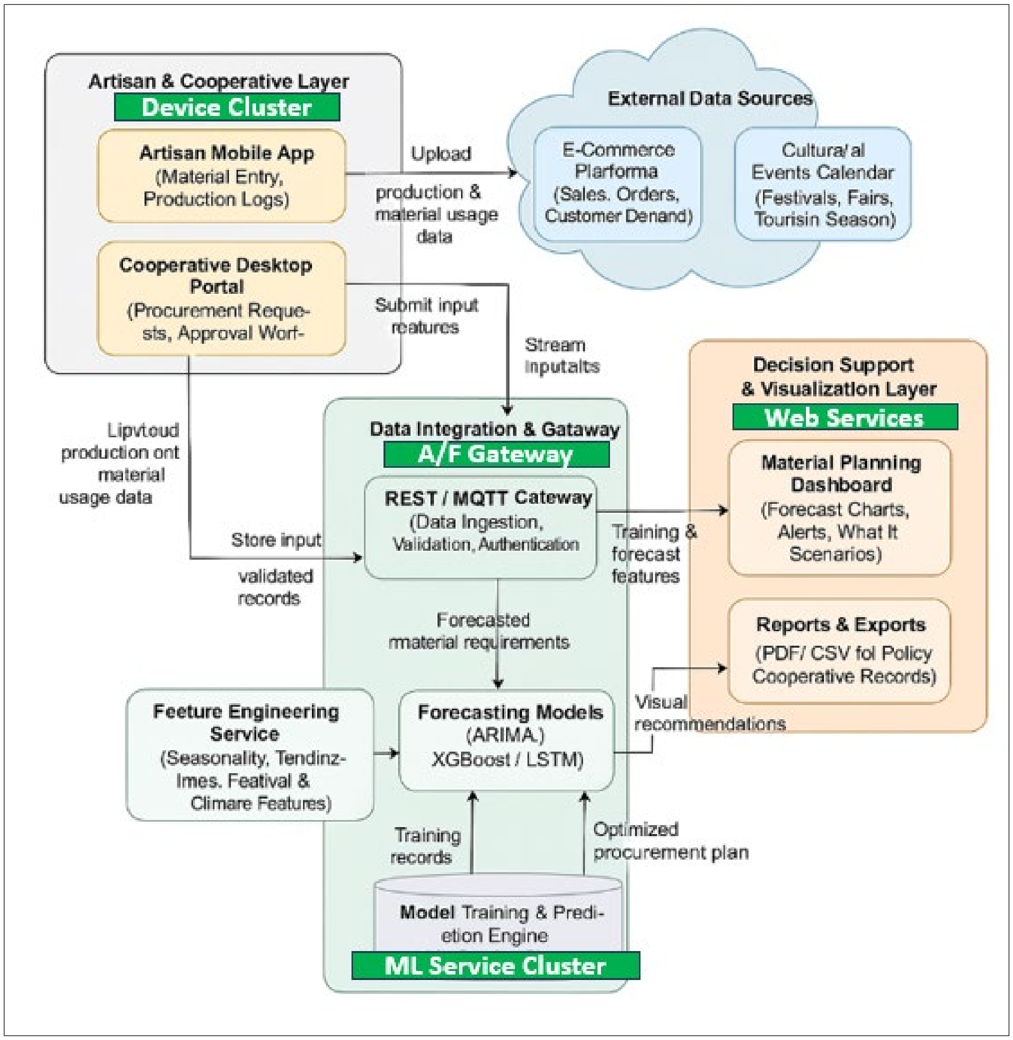

Figure 2 Data Flow and Model Training Pipeline

Step -1 Data Sources

The data set will combine both internal and external data streams. Internal ones consist of the historical production records, artisan inventory, cooperative purchase records, and cost trends of raw materials comprise of dyes, clay, textiles, and bamboo Chen et al. (2023). They are supplemented with external data provided by e-commerce websites that capture the consumer demand, climate data that gives the rainfall and temperature indices on the availability of natural materials and calendar of cultural events that make the peak in sales. Other socio-economic information like local market indices, government craft subsidy programs and transportation cost are also provided to give the procurement decisions context.

