Hindawi
Scientific Programming
Volume 2021, Article ID 4072499, 7 pages
https://doi.org/10.1155/2021/4072499

Research Article

Prediction of Urban and Rural Tourism Economic Forecast Based on Machine Learning

Wusheng Zhou

Business School, Guangxi University, Nanning, Guangxi 530004, China

Correspondence should be addressed to Wusheng Zhou; robin@gxu.edu.cn

Received 11 August 2021; Revised 23 August 2021; Accepted 23 August 2021; Published 22 September 2021

Academic Editor: Bai Yuan Ding

With the rapid development of tourism, tourism revenue, as one of the important indicators to measure the development of the tourism economy, has high research value. The quasi-prediction of tourism revenue can drive the development of a series of related industries and accelerate the development of the domestic economy. When forecasting tourism income, it is necessary to examine the causal relationship between tourism income and local economic development. The traditional cointegration analysis method is to extract the promotion characteristics of tourism income to the local economy and construct a tourism income prediction model, but it cannot accurately describe the causal relationship between tourism income and local economic development and cannot accurately predict tourism income. We propose an optimized forecasting method of tourism revenue based on time series. This method first conducts a cointegration test on the time series data of the relationship between tourism income and local economic development, constructs a two-variable autoregressive model of tourism income and local economy, and uses the swarm intelligence method to test the causal relationship and the relationship between tourism income and local economic development, calculate the proportion of tourism industry, define the calculation result as the direct influence factor of tourism industry on the local economy, calculate the relevant effect of local tourism development and economic income, and construct tourism income optimization forecast model. The simulation results show that the model used can accurately predict tourism revenue.

1. Introduction

Tourism economic forecasting [1–3] serves tourism economic decision-making and planning management. It is the premise of scientific decision-making and planning management and directly affects the accuracy and reliability of tourism economic decision-making [4, 5] and planning management [6, 7]. It is impossible to make an optimized tourism decision and planning without a tourism economic forecast that conforms to the objective reality. Tourism economic forecast participates in tourism economic decision-making and planning management and affects decision-making and planning. This important role is mainly reflected in the following aspects: first, through forecasting, reveal the changing trend of tourism economic development in the future [8], for the purpose of formulating tourism economic development. The strategy provides a reliable basis. The formulation of a tourism economic development strategy is the most important tourism economic decision, and every link and every factor that constitutes a tourism economic development strategy, including development goals [9], implementation steps [10], and measures, cannot be separated from the prediction of future trends. To formulate a tourism economic development strategy, first of all, it is necessary to predict and make reasonable predictions about a series of unknowns, such as the overall development of the national economy [11, 12], changes in economic structure, changes in national policies, and changes in population quantity and quality, in order to grasp the possibility of the development of the tourism economy of the country and propose feasible development goals; secondly, it is necessary to predict the changes in the market within a certain period of time, the changes in the industrial structure of the tourism economy, the changes in the

product structure, and the changes in reception capacity. Only by making scientific predictions on the status and level of tourism economic development can we accurately divide the development stages and strategic steps [13] and determine the approximate execution sequence and time range for related work; again, the flow direction and flow of the future tourism market [14] and the tourism economy [15] must be determined. Only by predicting the changing trends of the quality and abundance of regional resources can we reasonably formulate the strategic layout of tourism economic development and complete the optimal spatial configuration of tourism productivity [16, 17]. Obviously, leaving the basis of tourism economic forecasting, the entire tourism economic development strategy has become a castle in the sky. Second, through forecasting, reveal the various situations that may occur in the development of the tourism economy: mainstream and tributary [18], favorable and unfavorable factors [19], opportunities and risks [20], and achievements and problems [21], so as to be confident and avoid blindness and one-sidedness in decision-making [22–24]. For example, in 1982, Hong Kong's tourism industry still maintained a momentum of development despite the global economic downturn, and all walks of life were deeply affected. One of the important reasons is that the Hong Kong tourism authority [25] predicted the trend of the world economic downturn and made corresponding preparations in advance. Third, predicting the economic benefits of a number of alternative tourism development programs can provide a practical basis for choosing the best program. In other words, the tourism economy forecast not only proposes a variety of ways and plans for the development of the tourism economy but also analyzes and analyzes the possible losses and benefits of each plan and the possible consequences and impacts of each proposed tourism policy. Demonstration is to make a decision on the premise of comprehensively weighing the pros and cons. Fourth, the role of forecasting not only is limited to speculating on the economic process specified by tourism economic decision-making and planning management but also includes foreseeing the changes and prospects of the external environment related to it. Planning management provides more ambitious information in order to make tourism economic decision-making and planning management more comprehensive. The external environment mentioned here mainly refers to various external noneconomic factors that may have an impact on the development of the tourism economy, such as the trend of global climate warming, the peaceful trend of the international political environment, and the negative impact of the SARS epidemic. Forecasting the changes and prospects of the external environment of tourism is particularly important for macro decision-making.

