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Digital conservation and inheritance strategies of folk traditional crafts based on Light GBM model

Dan Li[1],Yanin Rugwongwan[1,*], Wei Min[1], Zhaodi Li[1]

Abstract

The role of digital technology in cultural heritage conservation should be diverse, and different types of traditional handicrafts should be protected using appropriate digital technology. In this paper, the Light GBM algorithm is used to reduce the total number of large samples and lower the level of representation to solve the correlation problem between large-scale statistical instances and large sample features, and improve the prediction efficiency and accuracy of the algorithm. The algorithm of this paper predicts the effect of traditional handicrafts in the Wuling ethnic region of China under various digital technologies, and the results of Enshu Yulu making and bamboo paper making using digital image processing technology are obtained. The best results were 73.17% and 89.38% for the production of Enshu and bamboo paper, 88.26% for the printing of blue printed cloth, 85.24% and 78.67% for the production of Miao silver ornaments and Yuping flute, 91.54% for the production of Dong brocade, and 91.65% for the construction of Tujia hanging foot tower using digital sand table. The best effect of using digital sand table technology for the creation of the Tujia hanging foot tower reached 91.65%. Therefore, the algorithm in this paper can match the appropriate digital technology for different types of traditional handicrafts to achieve a greater degree of preservation and inheritance.

Keywords: *Sparrow search algorithm; SSA-LightGBM algorithm; digital technology; traditional handicraft.*

Introduction

Intangible cultural heritage refers to traditional forms of cultural realization that have been handed down from generation to generation by peoples all over the world over a long period of time, and which are often closely linked to the lives of the people (Lombardo, Pizzo, & Damiano, 2016). Intangible cultural heritage embraces the cultural spirit, sense of thinking, world values and imagination that are unique to each people (Wu, 2016). As one of the categories of intangible cultural heritage, the category of handicrafts has many unique features in terms of its development and transmission, as well as the imprint of the development of the times (Dang, Luo, Ouyang, Wang, & Xie, 2021). Handicraft refers to arts and crafts with a unique artistic style made by manual labor. It is a fusion of aesthetics and life, a crystallization of technology and art (Fan & Feng, 2019).

However, traditional handicrafts are facing a crisis of survival (Zhang Y 2019). This is mainly due to the fact that traditional handicrafts are mostly the accumulation of long-term experience and are mainly passed down by oral transmission, which itself has various characteristics such as ecology,

[1] King Mongkut's Institute of Technology Ladkrabang, Bangkok, 10700, Thailand
Corresponding author: Yanin Rugwongwan (yanin.ru@kmitl.ac.th)

variability, inheritance and liveliness, so it is relatively difficult to protect them (Minfeng, 2017) (Hai, Duong, Huy, & Hien, 2021). At present, there are many issues facing the conservation of traditional handicrafts, among which the use of digital technology to collect and store traditional handicrafts and establish a digital resource database of traditional handicrafts is most important. This can realize the archiving and sharing of handicrafts, and then save, inherit and develop them (Shuang Z 2018) (Chen & Ren, 2021).

The research topic of the importance and value of non-heritage is relatively common both at home and abroad, and many scholars have elaborated on this topic. Literature (Slattery, 2005) and other scholars chose the value of heritage and the importance of NRM conservation as a research topic, and then completed the study by means of case studies. Literature (Guo H B 2012) studied the topic through literature analysis, individual interviews and observations, and then discussed the issue in the framework of role network theory, where education on the conservation of non-heritage needs to take into account the actual social situation as well as the development situation. The literature (Zhou, Geng, & Wu, 2012) takes the NRM project as an object of study and explores the importance of the project by analyzing relevant documents and books. The literature (Peters, Marinova, van Faassen, & Stasiuk, 2017) discusses the premise of the parallel use of the Traditional Features Guarantee Program and the UNESCO Intangible Heritage Convention and how they play a role in the preservation of the pizza ICH.

Literature (Ji et al., 2019) China has been actively responding to UNESCO's Convention for the Safeguarding of Intangible Cultural Heritage, and has taken positive actions on the road of traditional handicraft preservation. However, the development so far has mostly been based on the principle of "innovative development" and "creative transformation" from the traditional handicraft itself, hoping to realize the living heritage, and has also achieved considerable results. Literature (W, 2016) Japan is one of the first countries in the world to conduct research on traditional handicrafts. In the 1950s, a law on traditional handicrafts, the Cultural Property Protection Law, was introduced, and a legal basis for protection has been in place since then. Literature (Połeć & Murawska, 2022) Local governments in France not only set up folklore museums to display and exhibit local traditional crafts, but also encourage the integration of craft preservation and economic development. The city of Paris, for example, has created open studios where master craftsmen, artists, and designers are welcome to collaborate and innovate by combining traditional crafts with contemporary technology and fashion. Today, many French luxury brands get their designs from these studios.

