**Research Article**

**The Theme Evolution and Strategic Decision-Making of the Public’s Attention to the Theme of Aging in China Based on Big Data Analysis**

Ning Lu

School of Humanities and Law, Henan University of Animal Husbandry and Economy, Zhengzhou 450044, China

Correspondence should be addressed to Ning Lu; 81756@hnuahe.edu.cn

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Actively responding to population aging has become the new national condition of China’s aging society in the new era. To do a good job of actively coping with aging in the new era, it is necessary to take multiple measures and work together on the basis of clarifying the major realities and problems faced by China’s aging society. From the perspective of big data technology, this paper systematically studies the concerns of China’s aging through the method of artificial intelligence. In addition, with two typical aging indicators, three coupled intelligent algorithms are introduced in this paper. The prediction results show that the multi-dimensional support vector machine optimized by the immune algorithm shows good advantages compared with the other two algorithms. The multi-dimensional support vector machine optimized by the immune algorithm, one of the big data, has a good prediction effect on the performance indicators of China’s aging, which indirectly illustrates the applicability of big data analysis to the concerns of China’s aging.

1. **Introduction**

Population aging refers to an overall monotonic increase in the proportion of the elderly population in the total population over time. In addition, the overall sociodemographic structure is showing a state of gradual aging [1, 2]. The phenomenon of population aging runs throughout the world, and most developed countries, even some emerging countries, are already facing the arrival of population aging. This trend is difficult to contain and is getting stronger. At present, China has also reached a period of rapid development of population aging [3, 4]. The 14th Five-Year Plan period is a critical period for China to deal with the strategic and tactical reserves of aging. The Fifth Plenary Session of the 19th CPC Central Committee proposed to implement a national strategy to actively cope with population aging.

Since the beginning of the twentieth century, the demographic structure of industrialized countries began to break the stability that had been maintained for many years [5, 6]. A similar change in the demographic structure of developing countries followed. The phenomenon of population aging, caused by declining population growth rates and increasing per capita life expectancy, became a common phenomenon worldwide. In the 40 years since the reform and opening up, China has achieved a transition in the type of population reproduction that took developed countries a century or more to complete, completing the demographic transition and moving into the ranks of countries with low fertility levels [7, 8].

Since the reform and opening up, China’s economic development has made great achievements; the economic growth rate and total economic volume have created a miracle in the history of world development; and the demographic and socioeconomic structures have also undergone fundamental changes [9, 10]. Today, my country is at a critical juncture in the transformation of the social demographic structure from a society of pure labor to a society of skilled talents. The impact of population aging on the economy and society will be comprehensive and deep-seated. It includes the challenges of population aging on...
economic growth, labor supply, social medical security system, and intergenerational relations. In addition, it also provides opportunities to carry out reforms to the social medical security system, develop the aging industry, and change the domestic consumption structure [11, 12].

The situation of population aging in China is very serious, and the problem of an aging is very prominent [13, 14]. For a long time, there have been numerous studies based on the prediction of the development trend and analysis of the characteristics of aging, and there have been numerous policy proposals to deal with aging. A popular view is that as long as a comprehensive two-child policy is implemented or even further abolished, the aging situation will be effectively reversed and the aging problem will be solved.

Based on the above elaboration, in the new era, facing the new national situation of aging society, a combination of multi-dimensional design and multi-dimensional application is needed to cope with this prominent problem. With the continuous progress of technology, artificial intelligence methods with big data technology as the core have been applied to various fields and have demonstrated strong applicability and feasibility. Therefore, in response to the problem of aging in China, this paper intends to assess the quantitative indicators of several methods of aging in China through big data technology [15–17] based on intelligent algorithms, with a view to providing suggestions and reflections on the topics of concern and coping strategies for aging in China.

2. The Current Situation of Aging in China

As can be seen in Figure 1, China has experienced a dramatic shift in the birth rate after the reform and opening up. Due to demographic inertia, after experiencing two population birth peaks in the 1980s, China’s birth rate and natural growth rate continued to decline; the population mortality rate remained at a low level; and the demographic structure underwent a fundamental shift.

