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Research Article

Prediction of Economic Operation Index Based on Support Vector Machine

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Economic forecasting is not only an important field of economic research but also attracts extensive public attention. The results of the study are directly related to the accurate understanding and view of the economic situation, which in turn affects the rational formulation of macroeconomic policies. However, traditional estimation methods are often limited by expert experience and simple mathematical models, which are difficult to deal with on nonlinear models and do not meet the objective requirements for predicting macroeconomic performance indicators. Support vector machine is a popular new data mining technique. Benefiting from its good theoretical foundation and good generalization performance, SVM has become the starting point of research in recent years. Combining support vector machine research, fuzzy theory, and macroeconomic performance estimation, it attempts to develop a method for predicting macroeconomic function indicators based on support vector machines and expand the theory and projects of support vector machines. In addition, empirical evaluations of early financial forecasts are conducted to integrate theoretical and practical data. The characteristics of the traditional evaluation system are discussed in detail, and the standard model of the prediction system is established, including classical and modern forecasting theories and their forecasting systems. The theory of statistical learning and the theory and basic features of support vector machines are also discussed. For the analysis of the internal relationship between the distribution pattern, SVM, and the forecast of macroeconomic performance indicators, predictable economic activity forecast can be considered as a distribution system. Combining SVM with economic forecasting, SWE intelligent economic operation index forecasting is used for the first time, the automatic selection of symbolic parameters is recognized, and some algorithms and in-depth analysis methods are provided. The experimental results show that the prediction of economic operation indicators based on support vector machine technology is 57% faster than the traditional prediction method and the prediction accuracy rate is as high as 98.56%.

1. Introduction

The regional economy reflects the economic strength of a region and also considers the overall socio-economic and ecological benefits of the region. From the perspective of world economic practice, the role of economic planning is to resolve market deficits on the basis of respecting the role of the market, rather than actively intervening. However, some studies have pointed out that the research focuses on the overall layout and allocation of productive forces, and the problem of unbalanced and uncoordinated regional economic growth is not yet clear. On the issue of coordinated regional development, there are still ambiguities, such as urban division of labor in the region complements each other, replacement development, how to divide labor, how to replace, and replacement experience. The order of the questions is currently unclear. This is actually a long-standing but not properly addressed question of how the market understands the scale of economic regulation. At present, although the role of the market economy has been widely recognized, local governments have not launched the market competition, and border issues are plaguing the development of regional economies.

From an economic point of view, economic forecasting is the most dynamic, promising, and useful strategic resource. In the era of industrial economy, economic growth depends on the input of material capital, labor, and land, and various factors of input and output depend on the continuous economic growth. An increase in any factor of production generally brings little profit, known as the law of diminishing marginal returns. However, in the era of knowledge economy, knowledge as the main factor of production is not bound by the law of diminishing marginal benefits. The more intellectual resources are invested, the more peripheral benefits of knowledge, that is, information has the characteristic of increasing peripheral benefits. Therefore, knowledge has inestimable value and is a powerful force for economic and social changes. Predictors are decisive factors driving economic growth. The study uses the rate of return method to calculate the impact of predictors on U.S. economic growth. During the nearly 60 years from 1900 to 1958, U.S. agricultural capital investment increased by 4.5%, and the corresponding gain increased by 3.5 times; human capital investment increased by 3.5 times. During the period, profits increased by 17.5 times, fully demonstrating that profit multiplication is more predictive than physical capital.

A large number of facts show that the core competition in the era of knowledge economy is economic prospects rather than material factors. Economic factors have become the key to contemporary international labor sharing, and international competition is essentially the technological level and innovation ability of competition and is also a predictor of competition. In international competition, the important difference between developed countries and backward countries is that the former mainly provides products and services with high knowledge, high skills, and high additional cost, while the latter only provides products and raw materials with low technology content and low additional cost. This results in more developed countries getting richer and developing countries getting poorer. Today, comprehensive national competition between countries or regions in terms of economic strength, technology, military, culture, and control is ultimately economic competition. No matter which country and which enterprise, people with multiple economic forecasting indicator systems have a competitive advantage, dominate the competition initiative, and remain invincible in international competition. Therefore, the knowledge economy is a talent-based economy. In this study, SVM is applied to forecasting economic systems, and a method for forecasting economic operation indicators based on vector distribution support is proposed. Identifying SVM uncertainty, establishing the SVC uncertainty algorithm, and using expert knowledge to propose the SVC uncertainty algorithm are the steps involved in the prediction method for economic operation indicators. A mandatory support vector regression economic action index prediction model with USVC is established, and a new index selection algorithm is established in the economic operation index prediction system.

2. Related Work

Experts at home and abroad have also conducted many studies on support vector machines and economic operation indicators. The research purpose of Schittkowski is to apply the nonlinear programming algorithm to calculate the kernel and related parameters of support vector machine (SVM) through a two-stage method, and the derivative of the function that defines the optimization problem is evaluated analytically [1]. Yunlong et al. research investigated the application of nontraditional models in modeling travel mode choice, and a new artificial intelligence model, the support vector machine, was first applied to modeling travel mode choice [2]. Bouboulis proposed a new framework for complex support vector regression (SVR) as well as support vector machine (SVM) for quaternary classification. This method utilizes the concept of broad linear estimation to model the input-output relationship of complex-valued data [3]. Kyrkou argued that SVMs are optimized to efficiently handle problems where most of the data fall into one of two categories, such as image object classification, providing the speedup of a monolithic SVM classifier [4]. Wang believed that support vector machines (SVMs) are one of the well-known supervised learning algorithms. The basic SVM model is dealing with the situation where the exact values of the data points are known [5]. Hu studied a real-time decision-making method for power system emergency control based on support vector machine (SVM). The key technology is to use support vector machine to mine system stability rules from a large number of simulation data [6]. However, the above experiments have not been recognized by the public due to too few experimental samples and incomplete data.

