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Research Article

Macroeconomic Early Warning Method Based on Support Vector Machine under Multi-Sensor Data Fusion Technology

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This article focuses on the macroeconomic early warning based on support vector machines under multi-sensor data fusion technology. The economic crisis has always been a topic of great concern to the entire world, and there has never been a lack of research and prevention of it in the development process. At present, the economic early warning system that is frequently mentioned includes statistical models and artificial intelligence models. Economic early warning is not just a topic for discussion on a national basis. In the personal field, a thorough enough understanding of economic early warning can also better control investment incomes such as stocks. Analyzing the direction of macroeconomic policies has also become an indispensable ability for investors. In order not to be affected by the economic crisis, early warning is a crucial link. Therefore, in this article, a multi-sensor data fusion macroeconomic early warning model based on support vectors is proposed. In addition, this article also discusses each subpart separately. First, this article mentions the multi-sensor data fusion model. It conducts reasonable collection and control of data information in multiple sensors and uses computers and smart devices to improve system performance and make data clearer. At the same time, this article shows the JDL model of data fusion. It can optimize signals and processes and targets and conduct situation assessment and effect assessment. Then, this article analyzes the support vector machine economic early warning system. It discusses the four parts of linear support vector machine, nonlinear support vector machine, SVC macroeconomic early warning principle, and support vector classification macroeconomic early warning system. By gradually analyzing the macroeconomic early warning process of support vector machines, this study uses the optimal hyperplane to optimize toward the direction of minimizing economic risks. Then, this article talked about the macroeconomic early warning method based on neural network. The difficult points of traditional early warning models can be discarded. It more easily handles the complex algorithms, qualitative indicators, and quantitative indicators of highly nonlinear models, and it demonstrates the macroeconomic early warning system that optimizes the BP neural network with genetic algorithms to solve the various shortcomings of the macroeconomic early warning process. Finally, this study conducts the multi-sensor data fusion macroeconomic early warning model experiment based on support vector machine. It is divided into three parts. In the first part, the model, design system, and application of 60 sets of sensors are compared with traditional weighted least-squares filtering, and it is concluded that the accuracy and trustworthiness prediction effect of this model is better. The second part uses the data of listed companies to conduct experiments, which verify the performance of the model with different data sets. It can be obtained that its prediction effect is better. The third part is to compare the performance with several traditional models, and it is concluded that the convergence effect is good and the error is small. Its average accuracy is 5.63% higher than the average accuracy of the highest precision warning model in the traditional model. This article discusses and concludes that this model has a good future in macroeconomic early warning.

1. Introduction

A cyclical fluctuation in macroeconomic activities in most countries with business as the core is generally called the economic cycle. From this, we can see that they are bound to be many changes in this cyclical fluctuation. Economic prosperity and decline, depression and recovery, stagnation and expansion, etc., are all stages of change. Generally speaking, in the economic cycle, these kinds of changes are carried out alternately. The main two phases are prosperity and depression, and the two transitional phases are decay and recovery. It is conceivable that in a period of economic optimism that is prosperous, the entire society is uplifting. Productivity is growing rapidly, and the people's employment and labor demand are also rising, and the opposite is true during the economic recession. The emergence of the business cycle has also urged countries to conduct more discussion and early warning of this phenomenon. The economic cycle cannot be completely avoided, but the country can take effective measures to give early warning in time and implement reasonable policies to minimize risks and losses. Therefore, the macroeconomic monitoring and early warning system of various countries have emerged. This system is not only to effectively observe the changes in the business cycle and provide timely early warning but also to eliminate the delay in the implementation of economic policies. The main foundation of the system is to establish a data analysis database through fluctuation data during the business cycle. It uses relevant data processing methods to select appropriate sensitive index data to evaluate the current economic state. At the same time, it makes relevant predictions about possible changes in the future, thereby avoiding certain adverse effects. The adequacy of data can provide stronger theoretical support for future predictions, and the emergence of this early warning system in the economy has also given some enlightenment to other fields. In recent years, support vector machines have become an increasingly mainstream data research and mining technology. Through the research and evaluation of the early warning system of the business cycle, they have realized that the main technical source of the system is still the experience of a group of experts and related mathematical models. The results it can dig out are very limited. The support vector machine has become a more broad technology. What this study proposes is to improve its fusion performance by fusing data from multiple sensors based on support vector machines. At the same time, based on the principle of soft computing and the extended Kalman filter (EKF), a strong fusion framework is constructed in this multi-sensor data system. It uses the support vector machine to receive the input source and continuously learn and strengthen the reform system, thereby obtaining higher accuracy. The experimental results in this study also fully demonstrate that the implementation of the model is enhanced over the conventional model.