However, as can be seen in Figure 2, since the 1990s, the number of elderly people over 65 years of age has been increasing the dependency ratio of the elderly population, while the dependency ratio of the juvenile population has been decreasing. This phenomenon shows that in view of China’s national demographic conditions, the growth rate of the new population is smaller than that of the elderly population.

From 2000 to 2017, China’s elderly population aged over 65 years old increased from 88.11 million to 158 million, and the proportion of the total population increased from 6.96% to 11.4%, and the aging of China’s population showed the characteristics of a large scale and rapid speed. According to the statistics, China’s population aging is much faster than that of Europe and the United States; the proportion of China’s elderly population (65 years old or above) rose from 4.91% to 7.0% in just 18 years, while the proportion of Sweden’s elderly population rose from 5.2% to 8.4% in 340 years, France’s elderly population rose from 7% to 14% in 115 years, and the United States took 66 years. This shows that China’s population is aging at an unprecedented rate. Compared with other countries, China has a huge population; the situation of old age is serious; and the problems it faces are more complicated.

Based on the above data analysis [18, 19], the trend of population aging is not likely to be reversed. As the aging of the population continues to be a significant issue, it is bound to bring a series of further effects that will permeate different
areas of life. Based on the economic perspective, the aging population is bound to curb economic development and affect the direction of savings, investment, and taxation. Based on the social perspective, population aging involves healthcare, housing, family, and so on. To effectively deal with the aging population, the government has introduced several policies and measures. For this reason, our government has introduced several policies and measures. For example, governments at all levels are further enacting complementary measures such as delaying retirement and strengthening pension security to actively address the challenges posed by an aging society in all aspects.

With the arrival of “big data” and the concept of a “smart city,” “smart aging” [20, 21] also came into being. This model of senior care based on big data technology can ensure that the health and senior care services are more “intelligent” and achieve an all-around upgrade of efficiency and reliability. At present, China has set up a diversified elderly care system with home care as the main form, supplemented by community and institutions. The development of the “smart senior care” mode can help remote monitoring, real-time positioning, and unified platform information interaction to meet the modern, scientific, and humanized needs of modern family senior care, which is also an important aspect of smart city development. In addition, the application of emerging technologies can also facilitate the research process on aging in China. The specific technical route is shown in Figure 3. As shown in Figure 3, during the research process, firstly, the retrieval, collection, and cleaning of data related to aging in China are completed. Secondly, text mining and spatial vector modeling are used to deepen the performance related to aging in China. Again, the data reduction method and visualization analysis are used to identify technology vacancies and complete the initial prediction of emerging technologies. Finally, the social perception analysis is used to extract the views of domain experts, evaluate and supplement the predicted emerging technology areas, and provide prediction services for the data of aging in China.

For example, some scholars [22, 23] believe that artificial intelligence is a science that allows machines to do things that would otherwise require human intelligence. Other researchers [24, 25] believe that artificial intelligence technology refers to the development and creation of advanced machine programs that can replace human intelligent thinking. With the development of artificial intelligence and the arrival of the era of big data, coupled with the powerful information processing ability and absolute rationality of computers can break through the defects of limited rationality and information asymmetry. This can provide a series of solutions for China’s aging response program. In summary, the accuracy of using various performance indicators of aging in China, combined with the algorithm of artificial intelligence, to empirically study the influence law of big data analysis on the topic of aging concerns in China. As a comparison, the article also introduces the intelligent algorithms of pure support vector machine and particle swarm optimization support vector machine in subsequent chapters. At the same time, three intelligent algorithms based on the support vector machine are applied to the analysis and prediction of China’s aging status, in order to compare the similarities and differences in the prediction effects of the three methods.

The overall structure of the article can be expressed as follows. Firstly, based on the concept of a support vector machine, the paper introduces the realization process of a multi-dimensional support vector machine based on an immune algorithm and particle swarm optimization algorithm. Secondly, based on the specific problems of China’s aging, it is analyzed through the introduction of intelligent algorithms. Finally, based on the analysis results, a new strategy to solve the problem of aging in China is optimized.