3. Support Vector Machine Algorithm Theory

The purpose of this study is to review vector machine support, fuzzy processes and macroeconomic forecasting, evaluation system-based SVMs, and the development of SVM processes and algorithms [7]. At the same time, the impact of real data analysis on financial forecasting is combined to realize the combination of education and practice. The most common distribution algorithm is the perceptron algorithm, and SVMs are distributed algorithms for detecting any hyperplane. The samples can be separated from different classes in the training set. First, at the beginning of the algorithm, training is designed approximately, step by step, until all elements of different classes in the training class are connected to each other, or only a part of the hyperplane is extracted from different classes [8], so as to meet the design requirements of the network. If it just follow the requirements of the perceptron, there will be many such separating hyperplanes. In order to be able to distinguish between good and bad perceptron models, this definition can separate the most difficult points with a relatively large degree of certainty. Support vector machine is to satisfy this idea. It enables the hyperplane to make the point closest to the separation hyperplane the farthest while ensuring the classification accuracy. The advantage of this is that the influence of noise points is minimal, and it can be insensitive to the unique properties of a single sample, so the support vector machine algorithm is robust, and the generalization ability to unknown data is the best [9]. In theory, for linear classifiers, the training results of support vector machines are the best of course, and when the data cannot be

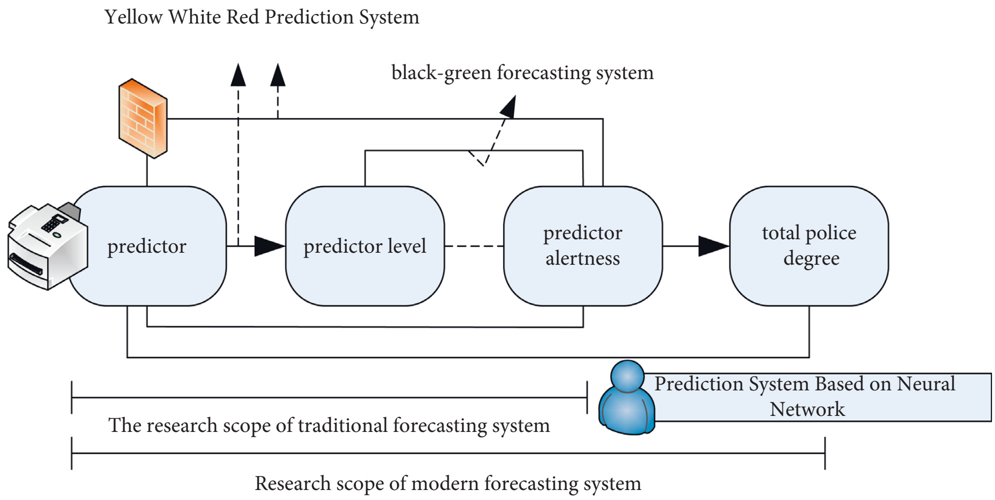

Figure 1: The scope of research in modern forecasting systems.

separated indirectly, the introduction of the kernel operating system turns the small invisible problem into a large vertical problem that can be separated. In this way, the linearly separable datasets are separated by the separation hyperplane, and the linearly inseparable datasets are separated by the separation hypersurface [10].

Further development of prediction research requires extensive study of other disciplines, especially the success of nonlinear disciplines such as artificial intelligence research, intelligence science and pattern recognition, and artificial neural networks [11]. Modern economic performance index forecasting systems are designed to take advantage of research results based on artificial intelligence, model recognition, neural networks, and other disciplines, as well as the remaining problems of traditional evaluation systems. The theory of most nonlinear systems is to prevent or minimize the influence of human factors on the evaluation process, which is more purposeful and reliable [12]. The research scope of the modern economic operation index forecasting system is an extension of the traditional forecasting system, as shown in Figure 1.

The use of neural networks and economic forecasting systems expands and narrows the foundations of traditional forecasting methods, which solve complex problems of traditional forecasting types. Dealing with nonstandard types and emphasizing quantitative indicators, it is difficult to resist the influence of qualitative indicators and does not have the ability to self-adjust and self-learn. The acquisition of predictive knowledge and information is indirect, time-consuming, and ineffective [13]. This lays the foundation for the practical application of prediction. Aiming at these problems, an improved genetic algorithm is used to optimize the forward three-layer BP network economic operation index prediction system. The indicator forecasting method is the basis of other traditional forecasting methods, and it is also the most commonly used forecasting method. Figure 2 shows a schematic diagram of the index prediction method [14].

The most widely used artificial neural network is the BP ternary organization. Figure 3 shows a schematic diagram of a three-layer forward BP network consisting of an input layer, a hidden layer, and an output layer. The shell layer is located between the input layer and the output layer, which is a feature that is different from other input forms present in the input template [15]. The deleted part is moved to the output layer. The final decision about the class of input samples is made at the output layer. Hence, the hidden layers are called feature extraction layers. The process of extracting a portion of the input pattern from the hidden layer is actually a "self-organizing" process that puts pressure on the connection between the input layer and the hidden layer. In the process of network training, the connection pressure between layers plays the role of "mutual transfer." Each connection weight gradually evolves from an initial random value and finally reaches the input pattern recognition process, that is, the "self-organizing process." The BP measurement prediction system requires a series of exercises and a series of tests to evaluate the effectiveness of the exercises [16]. The training and testing parts come from the same target with correct input and output. Since the training table is used for network training, the network can adjust the scale and path according to the BP algorithm to meet the requirements of the diagram. On the other hand, a series of tests are used to evaluate the performance of the trained network. If the organization formed does not work well with the pilot project, then the training set or test set is not representative. The predictor can be regarded as the "feature extractor" of the omen, so the lower limit of the number of hidden nodes can be defined as the class of the omen. The main defects of the neural network economic operation index prediction method are the structure selection problem and the local minimum point problem [17].