Since it is able to customize its fitness function in the sparrow search algorithm, it is chosen to define the LightGBM algorithm as the fitness function of the sparrow search algorithm, thus proposing the SSA-LightGBM classification and prediction algorithm. For the LightGBM algorithm, eight parameters that have a relatively large impact on the algorithm are screened out: learning_rate, n_estimators, num_leaves, min_data_in_leaf, max_steps, seed, bagging_fraction, and bagging_ freq, the optimal combination of these parameters is determined by the sparrow search algorithm, and finally the accuracy of the algorithm is verified on five data sets and the experimental results are compared with the classifiers SVM, XGBoost, RF, and LightGBM. Finally, the optimized LightGBM algorithm is used to predict the conservation effect of folk traditional handicrafts under each digital technology.

SSA-LightGBM classification and prediction algorithm

LightGBM algorithm

The LightGBM algorithm has the advantages of low memory consumption, fast training speed and high accuracy. Bundling (EFB). These two new techniques are each optimized from the perspective of reducing the total number of large samples and reducing the level of representation to address the correlation between large-scale statistical instances and large sample features. The GOSS method is introduced to solve the correlation problem of reducing the total number of large samples, and it also introduces a new approach to reduce the computational effort by compressing the training data set without modifying the feature classification and losing accuracy when replacing the weak classifier. . In order to reduce the number of feature dimensions, one advantage of EFB is that the weighted undirected graph is built, and the algorithm for constructing feature sets is transformed, which can eventually be turned into a graph coloring problem, and similar to the greedy algorithm is used to obtain the conclusion of the graph coloring problem, or the histogram is used to divide the histogram to bind the conflicting features in the feature combinations.

The LightGBM algorithm differs from the XGBoost algorithm in terms of the leaf-wise splitting strategy. The splitting strategy of XGBoost is shown in Figure 1. It will do indiscriminate splitting for all leaf nodes in each layer. Although the gain of some leaf nodes is smaller for the same layer, it will still split that part of the leaf nodes, which will cause some unnecessary overhead.

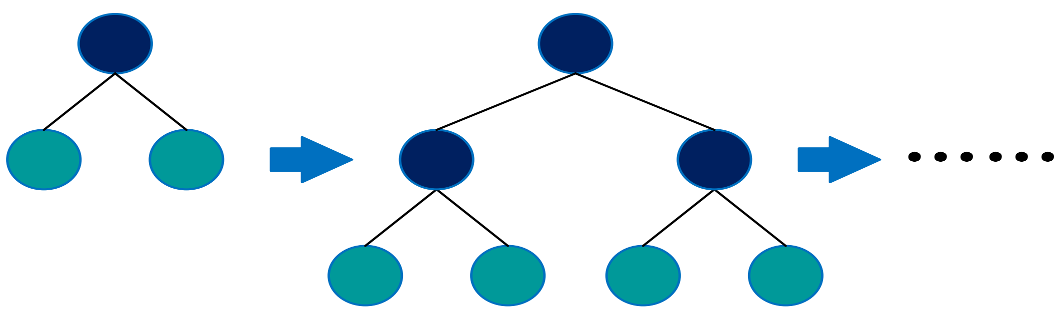

Figure 1. Leaf-wise splitting graph of XGBoost algorithm

The lightGBM algorithm's leaf-wise splitting strategy is shown in Figure 2. LightGBM introduces the Histogram algorithm, which mainly performs leaf-wise splitting, for transforming continuous floating-point features into discrete data and forming a Histogram of length K. Then the training data is traversed, and the final result is In order to calculate the total data volume, this data volume is accumulated in the histogram for all the discrete data. When implementing feature selection, only

Remittances Review
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Volume: 8, No: 2, pp. 430-445
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the gain of each current leaf node is selected according to the discrete value of the histogram, and the optimal segmentation node is traversed and then analyzed, which effectively avoids the problems caused by XGBoost.

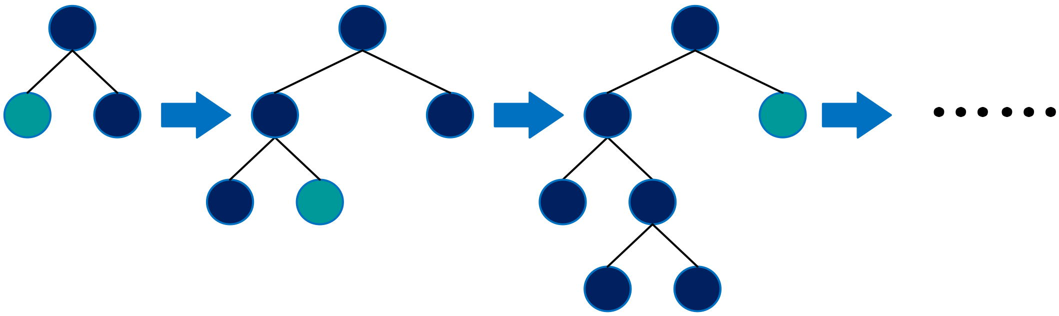

Figure 2. Leaf-wise splitting graph of Light GBM algorithm

Sparrow search algorithm

The Sparrow Search Algorithm (SSA) algorithm mainly simulates the division of labor and social interaction between different individuals in a population of sparrows while searching for food. Figure 3 shows the mathematical model of the SSA algorithm. In order to make the SSA algorithm simpler, some behaviors are idealized, and corresponding rules are formulated to build the mathematical model.