3. Big Data Technology Based on Coupled Intelligent Algorithm

With the rapid development of scientific innovation, big data technology can be seen everywhere in different fields around the world. For example, the aerospace field often uses big data methods to detect tiny damages to equipment. For some nonlinear phenomena or some seemingly irregular situations, the use of big data analysis can often summarize the development trend of such problems, which can play a better guiding role in future planning and development. This approach is not only used in science and engineering but is also favored by researchers in the social science research process. Taking the topic of aging in China covered in this article as an example, the introduction of big data technology can liberate the workload of manual calculation and statistics to a certain extent. This method starts from the importance of each student, reasonably analyzes and predicts the trend of each variable, and formulates corresponding solutions according to the degree of aging in different regions.

Fortunately, with the emergence of artificial intelligence technology, more intelligent algorithms are applied to various fields. Compared with earlier studies, there is only one prediction system, BP neural network, and various optimization algorithms are introduced. A genetic algorithm is considered to be an effective method to find the optimal solution. The neural network optimized by the genetic algorithm improves the solution method of weight and threshold in the original algorithm, making the whole calculation process more reasonable.

In the process of finding the optimal solution, particle swarm optimization is also applied. Compared with the genetic algorithm, the particle swarm optimization process does not need to set too many parameters in advance. It simulates the natural process of bird predation in nature. Before calculating the algorithm, researchers need to determine the fitness function first, which requires researchers to have certain prior knowledge.

In deep learning, support vector machines are supervised learning models associated with related learning algorithms.
This computational model can be used to analyze data and identify patterns. Also, it can be used for classification and regression analysis.

As an upgraded version of the genetic algorithm, the immune algorithm can make up for the deficiency of the inherent calculation principle of the genetic algorithm. The intelligent algorithm tries to selectively and purposefully use some characteristic information or knowledge in the problem to be solved to suppress the degradation phenomenon in the optimization process under the premise of retaining the excellent characteristics of the genetic algorithm.

The immune algorithm simulates the immune process of the human body against external antigens through antibodies. It is a swarm intelligent search algorithm with an iterative process of generation and testing. In the complex trial calculation process, the algorithm can maintain global convergence on the premise of retaining the best individuals of the previous generation. Therefore, this artificial intelligence algorithm has strong adaptability. Based on the above analysis, this paper optimizes the support vector machine through particle swarm algorithm and immune algorithm and compares it with the simple support vector machine, in order to provide some reference ideas for solving the problems of aging in China.

3.1. Multi-Dimensional Output Support Vector Regression.

The support vector machine learning method was proposed by Vapnik based on the theory of statistical learning. For the regression problem, it can be expressed as establishing a functional mapping relationship between the input and output quantities, with the function $y(x) = \omega \cdot (x + b)$, $\{x_i, y_i\} (i = 1, 2, \cdots, k), \{x_i, y_i\} \in R^d \times R^1$; according to the structural risk minimization principle of statistical learning, a certain fitting error is allowed to exist; a relaxation factor $\xi_i, \xi_i^* \geq 0$ is introduced; the optimization problem is minimized; and the optimization objective is established with the following expression:

$$R(\omega, \xi_i, \xi_i^*) = \frac{1}{2}\|\omega\|^2 + C \sum_{i=1}^{k} (\xi_i + \xi_i^*),$$ (1)

where $\omega$ is the fit coefficient; $\xi_i, \xi_i^*$ is the relaxation factor, $C$ is the penalty factor, and $k$ is the number of samples.

According to the KKT condition, the expression of its pairwise form maximization function is

$$W(\alpha_i, \alpha_i^*) = - \frac{1}{2} \sum_{i,j=1}^{k} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(x_i \cdot x_j)$$

$$+ \sum_{i=1}^{k} (\alpha_i - \alpha_i^*)y_i - \sum_{i=1}^{k} (\alpha_i + \alpha_i^*)\epsilon,$$ (2)

where $x_i$ is the $i$ sample input value and $x_j$ is the $j$ sample input value.

Solving the optimization problem yields the support vector regression model with the following expression:

$$f(x) = \sum_{i=1}^{k} (\alpha_i - \alpha_i^*) (x, x_i) + b,$$ (3)

where $x$ is the input value of the sample to be predicted.