In order to effectively play the role of tourism economic forecasting, machine learning algorithms [26] have played a big role. The application of machine learning in the economic field mainly includes helping scholars obtain data that was difficult to obtain in the past, exploring the correlation between variables and making predictions, predicting counterfactuals, and then identifying cause and effect. From the perspective of predictive ability, machine learning is a predictive method with strong applicability, good accuracy, and high efficiency. First of all, machine learning [27] is not limited to "interpretability"; it can flexibly choose functional forms to fit data, study highly nonlinear, unexplainable models, and make out-of-sample predictions. Its predictive power surpasses traditional econometric methods [28]. Although mainstream empirical methods mostly use econometric models based on causality, these models have strict application conditions. Even with the support of the correct economic theory, they are often unusable in research, or even though they can be used, they end up in failure. Secondly, machine learning can make full use of the value of big data, directly mining the relationship between data and "discovering nontrivial knowledge that is of interest to specific users from the database." Finally, when the machine classifies, almost no human judgment is added, so the objectivity is high.

The contribution of this paper is to study the effectiveness of machine learning methods, promote the application of machine learning methods in financial forecasting, and provide ideas and references for the intelligent and digital transformation of tourism economic forecasting. The research results of this article prove that machine learning is an accurate, simple, and objective forecasting tool suitable for listed companies in my country, and different models have their own strengths in tourism economic forecasting. As a forecasting tool that "advances with the times," machine learning can be self-optimized with the continuous enrichment of future tourism economic data so that the forecasting method can be constructed "once and forever" and "excellent" in terms of results. Therefore, machine learning can help companies discover financial problems in time to take remedial measures; provide investors, corporate partners, and other stakeholders with more financial information to optimize investment decisions; and provide effective methods for regulators to reduce human and material costs and improve market supervision.

2. Related Works

Machine learning methods have improved the economics research paradigm [29], and the academic results of applying them to financial forecasting have become increasingly abundant. Scholars at home and abroad have done more research on financial distress forecasting, but there are few results involving performance explosions. On the whole, machine learning provides ideas and methods for the prevention and discovery of financial problems of listed companies [30], and the predictive model trained by it provides an effective practical reference for the stakeholders of listed companies [31]. Chen et al. [32] used data from listed companies in Taiwan and found that the closer to the time point of financial distress, the higher the prediction accuracy of the prediction data and the accuracy of the neural network model is higher than that of the machine learning (clustering) model. Sun et al. [33] used Chinese ST companies as samples and used regression trees (CART)

[34], support vector machines (SVM) [35], K-nearest neighbors (KNN) [36], multiple discriminant analysis (MDA) [37], logistic regression [38], and other methods to make predictions. The results showed the prediction effect of the CART model. Sun et al. [33] also used Chinese ST companies as cases of financial distress, single-factor testing (SAT) [39], and decision trees as weak learners, and used the AdaBoost method [40] to integrate weak learners to predict the company's financial distress situation; combined with separate decision tree models, SVM is compared; and it is found that the AdaBoost method, which uses SAT as a weak learner, has the highest prediction accuracy. Sun and Lie [33] took Chinese listed companies as a sample and defined financial distress as two consecutive years of loss or the loss of the most recent year exceeding the registered capital, constructed a dynamic financial distress prediction model, and used minority oversampling technology (SMOTE) to solve the problem of sample imbalance. Financial fraud forecasts: there are also many research results in this area. Given the limited resources, it is unlikely to find all financial frauds, and the possibility of exploring causality is limited. The use of machine learning to predict is practical. Nasir et al. [41] used the support vector machine model to detect the financial fraud of listed companies. After adding a specific "core" to the model, the model worked well. Al-Hashedi et al. [42] summarized and compared the technologies and methods of financial fraud detection and found that there are applicable technologies and methods for different types of fraud.