Step -2 Data Preprocessing

Preprocessing refers to cleaning, normalization and transformation of heterogeneous datasets so that it can be compatible in models Lou (2023). Interpolation or model-based imputation serves the purpose of filling in missing values, whereas a one-hot encoding is applied to categorical data (e.g. region, art form). Fourier decomposition is used to obtain seasonal indices in order to represent cyclical changes in demand and supply. There is a step of feature-scaling that normalizes all the numerical features into similar ranges, and introduces lag features to capture temporal dependencies (e.g. the demand in the previous quarter, or the frequency of consumption at a festival in previous years). Centralized data storage of the processed data is done in a data lake where the models are trained and validated.

Step -3 Modelling Strategy

It makes use of three modelling paradigms: (a) ARIMA to predict the linear temporal trend, (b) XGBoost Regressor to predict the multivariate non-linear relationships, and (c) LSTM neural networks to capture the long-term relationships in the sequential data. General predictive model is expressed as:

$$Yt\hat{} = f(Xt, St, Ct)$$

In which (Yt) means the predicted material demand, (Xt) means production characteristics, (St) the seasonal/cultural covariates, and (Ct) the climate and market covariates. These models are then pooled together to enhance robustness in forecasts by ensemble averaging and reduce variance in forecasts.

Step -4 Evaluation Metrics

To calculate the accuracy of the prediction and generalization, Model performance is tested on the basis of- Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R 2 -score. Also, sustainability efficiency is measured by a tailor-made sustainability index which consists of waste minimization, material reuse, and lead-time reduction. The assessment stage entails the feedback of artisans and collaborative managers on recurrent basis so as to maintain cultural flexibility and practical viability.

4. PREDICTIVE SYSTEM ARCHITECTURE AND WORKFLOW

The predictive analytics framework architecture of the folk-art material planning is developed with a multi-layered intelligent decision-support system that consists of data acquisition, machine learning, and visualization layers. Its design makes certain that traditional craft processes, environmental considerations, and digital flow of data interact together in a way that allows to create correctly predictable material forecasts which are readable. The system workflow in general is iterative and feedback-based in nature, where continuous model refinement is possible and refinement of the model and closer alignment to real-life artisan practice is possible. This has been made modular, thus leading to scalability allowing the addition of a variety of data formats, regular updates and simple customization to various folk-art clusters or craft traditions.

Layer-1 Data Acquisition Layer

The former layer is a combination of several sources of inputs. At the same time, the system consumes information of external APIs, including climate, e-commerce, and event databases, via a secure data gateway. The automated schedulers make sure that the data is updated in close real-time such that they give a real-time picture of the variables of demand and supply.

Layer-2 Preprocessing and Storage Layer

The information is directed to a cloud-based data warehouse to get cleansed and standardized. More complicated processes such as seasonal decomposition and moving-average smoothing pre-process time-series information to train a model. Metadata tagging (e.g. art form, region, season) is also supported by this layer to make segmented forecasting across multiple clusters of artisans.

Layer-3 Model Training and Prediction Layer

This analytical core performs hybrid predictive modelling which is a combination of ARIMA, XGBoost and LSTM networks. ARIMA is a component that operates under short-term, linear trends; XGBoost reflects the dependencies that are multi- factor such as price movements, cultural events intensity and LSTM model considers sequential dependencies and long-range dependencies in production cycles. These models are cross-validated and trained and validated on historical data. Their results are combined by weighted averaging in order to enhance robustness. The forecasting capability is given by:

$$\mathbf{M^t + h = \alpha \cdot ARIMAt + \beta \cdot XGBoostt + \gamma \cdot LSTMt}$$