3.1. Nonlinear Separable Support Vector Machines. Linear SVM is a very efficient approach when dealing with linear datasets. However, in the global case, datasets are rarely well defined, which means that there is no hyperplane at the original location that can accurately divide the two sample types. The sample division is shown in Figure 4 [18, 19].

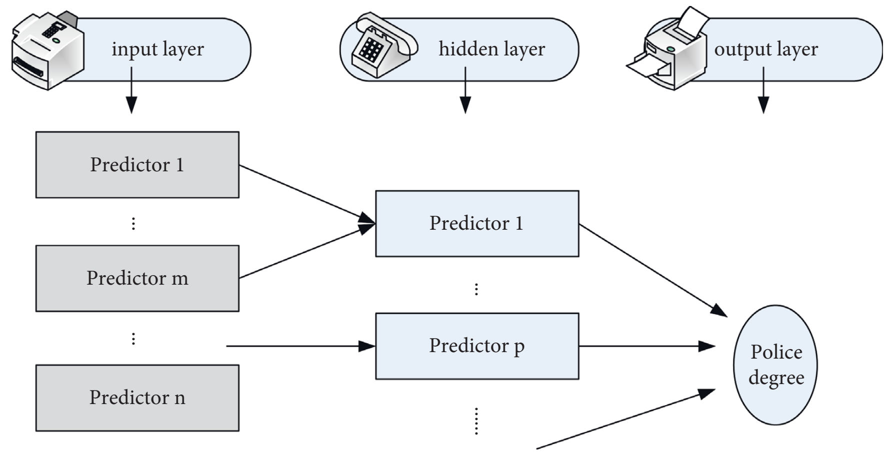

Figure 2: Prediction method based on neural network.

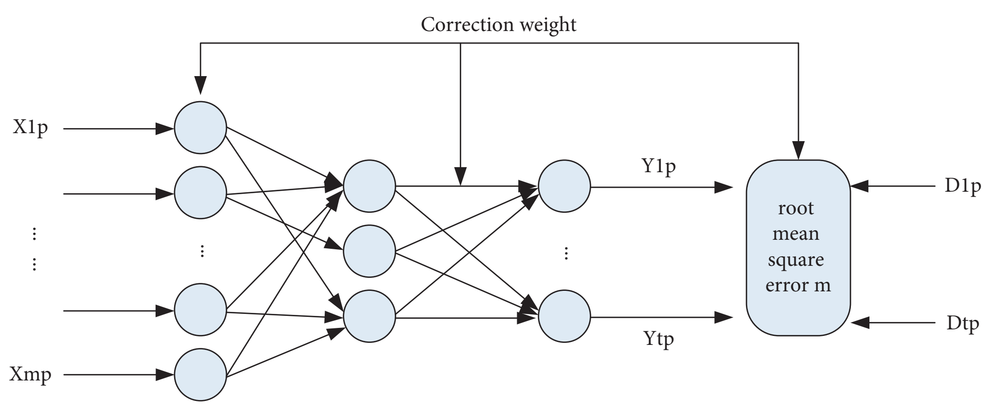

Figure 3: Forward three layers or network.

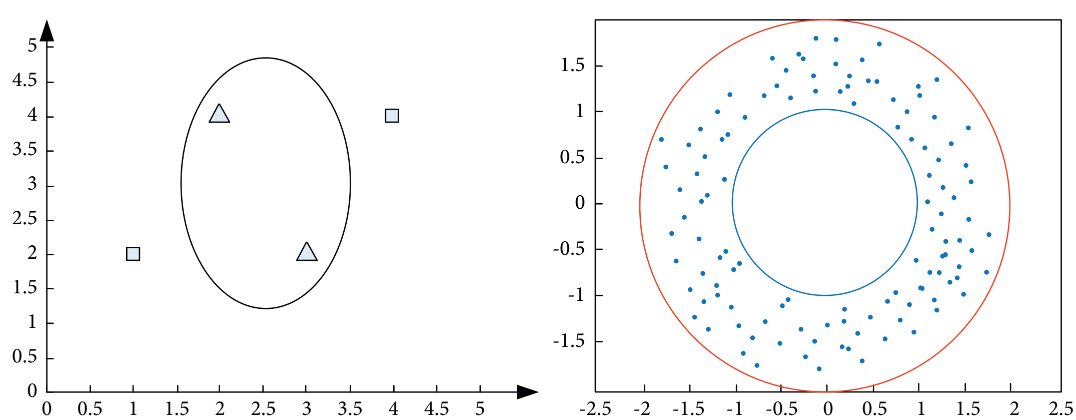

Figure 4: Linearly inseparable case.

In order to illustrate the advantage of the direction indicator-based support vector machine in terms of training time, this study tests 4 datasets such as ijcnn1, covtype, webspam, and cifar in the Matlab R2015b environment. This experiment mainly uses the following original datasets, in which the number of training samples, the number of test samples, and the number of features are listed in Table 1 [20]: for covtype and webspam datasets, it is divided into the training set and test set according to the ratio of 80%–20%. For ijcnn1 and cifar, the original training set and test set are used for experiments. In order to demonstrate the generality of the method, the article is compared with several recently researched algorithms [21, 22].

The article first shows the RBF kernel function in Figure 5, which uses different methods to screen the number of candidate samples on different datasets. The

Table 1: Training set information table.