In terms of predictors, scientific and complete data are necessary conditions for the success of machine learning models. The data of listed companies is relatively rich, and there are many variables that can be collected. Therefore, the selection of predictors has become a research topic. Liengaard et al. [43] believed that there are generally two methods for selecting predictor variables: one is to select variables based on financial accounting theory and the other is to select variables based on machine learning. They studied the financial distress prediction problem [44, 45] of listed companies in mainland China (using ST as the standard) and found that the selection of predictive variables based on data mining models has the same effect as the selection based on expert financial accounting knowledge, and ROA is the best predictor variables.

3. Methodology

In the process of forecasting tourism income, first, calculate the regional tourism income and tourism income growth rate indicators, obtain the promotion characteristics of tourism income to the local economy, describe the law of change between tourism income and economic growth, and build a tourism income prediction model. The specific steps are described in detail as follows: assuming that N_p represents the tourism output value, C_{cs} represents the connection between the tourism industry and other industries, and DW represents the elastic value of tourism income, then use equations (1) and (2) to calculate regional tourism income and tourism income growth rate:

$$Q_{JP} = \frac{D_{DS} \times w}{C_{cs}} \times \mathrm{TES} \times N_p \mathrm{DW}, \tag{1}$$

$$W^* = \frac{D_{DS} \times w}{C_{cs}} \times \frac{\mathrm{TES} \times N_p Q_{JP}}{\mathrm{DW}}. \tag{2}$$

Here, N_p represents the added value of tourism, w" represents the final demand for tourism in the place, and TES represents the income effect of the tourism economy.

Assuming that X represents the degree of dependence of tourism on other industries, formula (3) is used to obtain the promotion characteristics of tourism income to the local economy:

$$\phi''' = \left(Q_{JP} \times W^*\right) \times \frac{\varphi \times \kappa}{(H \cdot \chi)} \times \varsigma. \tag{3}$$

In the formula, φ represents the balanced relationship between tourism income and tourism growth, κ represents the income effect of tourism, H represents the factors influencing the development of tourism, χ represents the comprehensive employment coefficient of tourism to other industries, and W^* represents tourism income and the lag structure between the two variables of economic growth. The tourism income forecast model is shown in the following:

$$\mathrm{NA} = \frac{\nu\gamma \times \phi'''}{W^*} \otimes Q_{JP} \cdot \mathrm{DW}. \tag{4}$$

In the formula, VR represents the law of change between the two variables of tourism income and economic growth. However, traditional methods cannot accurately describe the causal relationship between tourism revenue and local economic development and cannot accurately predict tourism revenue. This paper proposes an optimized forecasting method of tourism income based on time series.

In the process of modeling and modeling of tourism revenue optimization forecast, obtain time-series data of tourism revenue and local economic growth, conduct cointegration test on tourism revenue and economic development time-series data, and build a vector autoregressive model of tourism revenue and economic development variables. To test the causal relationship between the models, the specific steps are described in detail as follows: Before the cointegration test on tourism income and economic development time-series data, the stability of tourism income and economic development time series data should be tested, respectively. Its function is to avoid false regressions with high $R2$ values between tourism income and economic development time series variables. Assuming that B represents the criterion for judging regional economic growth, use equation (5) to calculate the economic growth level of a tourist area:

$$p_\alpha(X, A) = \frac{B \cdot \Omega}{\mu_n \cdot R2} \times \frac{\varsigma^\gamma \cdot U_n}{M^{\nexists}}. \tag{5}$$

In the formula, Ω represents the total tourism income, μn represents the dynamic impact of random disturbances on the variable system, ς^γ represents the impact of economic lagging variable in the economic region on the current

Table 1: Index system of influencing factors of tourism income.

Explained variable	First level indicator	Secondary indicators
Domestic tourism income	Socioeconomic factors	Added-value of tertiary industry
		Regional per capita production value
	Residents' living standards	Per capita disposable income of urban residents
		Per capita consumption expenditure of urban residents
		The total retail sales of social consumer goods
	Traffic convenience	Passenger turnover
		Passenger volume
		Kilometers, railway density
	Tourism resources and services	Number of star-rated hotels
		Number of travel agencies
		Number of A-level and above sceneries
	Environmental quality factors	Green area rate of built-up area
		Harmless treatment rate of domestic garbage
	Regional demographic factors	Permanent population at the end of the year
		Number of students in the university

variables, U_n represents the availability of variable data, and $M^{\nexists}$ represents the tourism order of the time series of income and economic growth.