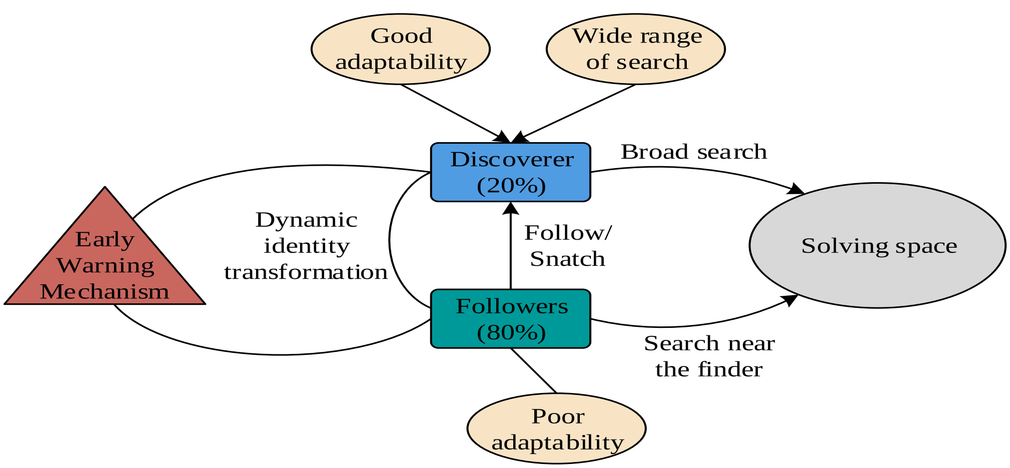

Figure 3. Mathematical model of SSA algorithm

In this model, the position of each sparrow represents a solution X, and the goodness of the food source concentration at that position, i.e., the fitness value F_X, represents the superiority of the solution. There are N sparrows in the D-dimensional search space, and the position of the i th

Volume: 8, No: 2, pp. 430-445
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sparrow in the D-dimensional search space is $X_i = [x_{i1}, \ldots, x_{id}, \ldots, x_{iD}]$, where $i = 1, 2, \ldots, N$. x_{id} denotes the position of the i th sparrow in the D th dimension. Generally, the discoverers account for 10-20% of the total number. According to rule 1 and rule 2 above, the position of the discoverer is updated in each iteration as shown in Equation (1).

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot iter_{\max}}\right) & if\ R_2 < ST \\ X_{i,j}^{t} + Q \cdot L & if\ R_2 \geq ST \end{cases} \tag{1}$$

where t is the current number of iterations. $X_{i,j}^{t}$ indicates the position of the i th sparrow in the j th dimension at the t rd iteration, $i = 1, 2, \ldots, d$. $iter_{\max}$ is a constant indicating the maximum number of iterations. α is a random number in the range of $(0,1]$. R_2 is an alarm value $R_2 \in [0,1]$ and ST represents a safety threshold $ST \in [0.5, 1.0]$. Q is a random number and follows a normal distribution. L is a matrix of $1 \times d$ and each element of L is 1.

When $R_2 < ST$, i.e., the alarm value of an individual is less than the safety threshold, it means that it is safe to have no predators around and the finder can search extensively for food. If $R_2 \geq ST$, it means that some alert sparrows found the predator and all sparrows immediately acted to fly quickly to other safe areas. Except for the discoverers, the remaining sparrows are followers, and for the followers, based on rule 4 and rule 5 above, their positions are updated as shown in Equation (2).

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}\right) & if\ i > n/2 \\ X_P^{t+1} + | X_{i,j}^{t} - X_P^{t+1} | \cdot A^{+} \cdot L & otherwise \end{cases} \tag{2}$$

where X_p represents the best position currently obtained by the discoverer. X_{worst}^{t} represents the current global worst position at iteration number t. A is a matrix of $1 \times d$ where each element is randomly assigned to 1 or -1, $A^{+} = A^{T}\left(AA^{T}\right)^{-1}$. The number of remaining sparrows is $n/2$. When $i > n/2$, this means that followers with poor fitness values are likely to starve and need to fly to another location to find food.