Dataset	#training samples	#testing samples	#features
ijcnn	49950	91750	22
covtype	456852	118631	54
webspam	241250	70000	254
cifar	50000	10000	3054

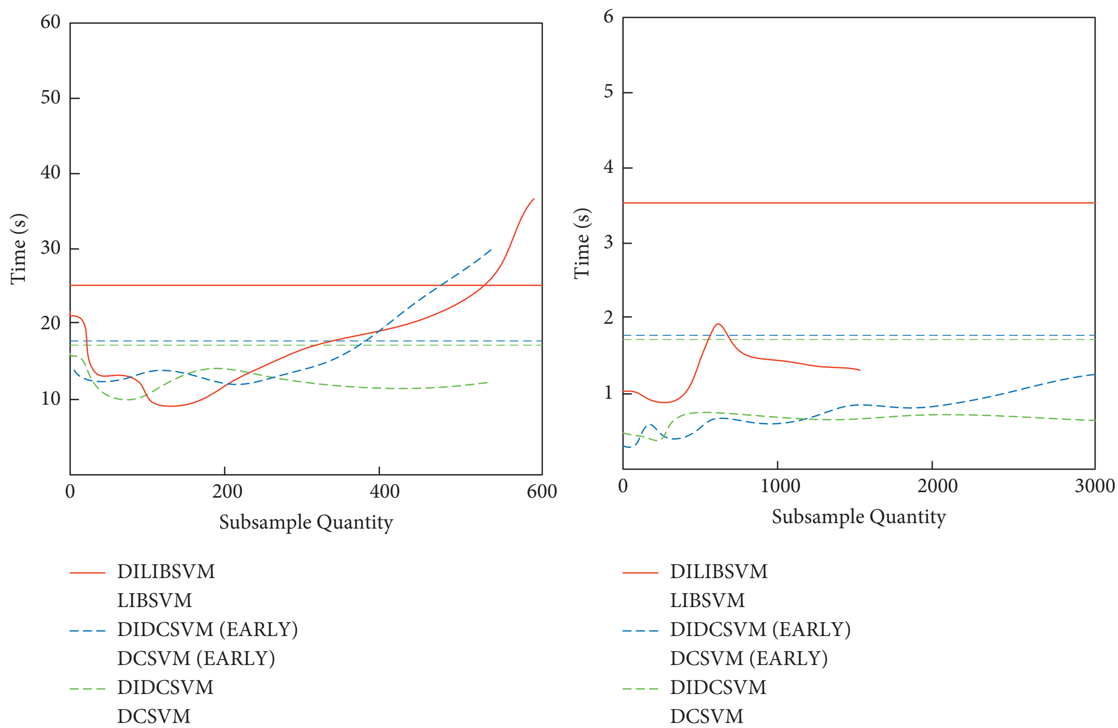

Figure 5: Support vectors filtered on each dataset using the RBF kernel function.

solid line part in the figure is the result of the original method, and the dashed line part is the result of the DISVMs. Through the experimental results, people found that on any dataset, the number of candidate support vector machines screened by DISVMS fluctuated within a certain range, and the number would not exceed half of the original dataset. It is proved that this method can effectively filter out a large number of nonsupport vectors, so as to eliminate useless samples and reduce the size of the dataset. Figure 6 shows the training time on different datasets with different methods using the RBF kernel function. Through experimental results, we found that DISVMs outperformed the original methods in terms of time. From Figure 6 and Table 2, we can draw similar conclusions, but the training rate improvement of DISVMs is high at the loss of training accuracy.

The experimental results show that the DISVMs algorithm can quickly identify nonsupport vectors, improve the efficiency of identification, and meet the accuracy requirements of support vector machines. Compared with the traditional support vector algorithm, it can reduce the original training time, which greatly improves training efficiency.

3.2. Statistical Learning Theory and Support Vector Machines. Based on the given training samples, the purpose of machine learning is to obtain an estimate of the dependencies between the input and output of a system, so that it can predict the unknown output as accurately as possible:

$$(x_1, y_1), (x_2, y_2), \ldots, (x_1, y_1),$$
$$R(w) = \int L(y, f(x, w)) dF(x, y),$$
$$L(y, f(x, w)) = \begin{cases} 0, & y = f(x, w), \\ 1, & y \neq f(x, w). \end{cases} \quad (1)$$

In the function approximation problem, y is a continuous variable, using the least square error criterion, and the loss function can be defined as follows:

$$L(p(x, w)) = 1np(x, w),$$
$$L(y, f(x, w)) = (y - f(x, w))^2, \quad (2)$$
$$\mathrm{Remp}(w) = \frac{1}{n} \sum_{i=1}^{n} L(y_i, f(x_i, w)).$$

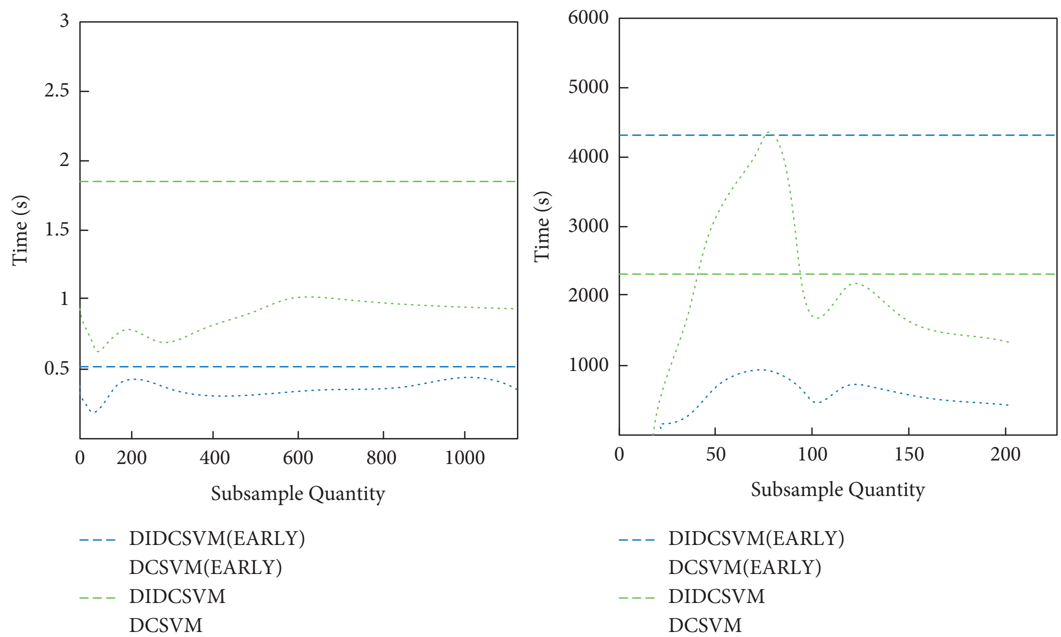

FIGURE 6: Comparison of training time on each dataset using the RBF kernel function.