Assuming that the tourism income time series represented by ξ is a first-order single integer and l represents the second-order difference sequence of the economic growth data series, then use equation (6) to obtain stable tourism income and economic development time series variable data:

$$p\left(\frac{\gamma}{\eta_1}\right) = \frac{\xi\left[\sum_{i=1}^{k} \eta_{1i}\right]}{\Gamma\left(\eta_{1i}\right)} \gamma\left(\eta_{1i} - 1\right). \tag{6}$$

In the formula, n_{1i} represents the cointegration relationship between tourism income and regional GDP, Γ represents the random disturbance term, Υ represents the n-dimensional endogenous variable, and k represents the lag period of economic growth:

$$P^L = \frac{\mu_{1n} - \mu_{jn}}{t_{ES} \times P\left(\gamma/\eta_1\right)} \cdot P_{\propto}\left(X, A\right). \tag{7}$$

The income effect of tourism is defined as the impact of tourism on domestic per capita income. Since the expenses spent by tourists on tourism in tourist destinations will directly become the income of local enterprises, tourism income will gradually be based on the correlation of its related industries. Infiltrate the local economic system, thereby driving the improvement of the overall local economy. The tourism effect of a place can be expressed as the direct and indirect impact of the tourism industry on the local economy. Obtain the causal relationship between local tourism revenue and economic growth as a basis, calculate the proportion of tourism industry, define the result of the calculation as the direct influence factor of tourism on the local economy, integrate the related effects of the local tourism industry, and establish the model of tourism revenue optimization forecast.

4. Experiment and Results

In order to prove the effectiveness of the proposed time-series-based tourism revenue optimization forecasting modeling method, an experiment is needed. The experiment takes Yan'n from 2009 to 2019 as an example to empirically demonstrate the relationship between tourism income and economic growth in Xi'an. The simulation tool for the experiment is python.

In view of the complexity of the tourism system, there are two internal and external systems for its impact factors. Taking into account the availability and quantification of data, an indicator system is constructed from the internal system of domestic tourism revenue impact factors. Table 1 shows the selected indicators.

According to the method proposed in the third part, Table 2 shows the prediction results of this method, including the original value, predicted value, error, relative error, and level error.

It can be seen from Figure 1 that the average relative error is 0.073923, the average grade ratio deviation is 0.1148, both are less than 0.2, and the posterior difference ratio C value is 0.021 less than 0.35, which means that the model accuracy meets the requirements. The combined effect is good, and the model can be used for prediction.

In order to reflect the superiority of our algorithm, we use the algorithm of this paper, SVM, and Naive Bayes algorithm to construct tourism revenue optimization forecasting models and compare different algorithm models to optimize tourism revenue forecast accuracy. The comparison results are shown in Figure 2.

It can be seen from Figure 2 that the accuracy of using the algorithm model in this paper for different algorithm models to optimize tourism revenue is better than the accuracy of the SVM algorithm model for time series testing. This is mainly because the algorithm is used to establish the model first. The time-series data of tourism income and local economy are tested for cointegration, which guarantees the accuracy of the algorithm in this paper to optimize the forecast of tourism income by using different algorithm models.

The algorithm of this paper, SVM algorithm, and Naive Bayes algorithm is used to construct tourism revenue optimization forecasting model, and the error rate (%), stability (%), and time efficiency (%) of tourism revenue optimization forecasting models of three different algorithms are

Table 2: The predicted value of our proposed method.

