Hindawi
Mobile Information Systems
Volume 2022, Article ID 1118941, 8 pages
https://doi.org/10.1155/2022/1118941

Research Article

Economic Efficiency Measurement Algorithm of Strategic Emerging Industries Based on Multifeature Fusion

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Received 13 July 2022; Revised 9 August 2022; Accepted 12 August 2022; Published 31 August 2022

Academic Editor: Santosh Tirunagari

The steady and healthy development of strategic emerging industries (SEI) can enable the Republic of China to smoothly transform its economic progression mode and realize the upgradation and optimization of its industrial organization. In this way, China can take the initiative in the process of globalization. The strategic emerging industry economy has long argued for the influence of resilient firm dynamic aptitudes on innovative product growth. This study takes strategic emerging industrial economies as an important part and establishes a comprehensive evaluation index system for economic efficiency of SEI in the Republic of China from the perception of interorganizational interactions and entrepreneurial coordination features. We use the Random Forest (RF) algorithm to perform multifeature fusion and establish an economic efficiency measurement algorithm for SET through survey data from several Chinese companies. We find, in addition, that entrepreneurial coordination affects the firms' inclination and aptitude to exploit relationship profits and by this means significantly strengthening the effects of vertical interactions however weakening the effects of horizontal interactions. When compared with the BP and MLP approaches, the suggested approach has achieved 86.98% accuracy, while the other has 86.02% and 85.75%, respectively.

1. Introduction

The 2016 Catalogue of SEI [1–3] is the clearest evidence yet of China's plan for technical growth and industrial upgrading [4–6] during the next five years. The industrial catalogue functions as a tool of policy transmission for the purpose of coordinating the evolution of the planned economy in my country [7–10]. The industrial catalogue, a tool of Soviet industrial planning, can be found in contemporary China's state-owned capital industrial sector. This can be said to be the case on an institutional level. They are command mechanisms that are hierarchical and work from the top down, and they are being copied ever more precisely at the lowermost stages of the administration in the bureaucratic structure of ministries.

A catalogue of SEI reveals that prevailing industrial clusters and industrial strategies are all parts of this initiative. The development of energy equipment and the technological updating of existing technologies have both come a long way in recent years. The satellite, aerospace, and other related skills will implement capacity cooperation policies to progress the China's global influence. These goals will be accomplished as a result of the civilian nuclear energy plan. Because the essential industrial complementarity cannot be coordinated, it is possible that other industrial advancements, such as robotics, innovative materials, and fresh forms of energy, will evidence to be desired. It is also possible that regional industrial clusters will be incapable to advancement into the Chinese version of the German Industry 4.0, phase out low-end industries, and encourage technological development and innovation in sophisticated manufacturing.

My nation's some structural problems have begun to appear in the development of the economy, such as excessive energy consumption, environmental degradation, widening income gaps, and insufficient innovation momentum. This is due to the fact that the economy has arrived the innovative normal. For that reason, the potential for economic evolution in our nation will be hampered as a result of these difficulties. The goal has been to increase economic efficiency and improve economic structure. This goal applies to both the supply-side structural reform that is centered on three eliminations, one reduction, and one supplement [11], and the institutional and mechanism innovations that clue the growth of the innovative normal. During the course of the past five years, the rate of economic development in my nation has shifted from focusing solely on increasing GDP without taking into account any other factors to reorganizing the economic and industrial organization in order to facilitate the development of the economy in a manner that is more symmetrical and consistent. This serves as the primary impetus for the expansion of my nation's economy, which has been proceeding in a measured and consistent fashion.

This system is constructed with the main contradictions of my country's economy and society in the new era as well as the five major development concepts as its starting points. We calculate a number of indices of my nation's economic development, including structural and efficiency metrics. The method of enhancing the effectiveness of economic development is evaluated based on the following five facets: the utilization of factor resources, the fundamental quality of the national economy, the momentum of expansion, the capacity to resolve conflicts, and the well-being of inhabitants. In every respect, an analysis is carried out to determine how effectively the process of economic development structure optimization is working. We will be able to increase the vitality of emerging economies if we focus on enhancing the quality and efficiency of economic development, advancing supply-side organizational developments, and accelerating the formation of institutional mechanisms and improvement methods that lead the way to the new normal of economic development.