TABLE 2: Training time and training accuracy comparison table.

Datasets	ijcnn1		covtype		webpam		cifar	
	$C = 32$ Time (s)	$Y = 2$ Acc (%)	$C = 32$ Time (s)	$Y = 2$ Acc (%)	$C = 8$ Time (s)	$Y = 16$ Acc (%)	$C = 8$ Time (s)	$Y = 2$ Acc (%)
LIBSVM	37.51	98.65	32831.3	96.09	29652	99.32	45236	89.14
DILIBSVM	14.52	98.65	15935.5	93.51	14235	98.41	18523	89.48
DCSVM (E)	17.82	98.65	8519.6	95.35	4262	97.62	3452	88.64
DIDCSVM (E)	11.51	97.65	4523.69	92.63	1354	97.65	869.65	86.65
DCSVM	17.5523	98.65	12035	95.65	2923.6	95.65	2035	86.64
DIDCSVM	10.46	98.65	4099	92.621	2154	98.35	1354	86.3

At present, there is no general theory about the calculation of VC dimension of any function set, and only the VC dimension of some special function sets is known. For example, in the n-dimensional real number space, the VC dimension of a linear classifier and a linear real function is $n+1$, while the VC dimension of the function is infinite:

$$\begin{aligned} &f(x,a) = \sin(ax), \\ &R(w) \le R_{\text{emp}}(w) + \sqrt{\frac{h(1n(2l/h)+1) - 1n(\eta/4)}{l}}, \\ &R(w) \le R_{\text{emp}}(w) + \Phi(l/h), \\ &y((w\cdot x)+b), \text{in} w = \frac{w}{\|w\|}, b = \frac{b}{\|b\|}. \end{aligned} \tag{3}$$

According to the above analysis, constructing the optimal hyperplane under the linearly separable condition is transformed into the following quadratic programming problem:

$$\begin{aligned} &h(x) = \operatorname{sgn}[(w\cdot x)+b], \\ &h \le \min\left(\left|R^2A^2\right|, n\right) + 1, \\ &\min \Phi(x) = \frac{1}{2}(w\cdot w), \\ &\text{s.t. } y_t\left(\left(w\cdot x_t\right)+b\right) \ge 1, \quad i = 1,2,\ldots,i. \end{aligned} \tag{4}$$

Since the gradient of b of w at the saddle point is zero,

$$\begin{aligned} &L(w,b,a) = \frac{1}{2}(w\cdot w) - \sum_{i=1}^{t} a_i\left[y_t\left(\left(w\cdot x_i\right)+b\right) - 1\right], \\ &\frac{\partial L}{\partial w} = w - \sum_{i=1}^{l} a_i y_i x_i = 0 \Longrightarrow w = \sum_{i=1}^{1} a_i y_i x_i, \\ &\frac{\partial L}{\partial b} = w - \sum_{i=1}^{l} a_i y_i = 0 \Longrightarrow \sum_{i=1}^{l} a_i y_i = 0. \end{aligned} \tag{5}$$

Table 3: Cross-sectional data of each city's economic year in 2010 after index preprocessing.

	×1	×2	×3	×4	×5	×6	×7	×8
N city	3.145	1.254	1.785	2.852	2.621	4.199	3.154	3.365
W city	2.521	1.752	1.741	2.542	3.654	2.036	2.054	1.853
X city	1.254	0.965	0.965	0.995	1.065	0.752	1.325	0.842
C city	0.752	1.185	0.354	0.865	0.625	0.852	0.754	0.248
S city	1.985	1.354	2.154	2.125	1.774	2.014	1.854	0.125
L city	0.652	1.152	0.354	0.652	0.563	0.658	0.521	0.075
H city	0.354	0.854	0.562	0.358	0.354	0.268	0.658	0.254
Y city	0.524	0.325	3.512	0.521	0.415	0.632	0.754	0.412
Z city	0.265	0.655	0.412	0.185	0.248	0.198	0.325	0.075
T city	0.752	0.965	0.952	0.065	0.732	0.445	0.524	0.006

Substituting the above formula in the following formula, the problem of constructing the optimal hyperplane is transformed into a simpler dual quadratic programming problem:

$$a_i\left(y_i\left(w\cdot x_i+b\right)-1\right)=0,\forall_i,$$

$$w=\sum_{SV} a_i y_i x_i, \tag{6}$$

$$\max W(a)=\sum_{i=1}^{l} a_i-\frac{1}{2}\sum_{i,j} a_i a_j y_i y_j\left(x_i\cdot x_j\right).$$

4. Empirical Analysis of Economic Operation Indicators Forecasting

The research content of the article takes province J as an example. The data of the article are all taken from the statistical yearbook. Due to the update of the statistical yearbook itself, the data shall be subject to the revised data in the statistical yearbook of the following year. According to the evaluation indicators selected above, the raw data of each indicator from 2011 to 2020 were collected respectively. Details are provided in the time-series data table of economic development evaluation and forecast research in J province (Table 3. For the following reasons, many indicators were selected for the study. This study selects time-series stereo data. Therefore, the amount of data studied will be very large, $13\times18\times10$ in total. Therefore, only data for 2011 and 2020 are given in Table 3. The economic development of 10 prefectures and cities in J province has its own characteristics, and its development is carried out under the combined action of the promotion of their respective advantages and the restriction of their disadvantages. How is it performing as a whole? What is the comprehensive ranking of the 10 cities? What are their advantages and disadvantages? What will be the future development direction? These are important issues that need to be paid attention to. On the basis of the discussion in the previous sections, and on the basis of "vertically and horizontally" opening the steps of the comprehensive evaluation method of grades, this study uses the data in Table 3 to fully mine the information contained in it. The economic performance of 10 cities in J province is reasonably and objectively evaluated from 2011 to 2020.