Year	Original value	Predictive value	Error	Relative error	Step ratio deviation
2009	53.1	53.1	0	0	53.1
2010	67.3	51.177	16.123	0.23957	67.3
2011	83.81	75.115	8.695	0.10375	83.81
2012	103.39	100.532	2.858	0.02764	103.39
2013	126.55	127.521	−0.971	−0.0077	126.55
2014	141.56	156.179	−14.619	−0.1033	141.56
2015	160.01	186.609	−26.599	−0.1662	160.01
2016	207.33	218.919	−11.589	−0.0559	207.33
2017	275.22	253.288	21.932	0.07969	275.22
2018	291.9	289.658	2.242	0.00768	291.9
2019	335.56	328.34	7.22	0.02152	335.56

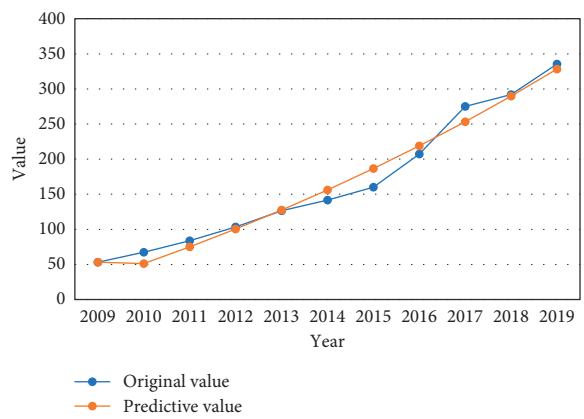

Figure 1: Comparison of predicted value with the original value.

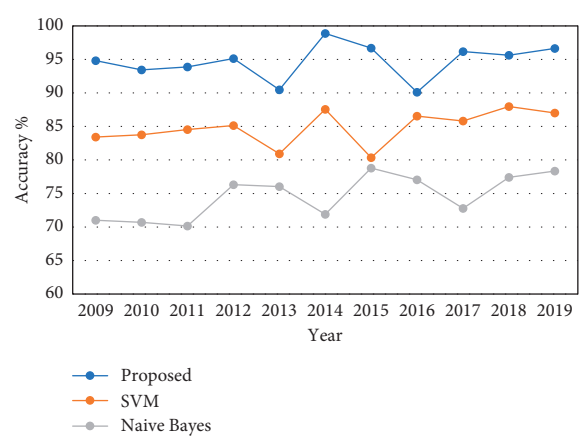

Figure 2: Comparison of prediction accuracy of three algorithms.

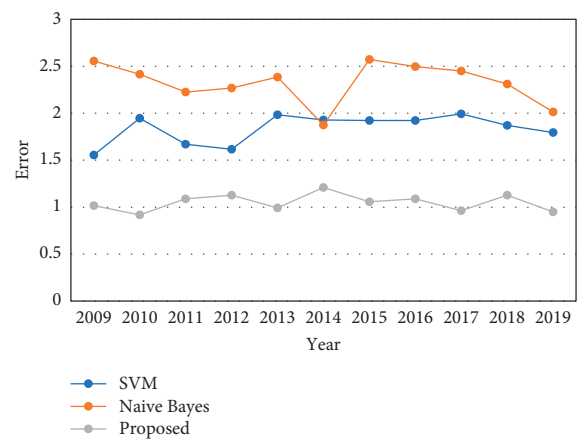

Figure 3: Comparison of modeling error rates of different algorithms.

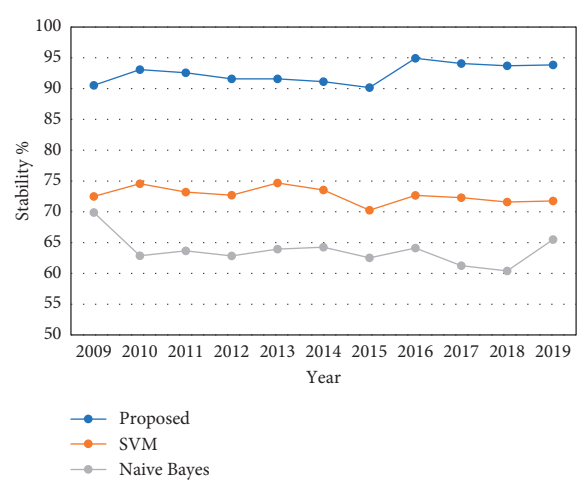

Figure 4: Comparison of stability of different algorithms.

compared. The results of the comparison measure the comprehensive effectiveness of the two different algorithms to establish the tourism revenue optimization forecast model. The results of the comparison are shown in Figures 3, 4, and 5.

From the analysis in Figures 3–5, it can be concluded that the comprehensive effectiveness of the establishment of the tourism revenue optimization forecast model established by the algorithm of this paper is better than the effectiveness of the SVM algorithm and the Naive Bayesian model. This is because when using the algorithm in this paper to establish a tourism revenue optimization forecast accuracy model, a vector autoregressive model based on tourism revenue and local economy two variables is constructed, and the relationship between the two variables is tested by the Granger method, and the proportion of tourism industry is calculated. On this basis, the correlation effect of local tourism income is calculated, and a tourism income optimization forecast accuracy model is established.