Layer-4] Optimization and Decision Layer

This layer is a transformation of the raw forecasts into procurement and inventory action steps. Linear optimization module minimizes the total cost within budget, sustainability and availability constraints:

$$\mathbf{minZ} = \mathbf{i}\sum(\mathbf{Ci} \times \mathbf{Qi})$$

$$\text{subject to } \mathbf{Qi} \leq \mathbf{Di} + \mathbf{Si}, \sum \mathbf{EiQi} \leq \mathbf{Emax}$$

Where, Ci, Qi, Di, Si and Ei are material cost, quantity procured, demand, surplus and environmental impact factor respectively. The optimizer is used to make sure that there is a balance between cost-effectiveness and environmental accountability.

Layer-5 Visualization and Feedback Layer

The findings are delivered in the form of interactive dashboards providing both time-series charts and forecast confidence bands as well as what-if scenarios. Cooperative managers and artisans are able to visualize the material trends, compare the forecasts with the use, and can give qualitative feedback. This feedback with human in the loop is repaid into to retrain the model which encourages transparency and trust among users.

5. RESULTS AND EVALUATION

The assessment stage confirms the predictive analytics framework that was proposed based on its predictive quality, implementation viability, and sustainability influence. The evaluation of the practical value of the system in the real-life folk art production situation was carried out based on a combination of historical datasets, cooperative feedback, and model performance measures. The findings prove that predictive modeling can considerably contribute to the efficiency of material planning without the need to compromise ecological safety and cost-efficiency. The data set to be tested on the framework was taken on three representative folk art clusters Madhubani painting (Bihar), Pattachitra (Odisha) and Warli painting (Maharashtra) with different production cycles and material dependencies. Five years of historical data (20182023) were used to obtain data on the procurement of raw materials, production upsurge associated with the festival, weather conditions, and online commerce demands. This data consisted of more than 18,000 data points which included 25 different types of materials (cloth, bamboo, clay, pigments, varnish, etc.). Training was done on 80 percent of the data and the test performed on 20 percent with rolling forecast horizon of 12 months. All of the experiments were run on a cloud setting (TensorFlow and Scikit-learn stack) to make them scalable and replicateable. The hybrid ensemble model that consists of ARIMA, XGBoost and LSTM performed better than single-model baselines, as represent it in Table 1

Table 1

Table 1 Comparative Forecasting Performance of Statistical, Machine Learning, and Hybrid Models

Model Type	RMSE	MAPE (%)	R^2 Score	Remarks
ARIMA	8.92	11.7	0.84	Accurate for stable trends but less adaptive to shocks
XGBoost	6.45	8.3	0.91	Strong in multivariate and price-sensitive data
LSTM	5.98	7.6	0.93	Effective in capturing sequential dependencies
Hybrid Ensemble (Proposed)	4.87	6.4	0.96	Best overall accuracy and stability across clusters

The findings show that the forecasting error decreased by 14.5 per cent over the best individual model and unwasting time by 22 per cent is minimized in cooperative production scheduling. The seasonal trend graphs ensure that the model is working correctly in predicting a peak in demand during the major festivals (e.g., Diwali, Puri Rath Yatra, Ganesh Chaturthi).