When used as a measurement of economic efficiency, a single feature pair is frequently erroneous. On the other hand, the algorithm that is based on multifeature fusion [12–15] is able to successfully integrate a number of different aspects that have an effect and may therefore accomplish the measurement of economic efficiency. Also in terms of economic efficiency, strategic rising industries are very significant to the economy of the country, and economic efficiency is very crucial to those industries. Therefore, the measurement of the economic efficiency of strategic emerging sectors based on the RF algorithm that is established over the multifeature fusion has the potential to well serve the growth of a high-quality and healthy economy in my nation. The main contributions of our research are as follows: (1) this study takes strategic emerging industrial economies as an important part and establishes a comprehensive evaluation index system for economic efficiency of SEI in the Republic of China from the perception of interorganizational interactions and entrepreneurial coordination aspects. (2) We use the Random Forest (RF) algorithm to perform multifeature fusion and establish an economic efficiency measurement algorithm for SET through survey data from Chinese companies.

In Section 2, we discuss the economic viability of newly developing sectors and the importance of RF algorithms. In Section 3, we present a sketch of both our data and the suggested RF technique. In Section 4, we will discuss the outcomes of our experiments. In the final Section 5, we will discuss what we have learned and how this work can be enhanced further.

2. Research Status and Background

The degree to which emergent sectors are efficient economically is a primary determinant of their level of economic development. Research conducted in the field of economics places a significant emphasis on the connection among the economic efficiency and economic evolution. In addition, there is a large body of literature, both domestically and internationally, on the subject. In recent years, the research literature on economic efficiency produced by Chinese researchers has been quite rich, and there has been an endless stream of related research published.

Emerging economies like China are leading the pack when it comes to the level of technological sophistication they possess from both an economic and social development point of view. In the first stages, the primary method of their promotion consisted of the importation of technology from wealthy countries. However, the technologies used in industrialized countries almost always result in a reduction in the amount of labor and capital required. This divergence is not only attributable to elements that are inherent to the technology itself but also to shifts in the relative prices of production factors as a result of market forces. To encourage businesses to replace cheap elements, which leads, to some part, to the use of the phrase technical deviation, the goal of lowering production costs is intended to serve as the motivation for this endeavor. As a consequence, this factor has been present for a considerable amount of time due to the long-term technological backwardness of our country. People in our society have a variety of sources of income, which has resulted in significant changes in those income sources. This is an example of healthy economic development. This is a very different approach to economic growth than the model used by other developed countries. As a result, they are hesitant to use the primary economic growth model of developed countries for our country's economic development. This is because such a model was designed for developed countries. It is imperative that we investigate the path that will best serve our progress and the advancement of our economy [16–18]. Instead, the production function that is most appropriate for the circumstances of the national economy ought to be chosen.

At the same time, we take note of the fact that the revenue share method is typically used to determine the capital share when employing the function estimation approach. Emerging economies typically suffer from a lack of data as well as unreliable statistical indicators and formulas. The quality of the statistics also frequently places a cap on the amount of capital that may be estimated. In this regard, some academics propose estimated elasticity [19, 20]. They argue that grounded on the expectations of perfect market competition, continuous earnings to scale, and the growth of profits, the appraised elasticity of both the labor and the capital can be identical to the value of the share of labor and capital. This is a reasonable explanation. This viewpoint has received endorsement from a wide variety of empirical research institutions and academics. This method, on the other hand, eliminates the limitations of geometric statistics to some degree, but in fact it is primarily grounded on the consistent economic development of technologically advanced countries, and the projected output elasticity is primarily perpetual. Moreover, this should be noted that it is perceptibly consistent with the communal growth model, which is inconsistent with the unstable economic growth of emerging economies.