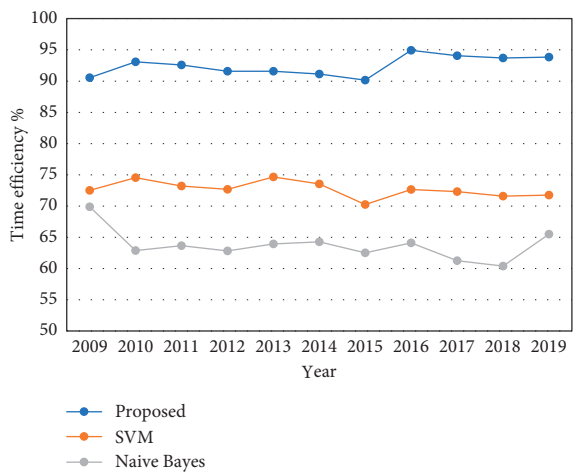

Figure 5: Comparison of time efficiency of different algorithms.

5. Conclusion

The development of modern tourism is closely related to the development of modern transportation. Transportation construction is an important condition for the development of tourism resources and the construction of tourist destinations. Related research shows that areas with obvious advantages in transportation accessibility have a relatively high level of regional tourism economic development. It is necessary to grasp the geographical position of the northwestern region to the east, seize the opportunity of the "Belt and Road" and the construction of the economic belt along the Yellow River, improve transportation services, speed up the construction of transportation networks, and continuously improve transportation accessibility. The development and construction of tourism resources are very important to the development of the tourism economy. In the development process, we must pay attention to the investigation of the tourist attraction radius of the scenic spot and the excavation of the characteristics of the scenic spot, avoid the appearance of homogeneous scenic spots, and establish a unique tourism brand image system. Furthermore, due to the low location and environmental carrying capacity of arid and semiarid areas, the stereotype that tourism is equal to a "smoke-free industry" must be changed, and the coupled and coordinated development of the environment and tourism must be emphasized to create a good environment for cultural tourism and natural tourism. The tourism service industry is a related industry generated by tourism activities. The more mature it is, the more prosperous the tourism economy will be. In order to promote the maturity of the tourism service industry, it is first necessary to establish a multichannel financing mechanism, increase capital investment in the tourism industry, and improve supporting service facilities; secondly, it is necessary to regulate the order of the tourism market and strengthen the supervision of the quality of tourism services; and finally, it is necessary to transform tourism services. The business philosophy is to establish a professional team of talents, pay attention to feedback from tourists, and advocate "refined" and "individualized" services.

Data Availability

The experimental data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

References

[1] S. Milne and I. Ateljevic, "Tourism, economic development and the global-local nexus: theory embracing complexity," *Tourism Geographies*, vol. 3, no. 4, pp. 369–393, 2001.

[2] G. Shaw and A. M. Williams, "Tourism, economic development and the role of entrepreneurial activity," *Progress in tourism, recreation and hospitality management*, vol. 2, pp. 67–81, 1990.

[3] W. Z. Danish and Z. Wang, "Dynamic relationship between tourism, economic growth, and environmental quality," *Journal of Sustainable Tourism*, vol. 26, no. 11, pp. 1928–1943, 2018.

[4] W. Edwards, "The theory of decision making," *Psychological Bulletin*, vol. 51, no. 4, pp. 380–417, 1954.

[5] K. L. Milkman, D. Chugh, and M. H. Bazerman, "How can decision making be improved?" *Perspectives on Psychological Science*, vol. 4, no. 4, pp. 379–383, 2009.

[6] X. Xiang, Q. Li, S. Khan, and O. I. Khalaf, "Urban water resource management for sustainable environment planning using artificial intelligence techniques," *Environmental Impact Assessment Review*, vol. 86, Article ID 106515, 2021.

[7] J. R. Lund and J. Wiese, "Less is more: exploring support for time management planning," in *Proceedings of the Designing Interactive Systems Conference*, pp. 392–405, Diego, CA, USA, June 2021.