When individuals in the population perceive danger, i.e., the sparrow's warning mechanism is triggered, between 10% and 20% of individuals in the total population are responsible for danger warning in the simulation. The position of the individuals responsible for the warning is randomly generated at the time of population initialization. Based on rule 6 above, the mathematical model of the warning mechanism can be defined as shown in Equation (3).

$$X_{i,j}^{t+1} = \begin{cases} x_{best}^{t} + \beta \cdot | X_{i,j}^{t} - X_{best}^{t} | & if\ f_i > f_g \\ X_{i,j}^{t} + K \cdot \left(\dfrac{| X_{i,j}^{t} - X_{worst}^{t} |}{(f_i - f_w) + \varepsilon} \right) & if\ f_i = f_g \end{cases} \tag{3}$$

where X_{best}^{t} is the best position of all individuals in the population so far. β is the step parameter of individual movement, which is a normally distributed random number with variance of 1 and mean of 0. K represents a random number with values between -1 and 1. f_i is the value of the fitness function of the i th individual. f_w and f_g are the current global worst and global best adaptation values, respectively. To avoid a denominator of 0, ε is added, which is the minimum constant. When $f_i > f_g$, it means that the sparrow is at the edge of the population and is vulnerable to external threats and needs to fly around the center of the population. X_{best}^{t} also represents the safest position in the population. When $f_i = f_g$, this means that the sparrow in the middle of the population is aware of the danger and needs to move closer to the other individuals. K is the step control factor, which indicates the direction in which the sparrow is moving.

Construction of SSA-LightGBM classification prediction algorithm

This paper chooses to define the LightGBM algorithm as the fitness function of the sparrow search algorithm.

LightGBM algorithm parameters

LightGBM parameters: learning control parameters, core parameters, IO parameters, objective parameters, metric parameters, network parameters and GPU parameters, among which IO parameters contain three kinds of data set parameters, prediction parameters and transformation parameters.

First of all, the core parameters of LightGBM algorithm are introduced, and the common core parameters are listed here: (1) Boosting parameter, default: GBDT.(2) Data parameter, the training data path, LightGBM will be trained according to this data. (3) num_iterations parameter, the

Volume: 8, No: 2, pp. 430-445
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

number of iterations of Boosting, default:100, type: int.(4) learning_rates, default:0.1, type:double.(5) num_leaves, default:31, type: int.(6) seed, default: None, type:int. type: int.

Among the learning control parameters of LightGBM algorithm, the common parameters are: (1) min_data_in_leaf, default value: 20, type:int. (2) bagging_fraction, which can be used to accelerate the training, default value:1.0, type: double.(3) bagging_freq, default value:0, type :int.

LightGBM algorithm IO parameters, common parameters are: max__bin, default value: 255, type: int; min__data_in_bin, default value: 3, type: int. LightGBM algorithm objective parameters, common parameters are: alpha, default value: 0.9, type: double.

LightGBM algorithm metric parameters, common parameters are: metric_freq, default value: 1, type: int.

LightGBM algorithm network parameters, common parameters are: num_machines, default value type: int.

GPU parameters of LightGBM algorithm, common parameters are: gpu_platform_id, default value: -1, type: int.

The ranges of the main parameters of the LightGBM algorithm are set as shown in Table 1:

Table 1. LightGBM algorithm parameter setting

Parameters	Lower limit	Upper limit	Type
learning_rate	0.1	1	double
n_estimators	1	1000	int
num_leaves	2	100	int
min_data_in_leaf	1	100	int
max_steps	1	50	int
seed	0	100	int
bagging_fraction	0.1	1	double .
bagging_freq	2	500	int

SSA-LightGBM algorithm

Let d denote the dimensionality of the variables of the problem to be optimized, and n denote the total number of sparrows. The sparrow population X consisting of n sparrows is expressed as shown in Equation (4):

$$X = \begin{bmatrix} x_1^1 x_1^2 \cdots x_1^d \\ x_2^1 x_2^2 \cdots x_2^d \\ \cdots\cdots \\ x_n^1 x_n^2 \cdots x_n^d \end{bmatrix} \quad (4)$$

Remittances Review
May, 2023
Volume: 8, No: 2, pp. 430-445
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Define the LightGBM algorithm as an adaptation function. Let the number of iterations be t and $iter_{\max}$: the maximum number of iterations. $X_{i,j}^{t}$ denotes the location information of the i th sparrow in the j th dimension, $R_2\left(R_2 \in [0,1]\right)$ and $ST\left(ST \in [0.5,1]\right)$ correspond to the safety and warning values of the sparrow population in the algorithm, respectively, then the formula to be followed when the discoverer's location is updated is shown in Equation (5):

$$X_{i,j}^{t+1}=\begin{cases} X_{i,j}^{t}\cdot\exp\left(-\dfrac{i}{\alpha\cdot iter_{\max}}\right), R_2<ST \\ X_{i,j}^{t}+Q\cdot L, R_2\geq ST \end{cases} \tag{5}$$

$\alpha \in (0,1]$ is a random number. Q denotes a random number that follows a normal distribution. L denotes a $1\times d$ matrix with each element being 1.

Let X_P represent the best position of the discoverer and X_{worst} represent the worst position in the global. Then the formula to be followed for the joiner's position update is shown in Equation (6):

$$X_{i,j}^{t+1}=\begin{cases} Q\cdot\exp\left(\dfrac{X_{worst}-X_{i,j}^{t}}{i^2}\right), i>n/2 \\ X_P^{t+1}+|X_{i,j}^{t}-X_P^{t+1}|\cdot A^{+}\cdot L, otherwise \end{cases} \tag{6}$$

A is a vector of $1\times d$ matrices where each element within the vector of the matrix can be assigned a random value, but the assignment can only be 1 or -1, and is subject to $A^{+}=A^{T}\left(AA^{T}\right)^{-1}$.