In light of the fact that China's economic enlargement has arrived to an innovative normal, and the economic progression degree has moved from high-speed progression to medium- to high-speed development, the traditional driving force of factor scale is gradually losing its strength, and economic growth relies more on the improvement in the quality of human capital and scientific as well as industrial evolution. At the moment, the sum total of China's economy has vaulted it to the position of second place in the globe. In spite of this, several sectors continue to struggle with issues like overcapacity and a dearth of self-sufficient innovation capabilities. Likewise, the difficulties associated with industrial upgrading and transformation require immediate resolution. There are gaps in development as well as structural flaws in my nation's capital market, which is lagging behind other countries. There is a mismatch between the industry characteristics and financial needs of SEI and the models of traditional financing used by most businesses today. This mismatch makes it difficult for some businesses operating in SEI to obtain adequate funding. As a consequence of this, the present-day financial industry continues to face various challenges and shortcomings in terms of its ability to support the growth of SEI, and the total capital allocation efficiency of SEI is not particularly high.

The Republic of China has so far issued a series of supportive policies and measures, which have played a certain part in encouraging the improvement of the SEI. However, financing constraints still restrict the development of SEI. Until now, the Republic of China has delivered a sequence of supportive policies and procedures. The influence that financing restrictions have on the investment efficiency of SEI is an unavoidable consequence of the situation. Therefore, does the limited availability of funding result in a loss of the investment efficiency of strategic new industries? If this is the case, how much of an impact does the lack of available finance have on the investment efficiency? Is this a typical occurrence, or is it something that just happens in specific fields? Corporations that are owned by the state exist any distinctions in comparison with businesses that are not owned by the state? Are there variations from one region to another? To answer these concerns, it is obvious that we need to quantitatively quantify and analyze the financing restrictions of important growing industries as well as the investment efficiency of such businesses [21–24]. According to the research that has already been done, scholars from both the United States and other countries rely primarily on descriptive study and case analysis. In fact, there is an absence of quantitative analysis regarding the impact of financing constraints and the investment efficiency of SEI. There is a lack of overall analysis of the development of SEI in an industry or province, and there is a lack of in-depth exploration of the factors that affect the investment efficiency of SEI due to financing constraints. Both of these issues are a result of a lack of overall data collection and analysis.

We use the RF algorithm of multifeature fusion to quantitatively analyze the investment efficiency of China's SEI based on micro-enterprise data, and we provide a basis for vigorously developing SEI. This is based on the fact that we use this information [25, 26].

The strategic emerging economy of our country is constantly being optimized and developed, and we need to look at its development from a long-term perspective if we want to ensure its success. To believe that the ongoing process of optimization and reform has had an effect on the growth of certain economies is an overly myopic viewpoint that should be avoided. We have researched the pertinent literature and have a comprehensive understanding of the multifeature fusion technology. This technology has been one of our primary areas of focus. The economic measurement algorithm of strategic emerging industries based on multifeatures is, as a result, an algorithm that is based on the fusion of multiple features. Because different angles are represented by a variety of features, we should be competent to accomplish a higher level of precision if we use this algorithm rather than an alternative feature algorithm [27]. As the angle grows, naturally, so do the benefits to which we can look forward. The suggested RF algorithm's structure is shown in Figure 1.

3. The Research Design

3.1. Introduction to the RF Algorithm. Breiman and Cutler made the initial suggestion for the RF algorithm in the Year 2001. The fundamental idea behind it is to combine a number of separate decision trees by making use of the concept of ensemble learning. It is an algorithm that may be used for classification as well as regression. During the process of building a RF, the bootstrap approach is utilized for resampling in order to randomly produce a variety of distinct training sets, and a decision tree is built based on each individual training set [28]. When separating internal nodes, the Gini value of each attribute is no longer taken into consideration. Instead, a number of attributes are chosen at random for evaluation. The RF has a great antinoise capacity and decreases the risk of overfitting as a result of the incorporation of two randomnesses in the process of generating the decision tree. Figure 1 illustrates the basic structure of the method for the RF.