[8] Y. Pan, G. Weng, C. Li, and J. Li, "Coupling coordination and influencing factors among tourism carbon emission, tourism economic and tourism innovation," *International Journal of Environmental Research and Public Health*, vol. 18, no. 4, p. 1601, 2021.

[9] Y. Huan, T. Liang, and H. Li, "A systematic method for assessing progress of achieving sustainable development goals: a case study of 15 countries," *The Science of the Total Environment*, vol. 752, Article ID 141875, 2021.

[10] E. Childs, C. D. Remein, R. M. Bhasin et al., "How to launch and continually enhance an effective medical campus faculty development program: steps for implementation and lessons learned," *Journal of Healthcare Leadership*, vol. 13, pp. 147–156, 2021.

[11] S. V. Bryukhovetskaya, K. A. Artamonova, A. A. Gibadullin, S. A. Ilminskaya, and Z. M. Kurbonova, "Management of digital technology development in the national economy," in *Proceedings of the IOP Conference Series: Earth and Environmental Science*, Krasnoyarsk, Russia, November 2020.

[12] X. Li, S. Zhou, and K. Yin, "Measurement of the high-quality development level of China's marine economy," *Marine Economics and Management*, vol. 4, 2021.

[13] D. A. Shepherd and M. Gruber, "The lean startup framework: closing the academic-practitioner divide," *Entrepreneurship: Theory and Practice*, vol. 45, Article ID 1042258719899415, 2020.

[14] N. Mou, Y. Zheng, T. Makkonen, T. Yang, J. Tang, and Y. Song, "Tourists' digital footprint: the spatial patterns of

tourist flows in Qingdao, China," *Tourism Management*, vol. 81, Article ID 104151, 2020.

[15] W. M. Lim and W.-M. To, "The economic impact of a global pandemic on the tourism economy: the case of COVID-19 and Macao's destination- and gambling-dependent economy," *Current Issues in Tourism*, pp. 1–12, 2021.

[16] V. K. Nguyen, R. Natoli, and S. Divisekera, "Innovation and productivity in tourism small and medium enterprises: a longitudinal study," *Tourism Management Perspectives*, vol. 38, Article ID 100804, 2021.

[17] A. Nieto Masot and N. Ríos Rodríguez, "Rural tourism as a development strategy in low-density areas: case study in northern Extremadura (Spain)," *Sustainability*, vol. 13, no. 1, p. 239, 2021.

[18] K. Wang, Y. Pang, C. He et al., "Three Gorges Reservoir construction induced dissolved organic matter chemistry variation between the reservoir and non-reservoir areas along the Xiangxi tributary," *The Science of the Total Environment*, vol. 784, Article ID 147095, 2021.

[19] K. Zhong, Y. Wang, J. Pei, S. Tang, and Z. Han, "Super efficiency SBM-DEA and neural network for performance evaluation," *Information Processing & Management*, vol. 58, no. 6, Article ID 102728, 2021.

[20] J. Pei, "Solving the problem of charging and discharging of electric vehicles based on particle swarm algorithm," in *Proceedings of the 2019 2nd International Conference on Information Systems and Computer-Aided Education (ICISCAE)*, pp. 534–538, IEEE, Dalian, China, September 2019.

[21] J. Su, X. Zhao, D. Hong, Z. Luo, and H. Chen, "Q-value fine-grained adjustment based RFID anti-collision algorithm," *IEICE-Transactions on Communications*, vol. E99, no. 7, pp. 1593–1598, 2016.

[22] Z. Kuang, L. Zhang, L. Zhao, and L. Zhao, "Energy- and spectral-efficiency tradeoff with α-Fairness in energy harvesting D2D communication," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 9972–9983, 2020.

[23] X. Liu, J. Zhang, and S. Jiang, "Accurate localization of tagged objects using mobile RFID-augmented robots," *IEEE Transactions on Mobile Computing*, vol. 20, 2019.

[24] J. Su, Y. Chen, Z. Sheng, Z. Huang, and A. X. Liu, "From M-ary query to bit query: a new strategy for efficient large-scale rfid identification," *IEEE Transactions on Communications*, vol. 68, no. 4, pp. 2381–2393, 2020.

[25] J. Pei, J. Li, and B. Zhou, "A recommendation algorithm about choosing travel means for urban residents in intelligent traffic system," in *Proceedings of the 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEA)*, pp. 2553–2556, IEEE, Chongqing, China, March 2021.