After the same derivation as for linear regression, the final support vector model fitting function is obtained as follows:

$$f(x) = \sum_{i=1}^{k} (\alpha_i - \alpha_i^*) K(x, x_i) + b.$$ (4)

The output variables of traditional support vector regression are one-dimensional variables (SVR), and this feature restricts its application scenarios. In some complex systems, a multi-input-multi-output mapping system is needed, and a one-dimensional SVR is not able to accomplish such tasks; therefore, this paper extends based on one-dimensional support vector machines to make them applicable to multi-dimensional output systems.
forming a multi-dimensional output vector machine to solve more complex problems in practical engineering.

Extending the one-dimensional insensitive loss function to multiple dimensions, the loss function is defined with the following expression:

\[ L(u_i) = \begin{cases} 0, & u_i \leq \epsilon, \\ (u_i - \epsilon)^2, & u_i > \epsilon, \end{cases} \]  

where \( u_i = \| e_i \| = \sqrt{\sum_i e_i^2}; e_i^T = (y_i^T - \varphi(T)) (x_i) (W - b^T); \)  
\( W = [w^1, \ldots, w^Q]; b = [b^1, \ldots, b^Q]^T \) is the nonlinear mapping kernel function; \( x_i \) is the sample input row vector; \( y_i \) is the sample output row vector; \( i = 1, \ldots, n \); \( n \) is the number of samples; and \( Q \) is the dimensionality of the output variable.

Based on the loss function shown in the above equation, construct the optimization objective function with the following expression:

\[ L_p(W, b) = \frac{1}{2} \sum_{j=1}^{Q} \| \omega^j \|^2 + C \sum_{i=1}^{n} L(u_i). \]  

To solve the mathematical optimization problem of the multi-dimensional output support vector regression model, this paper introduces the use of iterative reweighted least squares to solve the problem.

In the optimization objective function of (6), the loss function is approximated by replacing it with a first-order Taylor expansion, that is

\[ L_p(W, b) = \frac{1}{2} \sum_{j=1}^{Q} \| \omega^j \|^2 + C \left( \sum_{i=1}^{n} L(u_i) + \frac{dL(u_i)}{du_i} |_{u_i} (e_i^k)^T u_i^k [e_i - e_i] \right). \]  

(7)

Constructing a quadratic approximation of (7) instead, the approximation formula used in the literature is

\[ L_p(W, b) = \frac{1}{2} \sum_{j=1}^{Q} \| \omega^j \|^2 + C \left( \sum_{i=1}^{n} L(u_i) + \frac{dL(u_i)}{du_i} |_{u_i} (u_i^k)^2 - (u_i^k)^2 \right) \]  

\[ = \frac{1}{2} \sum_{j=1}^{Q} \| \omega^j \|^2 + \frac{1}{2} \sum_{i=1}^{n} a_i u_i^2 + CT. \]  

The reason for using this approximation formula is that \( W \) and \( b \) are decoupled in this formula, the optimization solution does not need to be iterated, and the approximate solutions of \( W \) and \( b \) can be calculated by taking the partial derivatives of \( W \) and \( b \) equal to 0 directly. The optimization objective is solved to obtain \( W \) and \( b \) that minimize the overall loss of the sample set, and the multi-output support vector regression model is established.

3.2. Immune Selection Optimization Algorithm. The biological immune system is a complex adaptive system. The human immune system is capable of recognizing pathogens and responding to them, thus having some capacity for learning, memory, and pattern recognition. This approach is analogous to an external stimulating antigen stimulating the body’s immune system to produce antibodies in response to it. That is, one input variable corresponds to a unique output function, and this approach allows the principles and mechanisms of its information processing to be described using computer algorithms to solve scientific and engineering problems. Castro was the first to propose the clonal selection algorithm (ICSA), an intelligent method for solving complex problems inspired by the human immune system, simulating the functions and mechanisms of action of the biological immune system, which preserves several characteristics of the biological immune system and introduces them to the solution of optimization problems.

A population suppression process is added to the immune algorithm to control the average concentration of the population and avoid premature convergence of the algorithm to a local optimum solution. This increases the global optimization capability. The detailed procedure of the immune algorithm is shown in Figure 4.