3.1.1. The C4.5 Algorithm. The C4.5 method constructs a decision tree by recursively making judgments on a given dataset. These decisions are made in accordance with a feature selection criterion that employs the information gain rate. If the dataset D is provided, A is the decision feature, n is the number of attribute values of feature A, k is the number of sample categories, D is the subset of dataset D divided by feature A, and p is the probability value of each

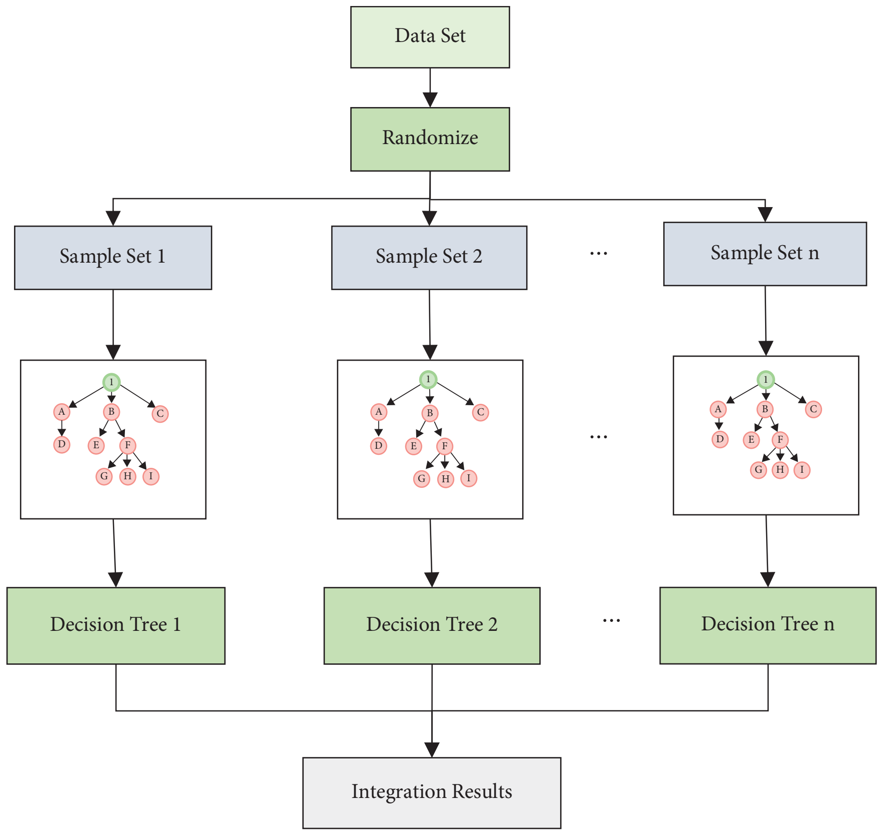

FIGURE 1: The RF algorithm structure.

category, then the following equation can be used to determine the $MS(D)$. The information $MS(D)$ pertaining to dataset D is as follows:

$$MS(D) = -\sum_{i=1}^{c} p_i \log_2 p_i. \quad (1)$$

The following (2) constitutes the empirical condition $H(D|A)$ of the feature A to the dataset D:

$$MS(D|A) = \sum_{i=1}^{n} \frac{|D|_i}{|D|} MS(D), \quad (2)$$

where $H(D|A)$ is the information descendent of a particular subdataset of D_i.

The following expression, as given in (3), represents the penalty coefficient for feature A in dataset D:

$$MS_A(D) = -\sum_{i=1}^{n} \frac{|D_i|}{|D|} \log_2 \frac{|D_i|}{|D|}. \quad (3)$$

The ratio of the amount of information gained by feature A to dataset D is illustrated mathematically using the following equation:

$$g_R(D,A) = \frac{g(D,A)}{MS_A(D)} = \frac{MS(D) - MS(D|A)}{MS_A(D)}. \quad (4)$$

3.1.2. The Basic Process of RF Algorithm Prediction. The following outlines the fundamental steps involved in the RF method.

(1) Using the bootstrap method for resampling, N training sets are generated at random, and the final training set has the same amount of samples as the initial training set P. This is because the final training set is equal to the original training set. Because of the replacement extraction, the newly created training set has a high possibility of including repeated data. This helps to ensure that the training sets are distinct from one another.

(2) construct the corresponding decision trees K_1, K_2, . . ., K_n by using the training set as the data source. Before each internal node chooses the splitting feature, you should first select $m\,(m \leq M)$ features at random from the M features in the training set to serve as the splitting feature set for the current internal node, and then choose the feature that has the smallest corresponding Gini value as the splitting feature. No pruning is done, so each tree reaches its full potential. The following mathematical expressions, given in (5) and (6), are the formulas that should be used to calculate the Gini value that corresponds to feature:

$$\text{Gini}\left(H^i\right) = 1 - \sum_{j=1}^{|y|} p_j^2, \tag{5}$$

$$\text{Gini\_index}(H, a) = \sum_{i=1}^{L} \frac{\left|H^i\right|}{|H|} \text{Gini}\left(H^i\right). \tag{6}$$

Here H denotes a particular data collection. The number of distinct permutations of feature a that are included in the dataset is denoted by the letter L.