When $i>n/2$, it means that the i nd joiner with low energy reserve needs more energy and flies to other places to feed.

Let X_{best} be the best global position and f_i be the fitness value of the i rd sparrow. f_g and f_w are when the global best and global worst sparrow positions are respectively. Then the condition that the vigilante must satisfy when it needs to update its position is Equation (7):

$$X_{i,j}^{t+1}=\begin{cases} x_{best}^{t}+\beta\cdot|X_{i,j}^{t}-X_{best}^{t}|, f_i>f_g \\ X_{i,j}^{t}+K\cdot\left(\dfrac{|X_{i,j}^{t}-X_{worst}^{t}|}{(f_i-f_w)+\varepsilon}\right), f_i=f_g \end{cases} \tag{7}$$

Volume: 8, No: 2, pp. 430-445
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β is the step control parameter, which has the characteristic of obeying the standard normal distribution, and it and K are random numbers, $K \in [-1,1]$ and ε are constants to avoid zero in the denominator.

When $f_i > f_g$, it means that the sparrow in a marginal position has found a predator and is relatively vulnerable to attack.

When $f_i = f_g$, it means that the middle sparrow perceives the danger and needs to walk at random to reduce the risk of being caught. K indicates the direction of movement of the random walk when the sparrow perceives the danger, and it is the step control parameter.

The settings of each parameter of the SSA-LightGBM algorithm are shown in Table 2.

Table 2. The parameter settings of SSA-LightGBM algorithm

Parameters	Value
pop	20
Max Iter	50
ST	0.6
PD	0.7
SD	0.2

The specific implementation steps of SSA-LightGBM algorithm are as follows:

Step1: Set the population size pop, the maximum value of iteration MaxIter, the expected value of alert ST, the percentage value PD between predators, joiners, the percentage SD of sparrows aware of the danger and the range of values of each parameter of the LightGBM algorithm as shown in Table 1, Table 2.

Step2: Calculate the fitness value of each sparrow, and sort the values from lowest to highest, where the first one is the best fitness value.

Step3: According to the value of the optimal fitness of the first ranking, find the position where the sparrow is located at this time, and the position is the optimal combination of parameters for LightGBM.

Step4: Determine whether it is necessary to terminate the iteration, if yes, stop the operation, otherwise, first update the discoverer, joiner and vigilant positions according to equations (5), (6) and (7), and then repeat the execution of Step2-4.

Step5: Output to the optimal fitness value, the position corresponding to this value, whose position is the LightGBM algorithm

The optimal combination of parameters for the LightGBM algorithm.

Digital preservation and inheritance strategy of traditional folk crafts

Performance Analysis of SSA-LightGBM Algorithm

To demonstrate the effectiveness of the SSA-LightGBM method, the classifiers LightGBM, SVM, RF, XGBoost and the SSA-LightGBM algorithm proposed in this chapter were selected for experimental comparison, and the performance results were averaged over 10 times of 5-fold cross-validation.

Performance evaluation index

This experiment uses the confusion matrix to determine the classification performance of the classifier. The confusion matrix and the formulas are detailed in Table 3.

Table 3. Confusion Matrix

True Value	Predicted value	
	Yes	No
Yes	TP	FN
No	FP	TN

Accuracy rate:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{8}$$

Recall rate:

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{9}$$

Check rate:

$$\mathrm{Pr}\,ecison = \frac{TP}{TP + FP} \tag{10}$$

F1:

$$F1 = \frac{2\left(\mathrm{Pr}\,ecison + \mathrm{Re}\,call\right)}{\left(\mathrm{Pr}\,ecision + \mathrm{Re}\,call\right)} \tag{11}$$

Five publicly available datasets were selected for validation in the simulation experiments to evaluate the effectiveness of the SSA-LightGBM classification prediction algorithm. The specific information of the datasets is shown in Table 4.

Volume: 8, No: 2, pp. 430-445
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Table 4. Parameter setting of SSA-LightGBM model

No.	Dataset	Characteristic number	Sample size
1	Sonar	55	213
2	Ionosphere	35	350
3	BreastEW	30	560
4	WDBC	30	560
5	KrvskpEW	35	3203

Accuracy analysis of the algorithm

In this experiment, four classification prediction algorithms, SVM, XGBoost, RF and LightGBM, were selected to compare with the proposed SSA-LightGBM classification prediction algorithm, and five public datasets were used for experimental validation. 70% of the data in these datasets were selected as the training set and 30% as the test set, and the Accuracy, F1 and AUC of these classifiers were used as the performance evaluation metrics of the algorithm.