This article has conducted a certain research. The economy is the lifeblood of a country and the foundation of an individual's survival, and an individual's investment ability establishes an individual's quality of life. The early warning system methods it uses are as follows: ① on the basis of monitoring indicators, the leading comprehensive index for early warning is used. ② Based on the inductive analysis of historical data of monitoring indicators, the type and characteristics of economic operation are determined, and then, the monitoring indicators are used to establish a predictive model. According to the forecast results, the economic operation status is comprehensively analyzed, which type of economic operation belongs to is determined, and then an early warning description and analysis of the economic operation trend are made. ③ Early warning indicator system: based on the monitoring index system, the design is similar to the traffic control light signal system to warn the operation of the national economy. It strives to minimize risks before they occur. Finally, through experiments, this study verifies that the multi-sensor data fusion macroeconomic early warning model based on support vector machine has high accuracy, small error, and good early warning effect. Therefore, this article has certain practical and theoretical significance.

Support vector mapping and multi-sensor data fusion techniques can be applied in many areas. Bouboulis P demonstrated that any sophisticated SVM/SVR assignment is equivalent to using a dedicated real kernel to solve two positive SVM/SVR assignments. Kernels are spawned from selected sophisticated kernels. In particular, the scenario of exclusively complex kernels will lead to the generation of new kernels, which in previous times has not been under consideration. In the categorization situation, the framework put forward inherently partitions the complexity space into four parts. This naturally leads to solving four types of tasks (four levels of classification) compared with the typical effective SVM of two types [1]. Zhang *L* said that support vector machine (SVM), as one of the machine learning methods, is impressive with its good generalization and powerful nonlinear processing capabilities. SVM combines the national preparatory course and uses six mock test results as training data to predict the final admission score. In all experiments, SVMs were compared with neural networks (NNs). Support vector machine is more stable and has the better predictive ability [2]. To surmount the ball screw health monitoring and troubleshooting issues, a new ball screw fault identification method is proposed by uni-P. The approach combines weighted data from multiple sensors at various positions with roll-up neural networks and distributes weights considering the sensitive parameters of distinct sensors for distinct faults [3]. Ferrer-Cid P explores how data merging captured by sensor arrays enables an enhanced calibration routine. The calibration using arrays of transducers, multi-sensor calibration with data fusion using balanced averaging, and multi-sensor alignment with data fusion using adaptive machine learning models are exactly what he compares. He estimates calibration by combining data from various sensors with regression models, both linear and nonlinear [4]. Maria proposed a mixed Heston model with common random volatility to describe the dynamics of government bond yields. The model is easy to deal with in analysis, so the maximum-likelihood method and specific extension can be used for effective estimation to deal with the curse of dimensionality. The result is an early warning indicator that predicts the unstable phase that characterizes the investigated time series [5]. Golosnoy V proposed an econometric method to monitor changes in the level of related agents in a daily frequency sequence. Its empirical evidence shows that online monitoring of risk-adjusted U.S. forward break-even inflation rates through the cumulative sum (CUSUM) detector seems to be helpful in extracting signals of potential changes in time [6]. Chrum J employs a structure called modular multi-object NEAT (MM-NEAT) to devise quantitative neural networks. An individual behavior is defined for each template. These modules are employed at separate times under strategies that can be designed manually (i.e., multitasking) or by evolutionary auto-discovery. A genetic operator called module bursting allows to fix or find the suitable number of categories of modules [7]. These studies have a certain degree of guidance, but there are insufficient arguments or insufficient precision, which can be further improved.