(3) For the data in the test set X, each decision tree provides its own unique prediction results $K_1(X), K_2(X), \ldots, K_n(X)$. Another way to say this is that each tree votes for itself.

(4) After tallying the results of each decision tree's forecast, we select the prediction value that received the most votes and use that as the final prediction result.

The flowchart of the specific algorithm of RF used in this paper may be found in Figure 2.

The ensemble learning model based on the RF algorithm has as its objective function to achieve which is expressed in the following equation :

$$F_M(x) = \arg\max_i \frac{1}{M} \sum_j^m \theta_j l\left(f\left(x, L_j\right) = i\right). \tag{7}$$

This should be noted that the value of f is an important factor in determining the voting weight θ_j of the model (x, L_j).

3.2. Data Sources. Our data are a set of time series data that were collected on China's strategically important rising sectors over the course of the past ten years. First, we perform some preprocessing on the data. For example, we normalize the data using the following equation:

$$A = \frac{RA - \text{Min}RA}{\text{Max}RA - \text{Min}RA}. \tag{8}$$

Among these, set RA has the original data, while set A contains the data after it has been updated.

First, we compute the correlation coefficient between each of the processed datasets using the following mathematical expression as given in the following equation:

$$\rho = \frac{\text{Cov}(x, y)}{\sqrt{D(x)}\sqrt{D(y)}} = \frac{E[(x - Ex)(y - Ey)]}{\sqrt{D(x)}\sqrt{D(y)}}. \tag{9}$$

Here, x and y are the values of the data.

We chose the precision rate P and the recall rate R as our metrics for evaluation from the available options. The precision rate is expressed mathematically using the following equation:

$$P = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}. \tag{10}$$

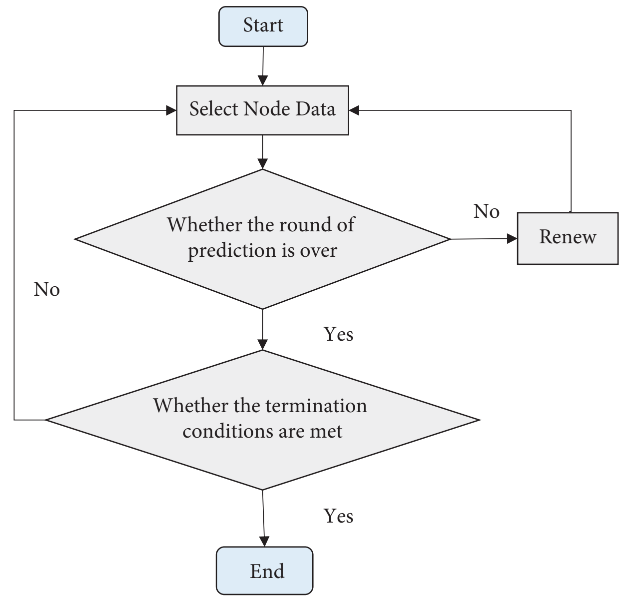

Figure 2: The algorithm flowchart.

In the above equation, TP and TN characterize true positive and true negative, respectively. Similarly, FP and FN denote the false positive and false negative, respectively. In fact, this metric is the percentage of total forecasts that turn out to be accurate in comparison with the total. Furthermore, the recall rate is expressed mathematically using the following equation:

$$R = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{11}$$

The actual right explanation takes into consideration all of the available positive proportions.

4. Results and Discussion

Within the framework of the RF algorithm, it is necessary for us to establish the optimum quantity of the decision trees to search for. This should be noted that the amount of decision trees is chosen to generate an improved RF in order to ensure high accuracy of diagnosis results, a low false negative rate, and a reduction in the complexity of the algorithm [29]. The performance evaluation of the accuracy of the improved RF algorithm with various numbers of decision trees is shown in Figure 3.