The results on the Sonar dataset are shown in Figure 4. For Accuracy performance: The SSA-LightGBM algorithm has the best classification prediction performance of 86.78%, which is 8.89% better than the SVM algorithm, 11.14% better than the RF algorithm, 9.8% better than the XGBoost algorithm, and 7.84% better than the LightGBM algorithm. For F1 performance: The SSA-LightGBM algorithm has the best classification prediction performance of 81.81%, which is 8.04% better than the SVM algorithm, 11.76% better than the RF algorithm, 6.8% better than the XGBoost algorithm, and 10.71% better than the LightGBM algorithm. For the AUC performance: SSALightGBM algorithm has the best classification prediction performance of 85.05%, which is 7.23% better than SVM algorithm, 8.37% better than RF algorithm, 6.97% better than XGBoost algorithm, and 6.51% better than LightGBM algorithm.

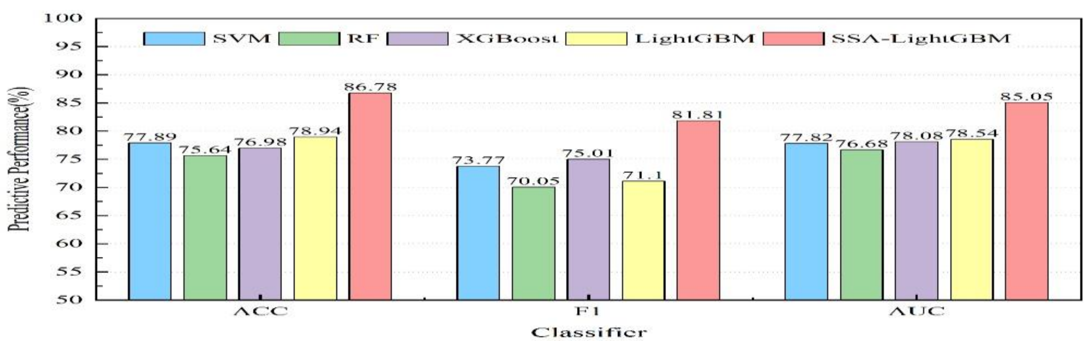

Figure 4. Performance comparison of sonar dataset under different classifiers

The results on the Ionosphere dataset are shown in Figure 5. For Accuracy performance: The classification prediction performance of the SSA-LightGBM algorithm is as good as that of the XGBoost algorithm, both 92.70%, which is 10.1% better than the SVM algorithm, 2.62% better than the RF algorithm, and 1.63% better than the LightGBM algorithm. For F1 performance: The

Remittances Review
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SSA-LightGBM algorithm has the best classification prediction performance of 95.31%, which is 7.34% better than the SVM algorithm, 2.14% better than the RF algorithm, 2.22% better than the XGBoost algorithm, and 0.13% better than the LightGBM algorithm. For the AUC performance: The XGBoost algorithm has the best classification prediction performance of 90.43%, which is 9.96% better than the SVM algorithm, 1.23% better than the RF algorithm, 2.92% better than the LightGBM algorithm, and 0.69% better than the SSA-LightGBM algorithm.

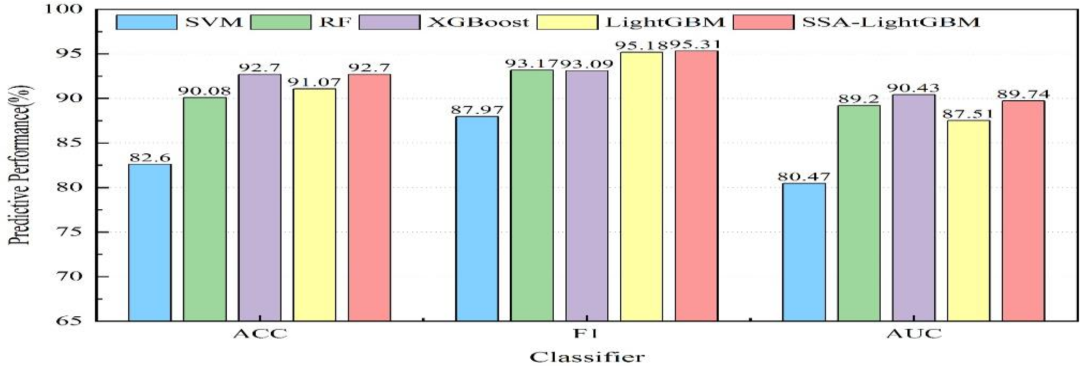

Figure 5. Performance comparison of Ionosphere dataset under different classifiers

The results on the BreastEW dataset are shown in Figure 6. For Accuracy performance: The SSA-LightGBM algorithm has the best classification prediction performance of 97.23%, which is 2% better than the SVM algorithm, 3.84% better than the RF algorithm, 4.33% better than the XGBoost algorithm, and 1.03% better than the LightGBM algorithm. For F1 performance: The SSA-LightGBM algorithm has the best classification prediction performance of 96.56%, which is 6.82% better than the SVM algorithm, 3.01% better than the RF algorithm, 5.16% better than the XGBoost algorithm, and 9.35% better than the LightGBM algorithm. For the AUC performance: SSA-LightGBM algorithm has the best classification prediction performance of 96.43%, which is 3.09% better than SVM algorithm, 2.89% better than RF algorithm, 1.34% better than XGBoost algorithm, and 2.03% better than LightGBM algorithm.