The support vector machine multi-sensor data fusion model discussed in this article has a good application prospect in macroeconomic early warning. Based on traditional models, it improves prediction accuracy and convergence, reduces errors, and has strong stability. In the method, this article separately explained the design of the multi-sensor data fusion model system, the support vector machine macroeconomic early warning system, and the neural network economic early warning system. This article has certain guidance in economic early warning, and it can also be used for reference in other fields.

2. Model and Methods

2.1. Multi-Sensor Data Fusion Model. Data fusion consists of nondestructive integration, destructive integration, data-level integration, signature-level integration, and policy-making-level integration [8]. Its representation and processing methods come from communication, pattern recognition, decision theory, uncertainty theory, signal processing, estimation theory, optimization technology, computer science, artificial intelligence, and neural networks. Data fusion can process data information autonomously. During this period, with the help of the computer's high-speed operation and intelligent technology, the complementarity of multisource data was used to improve the data processing ability [9]. In this study, reasonable collection and control of data information in multi-sensors are carried out. Multi-sensor mode can improve system performance and make data clearer. In a multi-sensor, the characteristics of each part are different. There are sensors with real-time data monitoring and non-real-time data monitoring and some with fuzzy or clearer data [10]. By observing, controlling, and using each module, it effectively utilizes resources and detects the target toward the optimal path. Figure 1 illustrates the functional modules within multi-sensor fusion systems.

In this functional module, the multi-sensor area is responsible for detecting the target and conveying the measured characteristics and state parameters to the fusion plate. The registration module can register and fuse time and space points through coordinate conversion and time transfer, and the joint correlation module is to scan the data features [11]. The situation database transfers the data measured by multiple sensors and other data to fusion reasoning [12]. Then, this article will show the JDL model of data fusion, as shown in Figure 2.

In 1984, the U.S. Department of Defense established the Data Fusion Joint Command Laboratory and proposed the JDL model, which has now become an actual standard model of the U.S. defense information fusion system. The JDL can be used for signal optimization, target optimization, situation evaluation, effect evaluation, and process optimization [13]. The situation assessment and threat assessment process is to compare the target states and types of all targets with the previously determined possible situational behavior patterns to determine which behavior pattern best matches the states of all targets in the surveillance area. The behavior mode here is an abstract mode, such as the attempt at the enemy's target can be divided into reconnaissance, attack, and anomaly. The output of the behavior estimation unit is situation assessment, threat assessment, trends, target attempts, etc.

2.2. Support Vector Machine Economic Early Warning System

2.2.1. Linear Support Vector Machine. The basic idea of the linear separable two-dimensional plane of the support vector machine is shown in Figure 3. The training error rate in the optimal classification line is 0, and the interval between classifications is the largest, the classification line $(u \cdot a) + m = 0$ is standardized, and the linearly separable data sample set is S, and there is $b_k((u \cdot a_k) + m) \geq 1$, $k = 1, 2, \ldots, n$ at this time. The optimal hyperplane is shown in Figure 3.

It can be obtained that the classification interval at this time is $2/\|u\|$, and the larger the value, the larger the interval. When the maximum is reached, the optimal classification surface is obtained. At this time, the training sample points on the dotted line are the support vectors. One of the cores of the support vector is to control the promotion ability. The indicator function set of the hyperplane can be expressed as follows:

$$g(a) = \operatorname{sgn}[(u \cdot a) + m]; \quad g \leq \min\left(\left|C^2 D^2\right|, h\right) + 1. \tag{1}$$

In this formula, h is the dimension of the vector space and C is the vector radius, and $\|u\| \in D$, so that the minimum $\|u\|$ value can realize the function complexity selection in SRM. The economic risk remains unchanged, and the minimum expected risk using the support vector becomes the minimum $\|u\|$. By establishing the optimal hyperplane, we can get the following:

$$\begin{aligned} &\min R(u) = \frac{1}{2}(u \cdot u); \\ &b_k\left((u \cdot a_k) + m\right) \geq 1, \quad k = 1, 2, \ldots, n. \end{aligned} \tag{2}$$

The optimal solution is the saddle point of the Lagrangian function. In mathematical optimization problems, the Lagrange multiplier method (named after the