From the comparison shown in Figure 3, it is clear that there is room for improvement in both the diagnostic accuracy and the false negative rate when the quantity of the decision trees is less than 500. On the other hand, when the total amount of decision trees is equal to or greater than 500, both diagnostic accuracy and false negative rate are within the optimal range [30]. Due to the possibility of overfitting, the accuracy may somewhat drop, in particular, when the amount of decision trees touches roughly 800. Hence, the optimum number of decision trees is 500.

The RF algorithm is referred to by us as the OUR algorithm, and we contrast it with the multilayer perceptron

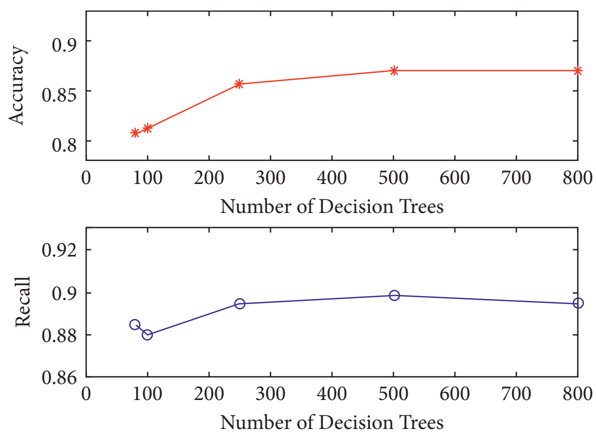

Figure 3: The accuracy and recall rates with different amounts of decision trees.

(MLP) algorithm and the BP neural network algorithm (BP). In fact, this can be understood from Table 1 that the RF algorithm suggested in this work has a higher accuracy and recall rate than the other two algorithms. Additionally, the running time of the OUR algorithm is lower than that of the MLP algorithm and the BP algorithm, which effectively reduces the running time.

As can be realized from the outcomes shown in Figure 4, the correctness of the OUR algorithm steadily improves as the sample size of the test set is larger. This is evidenced by the fact that the accuracy of the algorithm increases over time. The BP algorithm is also gradually improving in terms of its level of accuracy. The same MLP algorithm's level of accuracy is likewise gradually improving as time goes on. However, given the same number of test set samples, the accuracy of the MLP method and the BP algorithm are both lower than that of the OUR algorithm. The OUR algorithm has a better accuracy. In this manner, the horizontal and vertical comparisons can demonstrate that the OUR algorithm is the most effective of the three algorithms in terms of performance [30]. This substantiates the claim that the OUR algorithm has greater performance when it comes to generalization.

As can be comprehended from Figure 5, the recall rate of the OUR algorithm improves along with the expansion of the size of the test set data. This is something that can be observed in terms of the recall rate. The percentage of data that can be retrieved with the BP method is likewise gradually improving. When the test set sample data size hits 5000, the MLP algorithm's recall rate increases at a pace that is slower than the rate at which it increases overall. Under the same conditions, the recall rate of the MLP procedure is sophisticated than that of the BP algorithm, while the recall rate of the BP approach is greater than that of the suggested OUR algorithm when using the same amount of data from the test set.

We found that the suggested OUR algorithm has a sophisticated correctness and precision rate and a well-enhanced recall rate than the BP algorithm and the MLP algorithm by comparing the three approaches. This effectively demonstrates that our model is very useful for economic measurement of SEI in the case of integrating

Table 1: Comparison of various algorithms.

Algorithms	Accuracy (%)	Recall (%)	Operation hours (s)
MLP	85.72	88.53	13.85
BP	86.02	86.87	20.49
OUR	86.98	89.85	13.28

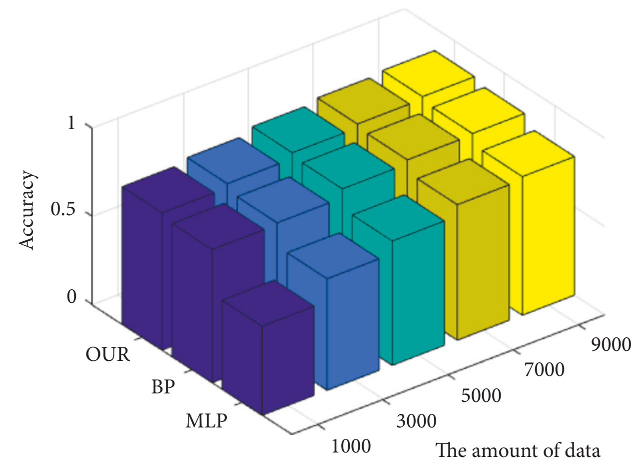

Figure 4: Assessment of the correctness attained through different algorithms.