The typical multi-peaked function is used to enhance the application of the immune algorithm. The function can be expressed as follows:

\[ f(X) = \sum_{i=1}^{n} \left( 100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2 \right), \]  

(9)

where \( X = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^n \). Through the above formula, we can clearly and conveniently obtain an effective way to solve the actual mathematical problem. Specifically, we can quickly and accurately obtain the calculation steps and calculation time of a function to obtain the optimal value through this banana function.

The global minimum point of the function is obtained when all independent variables take the value of 1. The minimum value of the function is 0. A 10-element function is used to test the optimization of the immune algorithm for multi-variates functions. The search interval of the independent variable is \((-10, 10)\), and the specific parameters of the algorithm are set in Figure 5. As shown in the figure, NP denotes the number of antibody population sizes, \( G \) denotes the maximum number of cycles, and \( NC \) represents the number of clones.

The optimization algorithm is run 10 times, and the minimum point of the function is found about 4 times, and the results of these 10 optimizations are shown in Figure 6. As shown in Figure 6, the immune algorithm has good multi-dimensional multi-peak function seeking capability and can be applied to solve optimization problems of multi-dimensional support vector machine models.

3.3. Particle Swarm Optimization Algorithm. Particle swarm optimization algorithm is used to simulate various biological social behaviors such as biological reproduction and
Each antibody clones $V_i$ to generate temporary population $C$. The first antibody in $C$ is retained and does not mutate, and the remaining antibodies are mutated. The $C$ population calculates the affinity and returns the mature antibody.

**Begin**

Antigen recognition

Generates a random initial population of Abs

Stop algebra is reached

Yes

Outputs optimization results

No

Calculate individual affinity in the population and sort

Count the number of clones per antibody, denoted $V_i$

The maturation process is performed on antibodies that meet affinity requirements

Remember the mature antibody population as $AB^*$

Generates a random population $Ab_{new}$, which is merged with $Ab^*$ to count as $Ab$

Calculate the concentration of $Ab$, the composition of the population with a concentration greater than the threshold $Ab_w$, the remaining antibodies constitute the $Ab_t$ of the population

Combine $Ab_t$ and $Ab_{wf}$ to form the overall population for the next iteration and proceed to the next cycle

Yes

Individual maturation process

No

Each antibody clones $V_i$ to generate temporary population $C$

The first antibody in $C$ is retained and does not mutate, and the remaining antibodies are mutated

The $C$ population calculates the affinity and returns the mature antibody

The individuals with the highest affinity in the retention $Ab_w$, the remaining individuals are replaced by random antibodies, and the population counted as $Ab_{wf}$

**Figure 4:** Flowchart of the immune algorithm.
upgrading and can be used to find the optimal solution to the problem. This artificial intelligence algorithm consists of a finite number of particles that are unrelated to each other. These particles automatically search for a single best position \((p_{\text{best}})\) and a global best position \((g_{\text{best}})\) according to the optimal problem solution, according to the optimization criteria found in nature. Each iteration the researchers got during the computation was reupdated based on the particle’s position and velocity. The calculation steps for updating the relative motion trajectory of each particle can be expressed as follows:

\[
\begin{align*}
\mathbf{v}_i &= \omega \times \mathbf{v}_i + c_1 r_1 (p_{\text{best}} - x_i) + c_2 r_2 (g_{\text{best}} - x_i), \\
x_i &= (x_i + \mathbf{v}_i),
\end{align*}
\]

where \(\mathbf{v}_i\) and \(x_i\) denote the velocity and position of the \(i\)-th particle, respectively; \(\omega\) is the inertia weight to reflect the real-time effect of the previous example velocity on the current particle velocity; \(c_1\) and \(c_2\) are the learning factors; and \(r_1\) and \(r_2\) are uniform random numbers between \([0, 1]\).

Equation (10) is the expression form of the standard swarm algorithm.

When solving practical mathematical problems or social problems, we can abstract the specific problem as a way to find the best fitness function. That is, each mathematical problem can be reduced to the problem of finding the minimum value of the fitness function.