After obtaining the annual cross-sectional data, the symmetric matrix H is obtained according to the formula. Figure 7 shows the obtained symmetric matrix of the economic dynamic evaluation research problem of each city in J province.

The maximum eigenvalue of the symmetric matrix and the eigenvector corresponding to the eigenvalue are obtained by SAS software, and the vector weight coefficient w is obtained by normalizing the eigenvector, as listed in Table 4. The scale sequence of dynamic comprehensive evaluation of values is shown in Figure 8. In recent years, the comprehensive evaluation value of cities has little difference intuitively, but in fact, there is still a big difference. All data are processed seamlessly. Not every town is very different, except in relatively small areas.

In the following, in order to analyze in more detail which aspects each city has advantages and which aspects are disadvantaged, the "horizontal" open level method is applied to comprehensively evaluate the annual status of urban development, select the corresponding index data, and form a data matrix for each year. That is, the economic, social, technological, ecological, and environmental indicators of each city are calculated, and the census results are given in the form of a data map, as shown in Figure 9. Judging from Figure 9. As the capital of J province, N city has the most colleges and universities and leads the share of scientific and technological progress, while other cities lag behind. Therefore, the exchange of science and technology will be very important. Judging from the ecological development index, the most striking feature is that the 10 prefectures and cities are in almost the same situation. This does not mean that the development among the cities is in a coordinated state, but only means that there are no better or worse cities. Therefore, to improve the level of regional competition, the development of the ecological environment is an important indicator of each city. In terms of environmental development index, the characteristic is that the gap between cities has gradually stabilized from the original state. But in general, compared with the economic, social, technological, ecological, and other aspects, the ranking of N city is still relatively high. This shows a problem. Under the rapid economic development, the environment is under increasing pressure. All cities have such problems in this regard. For a long time to come, coordinating economic development and environmental protection will be a very important issue.

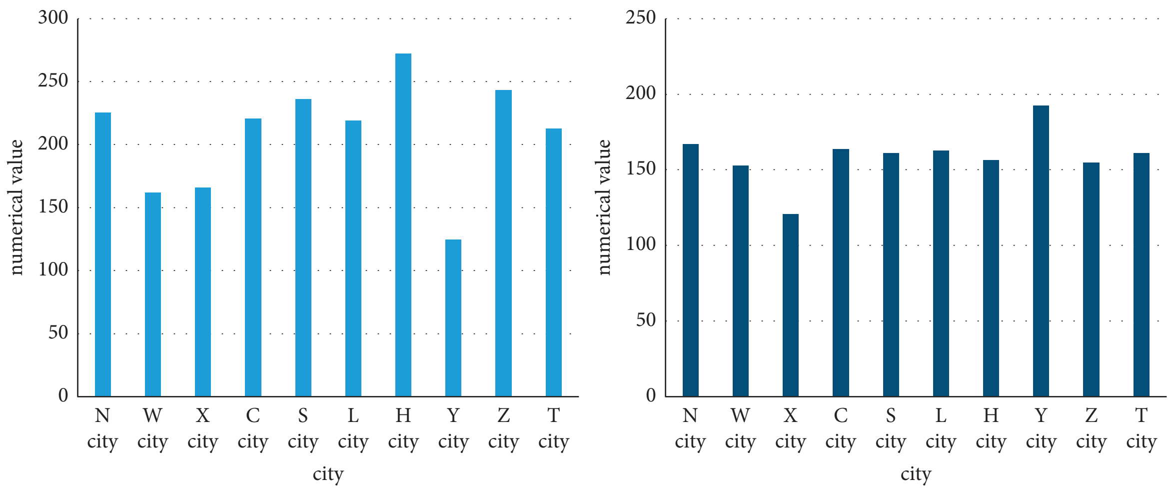

Figure 7: Symmetrical matrix H of economic dynamic evaluation of cities in J province.

Table 4: Standard weight coefficient of the economic evaluation system of cities in J province.

Index	×1	×2	×3	×4	×5	×6	×7	×8	×9
Weights	0.0576	0.0408	0.0445	0.0559	0.0609	0.0622	0.0577	0.0679	0.0594
Index	×10	×11	×12	×13	×14	×15	×16	×17	×18
Weights	0.0610	0.0327	0.0693	0.0744	0.0376	0.0357	0.0581	0.0658	0.0585

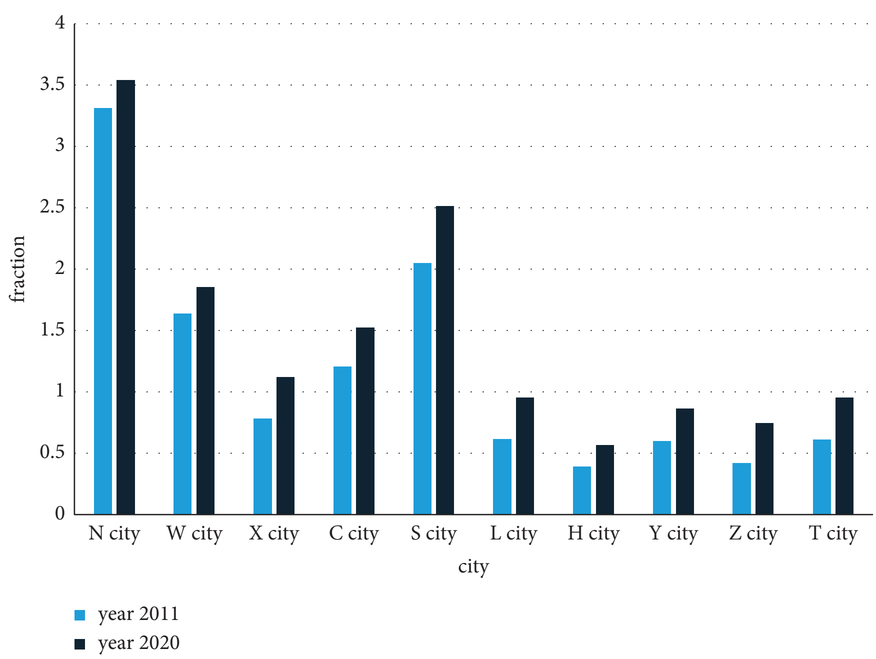

Figure 8: 2011–2020 comprehensive scores of cities in J province.