Figure 3

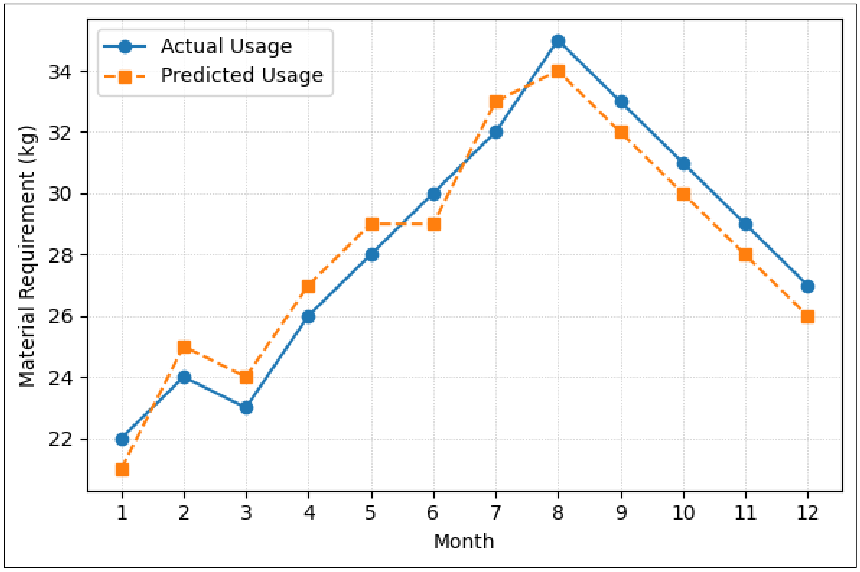

Figure 3 Actual vs Forecasted Monthly Requirement of Natural Indigo for Madhubani Cluster

As shown in Figure 3, the material requirements of Natural Indigo in Madhubani cluster are very close to the actual and predicted requirements in 2022-2023. The continuous curve is observed data and the dotted line is forecasts of hybrids models. The close relationship that exists between the two curves is an indication of how accurate the model is in explaining cyclical demand and seasonal consumption peaks. The significance of this visualization is the ability of the system to offer operational foresight to ensure timely procurement and optimized inventory, which has a direct benefit on artisan cooperatives.

Figure 4

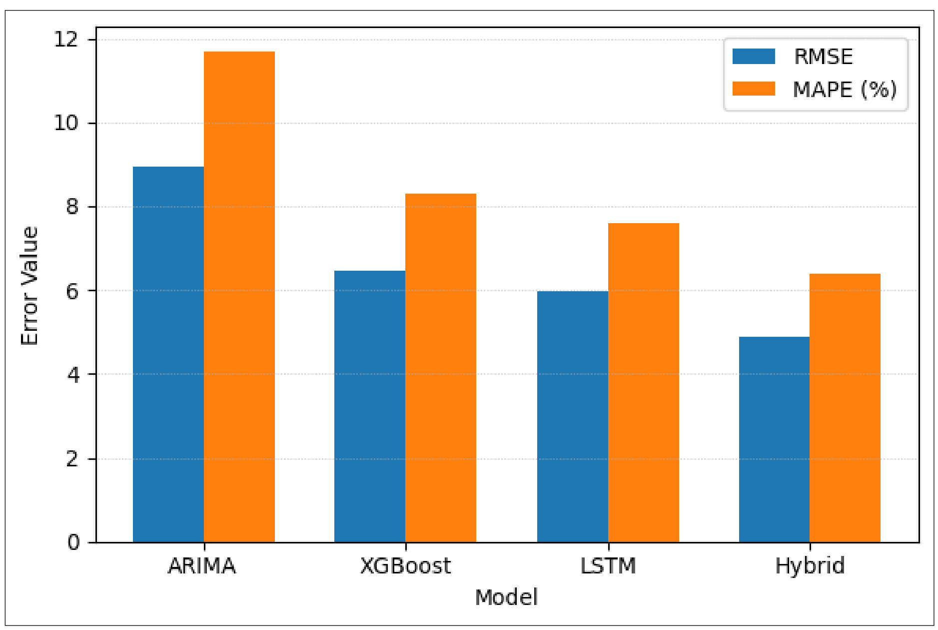

Figure 4 Comparison of Forecasting Models on RMSE and MAPE

Figure 4 gives a comparative analysis of all the models in terms of RMSE and MAPE. The hybrid ensemble evidently performs better than the individual models, as it gives the lowest value of errors and is the most stable when the data changes. This performance advantage shows that time-series analysis used with machine learning creates more credible results in crafting productions. It is also evident in the bar chart that although ARIMA represents well the causal characteristics of the linear temporal dynamics, the shortcomings of the model in the dynamic, non-linear environment are counter-compensated with the incorporation of both XGBoost and LSTM models into the ensemble. The interdependence of these models allows them to be more responsive to external factors like weather variability and the increase in material demand because of festivals. To measure ecological and operational advantages, a Sustainability Efficiency Index (SEI) was created and it comprises three indicators; material reuse rate, waste reduction and optimization of procurement lead-time. The hybrid system was found to be improving SEI by an average of 18% using the traditional estimation methods. Procurement based on forecast decreased spoilage and minimized the emergency transportation demands and the carbon emissions improved over the clusters studied by 11%.