### 3.4. Coupling Algorithm Based on an Immune Algorithm or Particle Swarm Algorithm-Multi-Dimensional Support Vector Machine

The values of the control parameters (penalty coefficient \(C\), sensitivity coefficient \(\varepsilon\), and kernel function parameter \(\sigma\)) need to be specified artificially in the process of building a multi-dimensional support vector machine prediction model. To control the parameter values to achieve the minimum sample training error and the best multi-dimensional support vector machine model generalization accuracy, the immune algorithm or particle swarm optimization is used to optimize the solution of the control parameters. In the model training phase, the overall error function of the set of training samples is defined as the optimization objective, and the same insensitive loss function is used for the errors of individual samples. The training samples are divided into learning samples and testing samples, and the \(K\)-fold cross-validation method is used to calculate the overall error of the samples, and the optimization objective function expression is

\[
(C^*, \varepsilon^*, \sigma^*) = \arg\min_{C, \varepsilon, \sigma} L_{\text{all}}(C, \varepsilon, \sigma),
\]

\[
L_{\text{all}}(C, \varepsilon, \sigma) = \sum_{m=1}^{k} \frac{1}{k_m} \sum_{i=1}^{k_m} L(u_i),
\]

where \(L_{\text{all}}(C, \varepsilon, \sigma)\) denotes the overall training loss function, \(k\) denotes the number of sample aliquots, \(k_m\) denotes the number of training samples per aliquot, and the superscript asterisk denotes the optimal parameter.

After the multi-dimensional support vector machine model is trained, that is, the optimal multi-dimensional support vector machine model parameters are optimized by the immune algorithm or particle swarm algorithm, the whole computational process of the coupling algorithm is completed. Given the range of values of the parameters to be inverted, several Chinese aging prediction performance index parameters are selected. The optimization objective function is the error function between the predicted and actual values of Chinese aging. Its expression can be expressed as follows:

\[
x^* = \arg\min_{x} \text{aff}(x),
\]

\[
\text{aff}(x) = [f_u(x) - u]^2 + [f_s(x) - v]^2,
\]

where \(x\) is the parameter vector to be inverted; \(f_u(x)\) is the value of the multi-dimensional output vector machine model prediction performance \#1; \(f_s(x)\) is the value of the
multi-dimensional output vector machine model prediction function; \( u \) is the value of the experimental test #1; \( v \) is the value of the experimental test #2; and \( \text{aff} \) is the affinity function, that is, the minimum value of the prediction error value.

In the optimization process of the immune algorithm, the parameters to be optimized are mapped exponentially to expand the search range and search efficiency of the parameters. That is, the range of values of the parameters in the population is the natural logarithm of the actual range of values, and in the actual affinity calculation, the antibody individuals are mapped exponentially, and the calculation formula is

\[
P' = \exp(P). \tag{13}
\]

However, it is worth noting that the model training process and the parameter identification process in the definition of the error function and the resultant output part will be different from traditional prediction models. The coupling algorithm implementation process for optimizing multi-dimensional output vector machines by particle swarm algorithm is similar to the immunization algorithm, except that the particle swarm algorithm needs to set a suitable fitness function in advance, and often we set the fitness function to be the square of the absolute value of the error function.

4. Example Verification and Analysis

In order to carry out further research work, we use panel data for 31 provinces in mainland China from 2010 to 2016 to study the impact of aging and AI on labor costs. We select two of the representative variables for the study. These two variables are the aging indicator (ODR) and birth rate (BR). Referring to existing empirical studies for quantitative indicators of population aging, the aging indicator (ODR) is the ratio of the older portion of the nonworking-age population to the working-age population and is used to indicate how many older people are burdened for every 100 working-age people.

The birth rate reflects the changing trends in the country’s demographic structure.

Before the calculation starts, the convergence of the two coupling algorithms is first verified by trial calculations. At the scheduling scale of 200 cloud tasks and 10 virtual machines, the convergence speed of two coupled intelligent algorithms, particle swarm optimized multi-dimensional support vector machine and immune algorithm optimized support vector machine, is compared and analyzed by the relationship between the number of algorithms iterations and task completion time. The specific analysis results are shown in Figure 7.