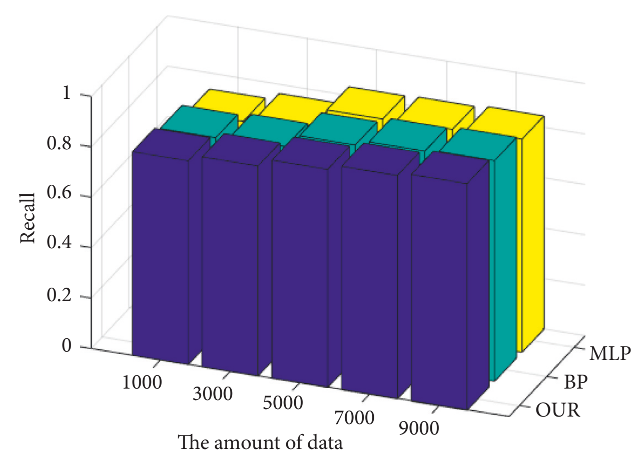

Figure 5: Comparison of the recall of different algorithms.

multiple features. It is possible to produce an accurate prognosis regarding the growth of the economy of the new industry. In fact, we make a contribution to the realignment of the industrial organization and the continued growth of the economy in the Republic of China.

5. Conclusions and Future Work

The measurement of the efficiency of capital allocation reveals that there is inefficient capital allocation in my country. It is possible for my country's economic growth rate to be increased, total factor productivity to be improved, and high-quality economic development to be accomplished through the realization of the flow of factors through market allocation. Changing the economic structure of each factor, adjusting the track of ideal allocation, increasing the entire factor throughput over ideal allocation, and promoting ecological economic growth can all be accomplished through appropriate capital factor allocation. The economic measurement model of multifeature fusion delivers an innovative approach for China and other developing economies to quantity the effectiveness with which capital is allocated. This model also measures the effectiveness of resources and reflects the structural changes that have taken place in developing countries. It is possible that utilizing a multifeature fusion economic measurement model to guess the capital allocation efficiency is an enhanced approach. The accuracy of measurement results can be improved to some extent by using this method, which can more accurately reflect changes in capital allocation efficiency in emerging economies.

Our multifeature fusion model of developing economic measurements is able to provide some ideas for how national resources should be distributed. At the same time, we discovered that the only way for our developing economy to continue growing, for our government to continue advancing reforms, and for our nation's industrial structure to be optimized was to continue developing. The economies of our burgeoning industries will be able to continue expanding and maturing thanks to this strategy. This study investigates a multifeature fusion model as a means of gauging strategic developing economies due to the fact that the expansion of my nation's economy is followed by technical biases and shifts in the communal organization. Moreover, the efficiency of factor allocation in comparison with other developing economies is not measured in this article. In the future, studies might combine data from multiple emerging economies in order to evaluate the effectiveness of resource allocation in multiple emerging economies. In addition, it is necessary to conduct additional research on the multifeature fusion model of the strategic emerging economy measure and extend it to the micro level. This will allow for the examination of the resource allocation behavior of businesses, the study of the impact mechanism, and influence of the enhancement of capital allocation competence on total factor productivity, as well as the application of the improved method. The subsequent research ought to include estimations as well as comparative analyses of the efficiency with which capital is allocated in other developing economies. The focus of the following reform should be on advancing market-based changes to labor variables and enhancing labor allocation effectiveness. These should be the primary goals of the reforms that we plan to consider in the future research. Furthermore, we will develop new models to further improve the rate of the precision. An important aspect is to reduce the duration, which is needed to train the learning models. We believe emergent techniques within in the range of edge and cloud computing will help to address these issues.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest.

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