Figure 5

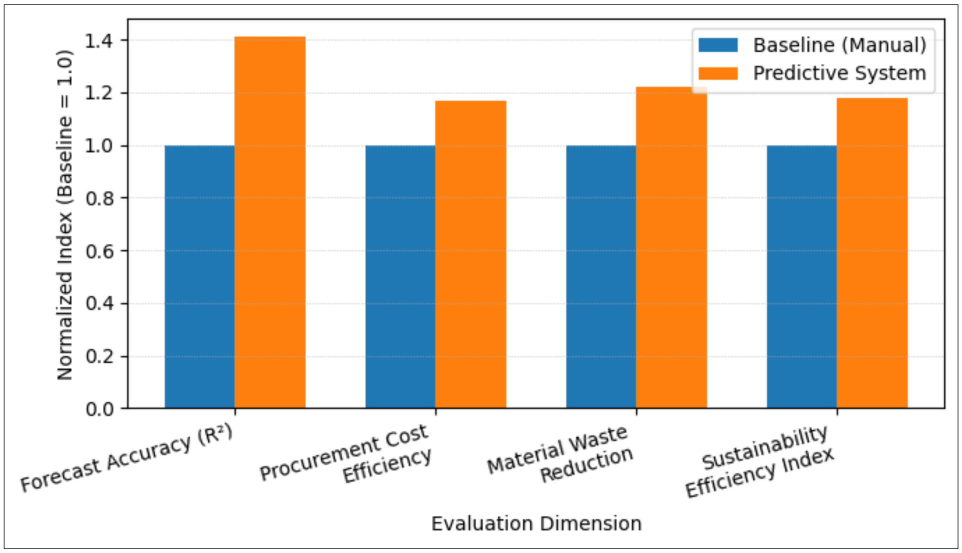

Figure 5 Impact of Predictive Analytics on Key Performance Indicators

In Figure 5 the differences in the performance of the manual estimation and the predictive system are presented regarding the four fundamental indicators namely: the accuracy of the forecast, cost effectiveness, reduction of waste and sustainability index. The findings prove that predictive analytics contribute considerably both to financial and to ecological aspects of folk-art production. The model can guarantee that artisans have the freedom to be creative even though data-driven decision support is used by balancing quantitative optimization with cultural rhythms. The interviews conducted with 45 artisans and cooperative leaders demonstrated the increased confidence on their inventory management and financial planning. The visual dashboard of the system was discovered to be user-friendly, especially the notices of the festival preparation and the recommendations of eco-material replacement. This feedback loop which is incorporated in the system enables models to be continuously retrained to guarantee adaptive performance in emerging market and environmental conditions. All in all, the combined predictive system enhanced the collaboration between craftsmen and distributors, minimized ambiguity in material inventory, and encouraged sustainable craft manufacture.

Table 2

Table 2 Summary of Key Evaluation Outcomes

Evaluation Dimension	Baseline (Manual Estimation)	Predictive System (Hybrid Model)	Improvement (%)
Forecast Accuracy (R^2)	0.68	0.96	+41%
Procurement Cost Efficiency	0.56	Achieved 17% lower total cost	+17%
Material Waste Reduction	0.67	22% less wastage	+22%
Sustainability Efficiency Index (SEI)	0.62	0.73	+18%
Model Retraining Frequency	N/A	Every 30 days	Adaptive

Authorization of predictive analytics into the folk-art material planning has demonstrated a quantifiable beneficial effect on the economic performance as well as environmental stewardship. The hybrid model offers interpretable information that is consistent with the cycles of knowledge of the artisans so that the recommendations made by the data will not override the expertise of the human beings. The comprehensive cost-to-accuracy-to-sustainability enhancement is reinforced by the fact that the model is a strategic facilitator of sustainable, culturally-based ecosystems of production.