Figure 9 analyzes the horizontal comparison of different cities in terms of economy, society, technology, ecology, and environment each year and finds out the degree of coordinated development among different cities, as well as the existing advantages and disadvantages. Figure 10 uses a "vertical" pull-down approach to analyze different cities, and understanding these trajectories is important for uncovering problems that arise within the economic system.

Judging from the economic development index in Figure 10, cities represented by cities N and C began to recover after China's entry into the WTO and embarked on a road of rapid development with relatively strong development. After the financial crisis in 2009, the economic development of each city accelerated significantly, which can be clearly seen in the figure. From the perspective of social development index, there is a big contrast. The social development index

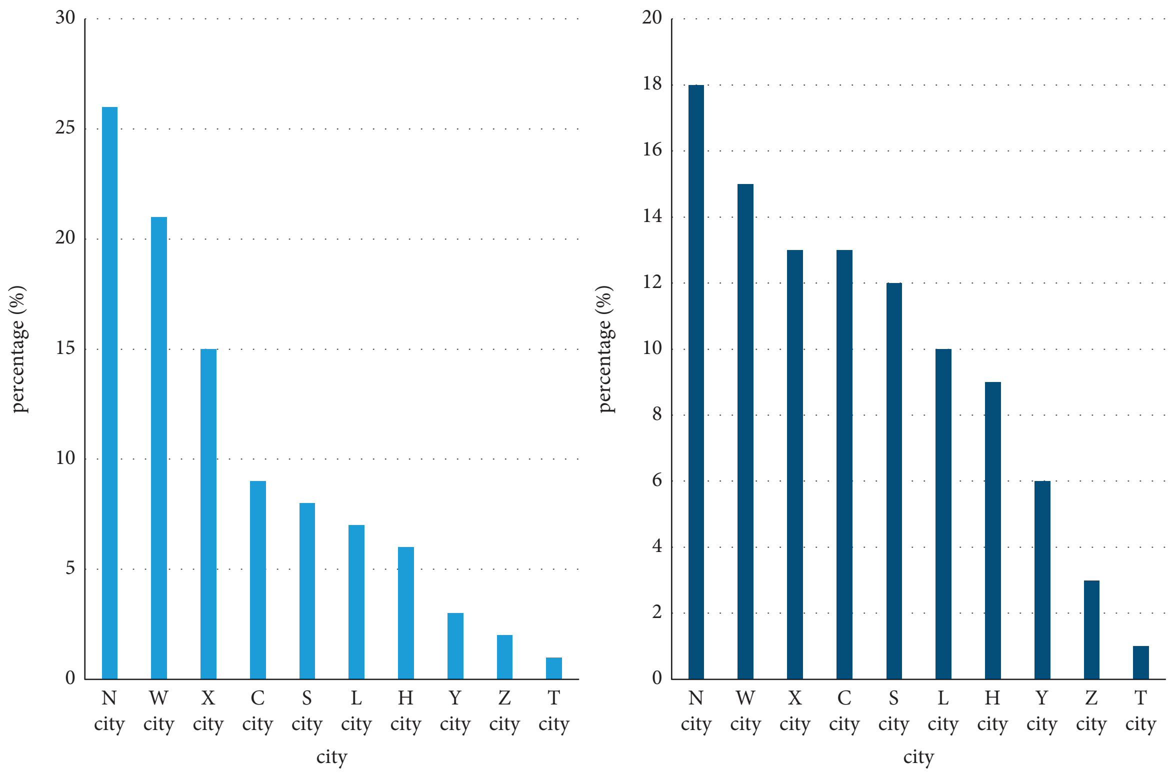

FIGURE 9: Applying the method of horizontally widening the grades to obtain the science and technology development index of each city.

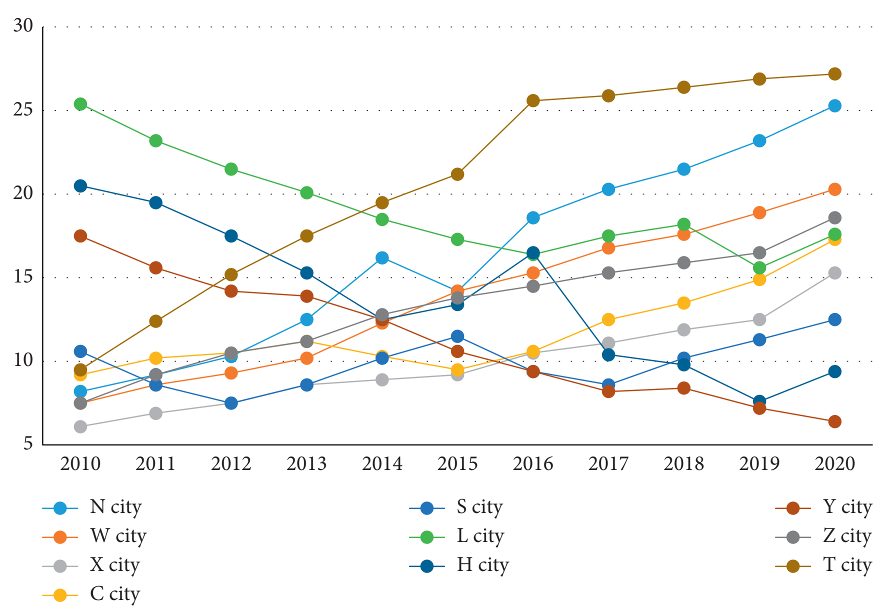

FIGURE 10: Applying the vertical scale method to seek the social development of cities.