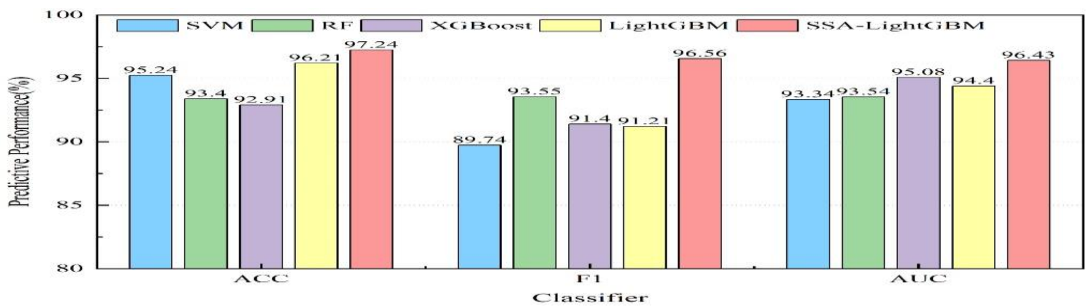

Figure 6. Performance comparison of BreastEW dataset under different classifiers

The results on the WDBC dataset are shown in Figure 7. For Accuracy performance: SSA-LightGBM algorithm has the best classification prediction performance of 96.17%, which is 2.97%

Remittances Review
May, 2023
Volume: 8, No: 2, pp. 430-445
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better than SVM algorithm, 1.39% better than RF algorithm 2.74% better than XGBoost algorithm, and 3.25% better than LightGBM algorithm. For F1 performance: The SSA-LightGBM algorithm has the best classification prediction performance of 97.51%, which is 2.12% better than the SVM algorithm, 1.25% better than the RF algorithm, 5.47% better than the XGBoost algorithm, and 2.21% better than the LightGBM algorithm. For the AUC performance: The SSA-LightGBM algorithm has the best classification prediction performance of 96.04%, which is 4.06% better than the SVM algorithm, 1.12% better than the RF algorithm, 1.95% better than the XGBoost algorithm, and 2.39% better than the LightGBM algorithm.

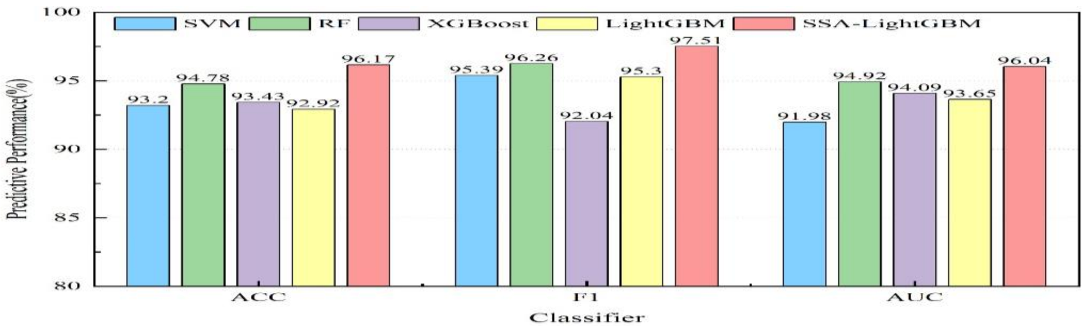

Figure 7. Performance comparison of WDBC dataset under different classifiers

The results on the KrvskpEW dataset are shown in Figure 8. For Accuracy performance: The SSA-LightGBM algorithm has the best classification prediction performance of 97.09%, which is 16.26% better than the SVM algorithm, 5.16% better than the RF algorithm, 4.22% better than the XGBoost algorithm, and 2.16% better than the LightGBM algorithm. For F1 performance: The SSA-LightGBM algorithm has the best classification prediction performance of 97.1%, which is 11.8% better than the SVM algorithm, 2.76% better than the RF algorithm, 3.83% better than the XGBoost algorithm, and 2.49% better than the LightGBM algorithm. For the AUC performance: The SSA-LightGBM algorithm has the best classification prediction performance of 96.56%, which is 15.9% better than the SVM algorithm, 3.44% better than the RF algorithm, 3.61% better than the XGBoost algorithm, and 3.37% better than the LightGBM algorithm.