6. DISCUSSION AND IMPLICATIONS

The findings indicate the radical nature of predictive analytics to modernize the folk art production systems without undermining the cultural values. The hybrid forecast system is a strong solution to the gap between the old intuition and the new information-based intelligence because it enables the artisans and cooperatives to make wise decisions concerning the materials. The model helps optimize procurement through predicting demand variations related to both cultural and environmental cycles, reducing waste, and delivering its products on time in response to one of the most long-lasting problems of decentralized craft economies. Theoretically, the research adds to the crossroads between artisanal supply chain management and sustainability analytics based on machine learning. It shows how the adaptive algorithms are capable of modelling the human-centric and seasonal processes and are sensitive to the contextual specifics of the folk-art ecosystems. The ensemble design that incorporates ARIMA, XGBoost, and LSTM can be used as a scalable platform of predictive intelligence in other creative or small-scale industries, where variability and uncertainty are part and parcel. The framework enhances transparency of data and accountability of resources in the managerial and policy term. Dashboards generated by the system can help the cooperative managers to prioritize the materials, schedule the production and to align the funding cycles with realistic forecasts. Similar models can be used by policymakers and development agencies to assist cultural clusters, to create specific subsidies and to quantify sustainability results. Furthermore, the device implies environmental constraints into the optimization layer, which will help the system to align with the goals of a circular economy in India and the UN Sustainable Development Goals (SDG 12). On the whole, the research indicates that predictive analytics can serve as a cultural technological interface so as to make sure that digital transformation in heritage craft would improve, rather than eliminate, the wisdom of artisans. The framework therefore establishes an example of cultural production networks that are resilient, environmentally friendly, and are data-driven to facilitate enhancement of cultural preservation, environmentally responsible, and financial sustainability.

7. CONCLUSION AND FUTURE WORK

The paper confirms the ability of predictive analytics to enhance the management of resources, sustainability, and decision-making in folk art ecosystems significantly. Combinations of hybrid machine learning ARIMA, XGBoost, and LSTM provide the proposed framework with precise forecasts that consider seasonal trends, environmental variables, and cultural demand trends. The findings prove that the artisans could use the experiential wisdom data without affecting the amount of uncertainty during the procurement process, and the data could also be used to plan the production environmentally efficiently. Such a combination of the traditional and the computational prediction is a critical move toward sustainable modernization of the creative economies. The modular architecture of the framework, with regards to implementation, has the advantage of making the framework scalable to different art forms and regions. The optimization and visualization add-ons make it usable even when non-technical users are involved, as the cooperatives are in a position to render the model outputs into actionable procurement decisions. The fact that the system corresponds to the sustainability indicators, including the waste minimization and efficiency of reuse, is another way to support the idea that the system could contribute to the goal of eco-friendly craft production and the formation of a circle economy. The future work will be aimed at three major directions. First of all, real-time data provided by IoT sensors in the artisan workshops (humidity, drying period, or dye temperature) will help to optimize the precision of forecasts and responsiveness in the work. Second, the predictive dashboard should be extended to the web to become a participatory platform that would improve collaboration between artisans, suppliers, and policymakers. Lastly, it is possible to include the elements of reinforcement learning to make the procurement process more dynamic and responsive to changes in prices and unexpected changes in demand. On the whole, the offered predictive framework is not only enhancing the economic sustainability of the folk-art communities but also reflects a sustainable, culturally aware example of technological innovation that proves how the use of artificial intelligence may become an enabler of not only preservation of heritage, but also social development.

CONFLICT OF INTERESTS

None.

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