[26] D. Hong, L. Gao, and J. Yao, "Graph convolutional networks for hyperspectral image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, 2020.

[27] D. Hong, N. Yokoya, J. Chanussot, and X. X. Zhu, "An augmented linear mixing model to address spectral variability for hyperspectral unmixing," *IEEE Transactions on Image Processing*, vol. 28, no. 4, pp. 1923–1938, 2019.

[28] D. Hong, L. Gao, N. Yokoya et al., "More diverse means better: multimodal deep learning meets remote-sensing imagery classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 5, pp. 4340–4354, 2021.

[29] E. Brynjolfsson, C. Wang, and X. Zhang, "The economics of IT and digitization: eight questions for research," *MIS Quarterly*, vol. 45, no. 1, pp. 473–477, 2021.

[30] K. A. Fachrudin, "Financial Health Assessment Model for Listed Companies in Indonesia," in *Proceedings of the 2nd Economics and Business International Conference*, Vienna, Austria, June 2021.

[31] A. Sutantoputra, "Do stakeholders' demands matter in environmental disclosure practices? Evidence from Australia," *Journal of Management & Governance*, pp. 1–30, 2021.

[32] J.-H. Chen, T.-S. Chou, J.-P. Wang, H.-H. Wei, and T.-H. Yang, "Sustainable corporate governance: the impact factors for top consulting engineering companies in taiwan," *Sustainability*, vol. 13, no. 14, p. 7604, 2021.

[33] X. Sun and Y. Lei, "Research on financial early warning of mining listed companies based on BP neural network model," *Resources Policy*, vol. 73, Article ID 102223, 2021.

[34] R. Sparapani, C. Spanbauer, and R. McCulloch, "Nonparametric machine learning and efficient computation with bayesian additive regression trees: the BART R package[J]," *Journal of Statistical Software*, vol. 97, no. 1, pp. 1–66, 2021.

[35] A. Kammoun and M.-S. AlouiniFellow, "On the precise error analysis of support vector machines," *IEEE Open Journal of Signal Processing*, vol. 2, pp. 99–118, 2021.

[36] K. K. Sharma and A. Seal, "Spectral embedded generalized mean based k-nearest neighbors clustering with S-distance," *Expert Systems with Applications*, vol. 169, Article ID 114326, 2021.

[37] Z. Zheng, H. Sun, and Y. Zhou, "Multiple discriminant analysis for collaborative representation-based classification," *Pattern Recognition*, vol. 112, Article ID 107819, 2021.

[38] R. Xiao, X. Cui, H. Qiao et al., "Early diagnosis model of Alzheimer's disease based on sparse logistic regression with the generalized elastic net," *Biomedical Signal Processing and Control*, vol. 66, Article ID 102362, 2021.

[39] C. Nicolaidis, G. Schnider, J. Lee et al., "Development and psychometric testing of the AASPIRE adult autism healthcare provider self-efficacy scale," *Autism*, vol. 25, no. 3, pp. 767–773, 2021.

[40] B. T. Pham, M. D. Nguyen, T. Nguyen-Thoi et al., "A novel approach for classification of soils based on laboratory tests using Adaboost, Tree and ANN modeling," *Transportation Geotechnics*, vol. 27, Article ID 100508, 2021.

[41] M. Nasir, S. Simsek, E. Cornelsen, S. Ragothaman, and A. Dag, "Developing a decision support system to detect material weaknesses in internal control," *Decision Support Systems*, Article ID 113631, 2021.

[42] K. G. Al-Hashedi and P. Magalingam, "Financial fraud detection applying data mining techniques: a comprehensive review from 2009 to 2019," *Computer Science Review*, vol. 40, Article ID 100402, 2021.

[43] B. D. Liengaard, P. N. Sharma, G. T. M. Hult et al., "Prediction: coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling," *Decision Sciences*, vol. 52, no. 2, pp. 362–392, 2021.

[44] J. Sun, H. Fujita, Y. Zheng, and W. Ai, "Multi-class financial distress prediction based on support vector machines integrated with the decomposition and fusion methods," *Information Sciences*, vol. 559, pp. 153–170, 2021.

[45] M. Durica, L. Svabova, and J. Fonda, "Financial distress prediction in Slovakia: an application of the CART algorithm," *Journal of International Studies*, vol. 14, no. 1, 2021.