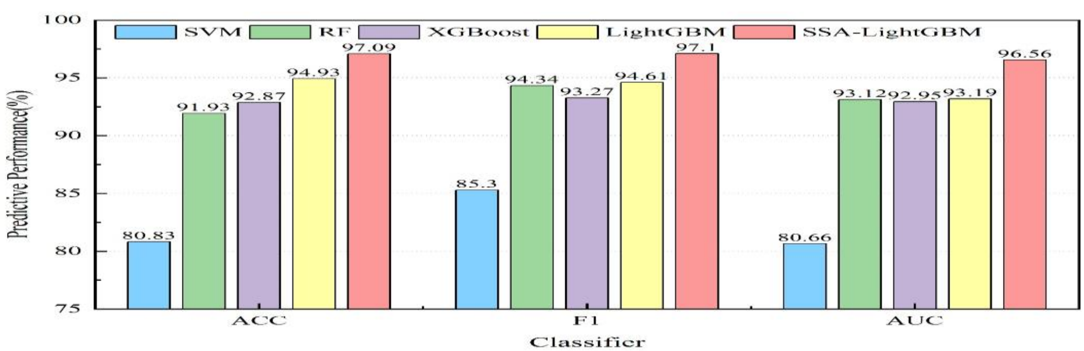

Figure 8. Performance comparison of KrvskpEW dataset under different classifiers

Remittances Review
May, 2023
Volume: 8, No: 2, pp. 430-445
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In summary, the SSA-LightGBM classification prediction algorithm proposed in this chapter is superior to several other classification prediction algorithms.

Analysis of digital protection and inheritance methods of traditional folk crafts

The Wuling ethnic region in China, for example, is geographically located at the junction of Hunan, Hubei, Chongqing and Guizhou, and is famous for its multi-ethnic population. Currently, there are more than ten ethnic minorities in the Wuling region, including the Tujia, Yao and Bai. Numerous traditional handicraft techniques have been passed down in the Wuling ethnic area, covering a wide area. Its representative traditional handicrafts include Enshi Yulu making, blue print fabric printing, Miao silver forging, bamboo paper making, Dong brocade weaving, Tujia hammock building construction, and Yuping Ce flute making.

There are many methods for digital preservation and inheritance of these traditional crafts, such as: digital image processing, virtual interactive restoration and reproduction, digital simulation, digital sandbox, holographic projection, etc. In order to understand the digital preservation techniques suitable for various traditional handicrafts, this paper uses the SSA-LightGBM algorithm for classification prediction, and the results are shown in Figure 9.

It can be seen that the best effect of using digital image processing technology for Enshu Yulu making and bamboo paper making reaches 73.17% and 89.38%, the best effect of using digital simulation technology for blue print printing reaches 88.26%, the best effect of using virtual interactive restoration technology for Miao silver forging and Yuping Ce flute making reaches 85.24% and 78.67%, the best effect of using holographic projection technology for Dong brocade weaving reaches 91.54%, and the best digital sandbox technology for the creation of the Tujia hanging foot tower was 91.65%.

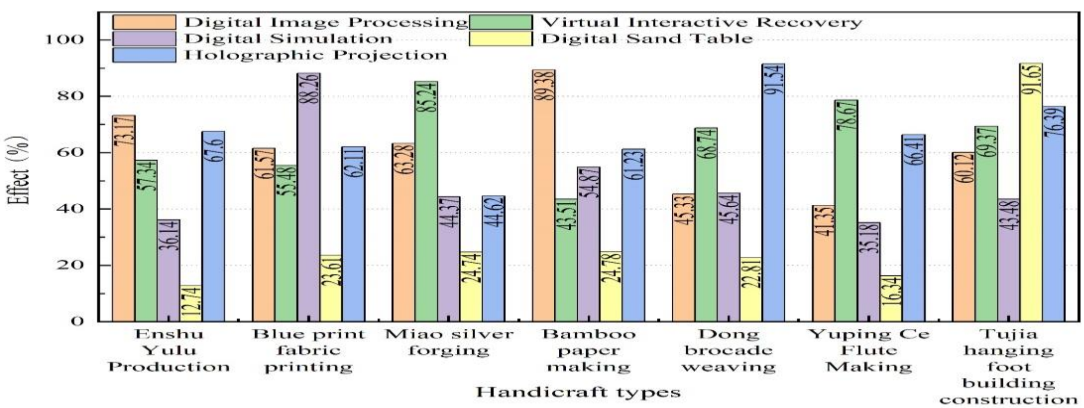

Figure 9. Effect of digital technology on each handicraft

Conclusion

This paper chooses to use the LightGBM algorithm to predict the effect of each digital technology

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on the conservation of traditional folk crafts, but the LightGBM algorithm suffers from the problem of hyperparameter search, so this paper proposes the SSA-LightGBM classification prediction algorithm. The algorithm is mainly used to improve the hyperparameter search problem of LightGBM algorithm by using the sparrow search algorithm to search the hyperparameters of LightGBM algorithm and finally output an optimal combination of parameters. After the algorithm performance verification, the method can well solve the shortcomings of LightGBM and has a good accuracy.

Using the optimized LightGBM algorithm to predict and analyze the digital preservation and inheritance methods of folk traditional crafts, we obtained that the effect of using digital image processing technology for Enshu Yulu making and bamboo paper making reached 73.17% and 89.38%, the effect of using digital simulation technology for blue printing fabric printing reached 88.26%, the effect of using virtual interactive restoration technology for Miao silver ornament forging and Yuping Ce flute making The effect reached 85.24% and 78.67%, the effect of using holographic projection technology for Dong brocade weaving reached 91.54%, and the effect of using digital sand table technology for Tujia hanging foot tower creation reached 91.65%.

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