It can be seen from Figure 7 that the convergence effect of the immune algorithm optimization is better than that of the particle swarm optimization, and both converge quickly in the first 100 iterations. But the immune algorithm optimized multi-dimensional support vector machine converges faster. The support vector machine optimized by the immune algorithm gradually smoothed out after 250 iterations. In addition, the immune algorithm optimization takes less time to complete the convergence task compared to the particle swarm algorithm. We compare the computation completion time of three algorithms, namely, immune algorithm optimized multi-dimensional support vector machine, particle swarm optimized multi-dimensional support vector machine, and multi-dimensional support vector machine, in the practice of big data technology application when the number of cloud tasks is 40, 80, 120, 160, and 200. The specific test results are shown in Figure 8.

As can be seen in Figure 8, the support vector machine optimized by the immune algorithm requires less computation time and better optimization results compared to the support vector machine optimized by the particle swarm and the pure support vector machine. When the number of tasks is 40, the task completion time of ICSA-MSVR is the 80s and 200 s less than that of ICSA and MSVR, respectively, and the number of tasks gradually increases; the task completion time difference of each algorithm increases; and when the number of tasks reaches 200, the task completion time of ICSA-MSVR is 240 s and 350 s less than that of ICSA and MSVR, respectively, which decreases by 3.7% and 5.3%.

The experimental values of the two Chinese aging performance indicators (ODR and BR) involved in this case are shown in Figure 9.

We can calculate the monitoring values by using the MATLAB calculation platform. It is well known that the coefficient of determination \( \left( R^2 \right) \) and the root mean square error (RMSE) are two prediction studies of the measured data in Figure 9 through the three intelligent algorithms mentioned above: the support vector machine optimized by the immune algorithm, the support vector machine optimized by the particle swarm, and the simple support vector machine. A typical forecast indicator was built. The next step
is proposed by comparing the $R^2$ and RMSE of the three algorithms. $R^2$ and RMSE can be calculated by the following equation:

$$
R^2 = \frac{\sum_{i=1}^{n} (x_i - x_{\text{mean}})^2 - \sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (x_i - x_{\text{mean}})^2},
$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2}.
$$

As we all know, the larger the value of $R^2$, the closer to 1, the better the prediction effect. At the same time, we are all familiar that the smaller the RMSE, the better the prediction. The predictive metrics obtained by the three coupled algorithms are plotted in Figure 10.

As shown in Figure 10, I represent the support vector machine for particle swarm optimization, II represents the support vector machine for immune algorithm optimization, and III represents the simple support vector machine. As can be seen from Figure 10, the support vector machine optimized by the immune algorithm obtained the largest coefficient of determination and the smallest root mean square difference compared to the three algorithms. This indicates that the immune algorithm optimized support vector machine has the best computational results and can be applied as a big data technique for the study of aging topics in China. At the same time, this algorithm also provides some lessons for the development of aging coping strategies.

In addition, we used a linear interpolation method to interpolate the predictive performance parameters (ODR) of the support vector machine optimized by the immune algorithm for this case, and the processing results are shown in Figure 11. As shown in Figure 11, the predictive performance metrics obtained from the support vector machine
interpolation optimized by the immune algorithm have good continuity.

Based on the above results, it can be seen that the representative method of big data technology introduced in this paper has a good prediction effect on various performance indicators of China’s aging. This prediction also indirectly illustrates the applicability of big data analysis to China’s aging concerns.

5. Conclusion

(1) China’s new era faces the new national conditions of an aging society. In response to the theme of China’s aging, we need to design relevant policies and regulations from multiple dimensions, jointly promoting and comprehensively responding. Big data technology came into being. The smart old-age care model based on big data technology will become a solution to the strategic decision-making of China’s aging problem in the future.

(2) Taking two specific indicators of China’s aging as an example, the prediction performance of three coupled intelligent algorithms is compared. The prediction results show that the multi-dimensional support vector machine optimized based on the immune algorithm shows stronger adaptability than the other two algorithms. This result demonstrates the applicability of big data analysis techniques to the concerns of China’s aging population. This approach can also provide a solution for future strategic decisions to address aging issues.

(3) This paper systematically analyzes and studies China’s aging problem by means of theoretical inversion, model experiment, and intelligent computing. The results show that the prediction method based on big data technology has strong guiding significance for the follow-up solution to China’s aging.

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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