in the next five years is significantly better than that in the previous five years, which has a lot to do with the reform of the medical security system implemented in China in recent years. The role of government macromanagement in the economic operation system is evident. In the future economic development, government departments should play a leading role in policy. From the perspective of the technology development index, it is consistent with the information described earlier. Moreover, it can be seen that in terms of technological development, the pace of development is still very slow, which is related to the difficulty of technological innovation itself. Judging from the ecological development index, the gap between the ecological status of each city is relatively small compared with other aspects, and the level is almost the same. It is worth mentioning that the ecological development of S city is relatively good, which is related to the industrial development level of S city itself. Therefore, the correct use of this advantage can effectively enhance the city's core competitiveness. In terms of environmental development index, there were changes in each city in 2012 and 2013. It should be noted here that since the environmental indicators selected in the article are all negative indicators, the lower the numerical score, the better the natural state. In 2012, about 10 prefectures and cities in J Province suffered damages to varying degrees, which were related to the floods at that time. In the following years, the environment of each city improved year by year.

5. Discussion

For a comprehensive evaluation, evaluation object, evaluation index system, weight determination, model selection, and evaluator, these elements are the main content of comprehensive evaluation. The following introduces the background of understanding the regional economy. The problem to be studied in this article is the dynamic evaluation and prediction of urban economic development in the province. J Province chooses to establish an evaluation index system on a reasonable basis. Then, the comprehensive evaluation method of determining the weight based on the "vertical and horizontal" method of splitting grades is expounded in detail. After that, it mainly discusses the economic development of the cities in J province during the ten-year period, makes a grey forecast on the main economic indicators of J province, and looks forward to the future. The "vertical and horizontal" method is used to open the grades to analyze the economic development of each city. The "horizontal" method of opening grades is used to discuss the differences in development between cities and find out the reasons for this gap and the development trend of this gap, that is, expanding or narrowing. In addition, it also analyzes the development status of the transfer between different cities. The "vertical" open-level method is used to discuss the development status of the same system at different times, find its development trajectory, and consider whether the system is developing in a good direction or a bad direction. When the system is developing well and when it is developing poorly are analyzed. Understanding these problems is of great benefit to grasping the main contradictions in the system development and resolving them. When determining the overall development level of each city in J province, the article is divided into four factors: economy, society, technology, and environment, and evaluates the economic development level of each city. The economic development index, social development index, science and technology development index, and environmental development index in different periods are some creative elements of this research. Two separate weighted averages are used in solving the comprehensive pressure evaluation using the micro-opening "longitudinal" method. That is, the first weighted average emphasizes the role of each indicator at different times, and the second weighted average emphasizes the role of longitudinal time on the basis of the first weighted average. In this study, after obtaining the score values of each city in different years, the third weighted average is used to obtain the comprehensive score of each city, and then the scores are sorted. This is another innovative point of this study.

After analyzing the relationship between model distribution, support vector machine, and the estimation of macroeconomic function index, it is concluded that the evaluation of economic activity index can be regarded as a model classification process. SVM is an effective method to solve distribution problems, and the SVC intelligent model is proposed to predict economic indicators, automatically select appropriate model parameters, and perform specific algorithm steps and empirical analysis. Due to the uncertainty in the evaluation process of economic forecast indicators, this study presents, for the first time, a method for estimating the distribution of uncertain support vectors (USV). This method combines expert judgment information and uncertainty with an evaluation system, understands the organic economic combination of financial and economic indicators and expert knowledge, and presents the results of economic forecasting and economic research and development. Evaluation provides new ideas and methods, introducing obscure theories and support vector machines into new application spaces; evaluating various indicators of economic forecasts is considered a regulatory issue. In association with USVC, a vector uncertainty regression (UOSVR) model was developed to assess financial performance. It also discusses the practical application of the USVC and SMVM special cases in predicting economic performance and suggests ways to become a member of the WBM. An important step in feature selection model classification is that, given the linkages and benefits of early economic warning indicators, this study proposes a new approach to computerized forecasting of economic performance indicators. This method is also proposed for the first time in the field of economic operation indicator forecasting.

6. Conclusions

The 21st century is the era of knowledge economy, and economic growth is a common concern all over the world. Economic forecast resources play an important role in economic growth. In today's international and local environment, economic growth is no longer determined by the abundance of natural resources but by the efficiency of resource use, as predicted by economic and resource flow indicators. Since the implementation of the development policy, the economy of some provinces has improved, but there is still a significant gap compared with developed countries, and the change in resources has not brought the benefits of economic growth. Economic growth in different regions is not divided by access to and development of natural resources, technological development, and sustainable economic growth. Therefore, in order to achieve faster and more efficient economic growth, it is important to pay attention to economic activity forecasts and the consequences of economic growth. This study focuses on the current thinking such as human economics and economic development, summarizes the laws about human capital and economic growth, and analyzes the important role of economic operation index forecasting on economic growth. On the basis of theoretical analysis, this study innovatively constructs a forecasting index system for economic operation indicators, collects official statistical data, and uses support vector basis (SVM) as a basis to build a forecast model of economic operation indicators and economic growth. Compared with the previous methods based on BP neural network, it is proved that the prediction model based on SVM is better than the model based on BP. Through quantitative analysis, it proves that the forecast of economic operation indicators is crucial to economic growth. This study analyzes the formation and current situation of the forecast of economic operation indicators in the economic growth of different regions and points out the problems existing in the forecast of economic operation indicators in terms of structure and utilization efficiency. Finally, some countermeasures and suggestions are put forward to play the role of forecasting economic operation indicators in economic growth.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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