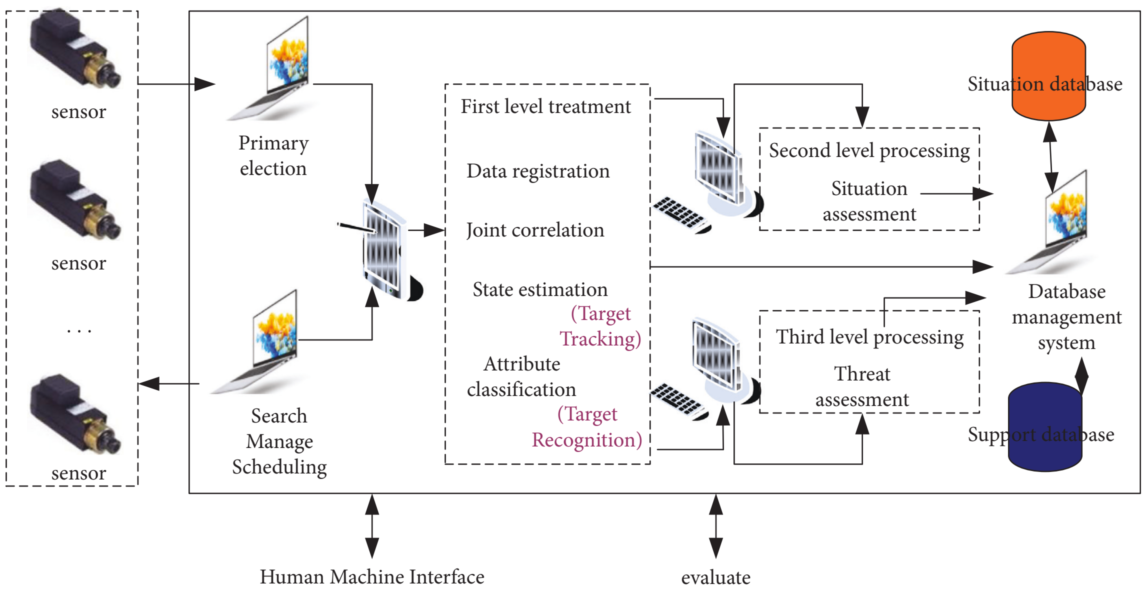

Figure 1: General functional modules of a multi-sensor data fusion system.

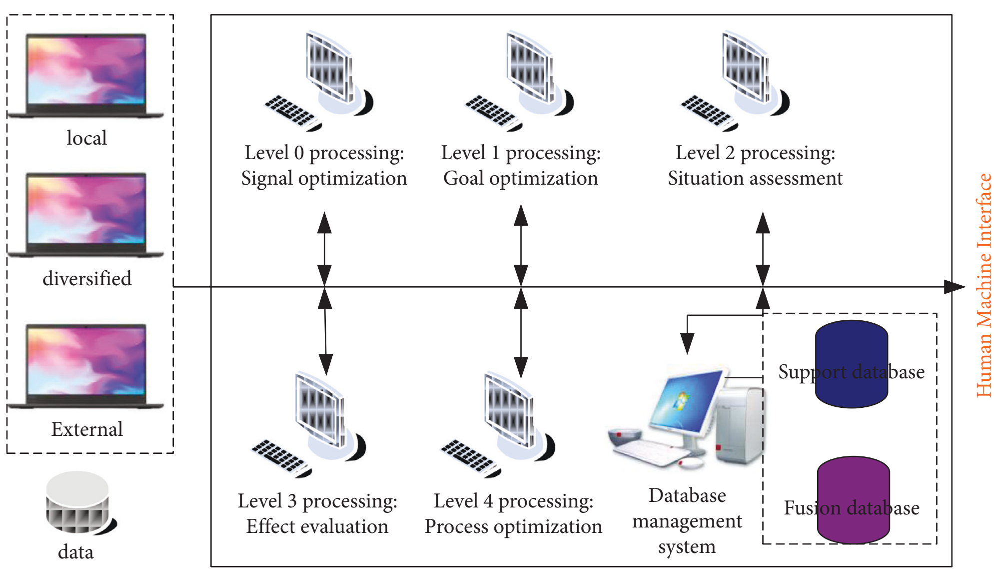

Figure 2: JDL data fusion model.

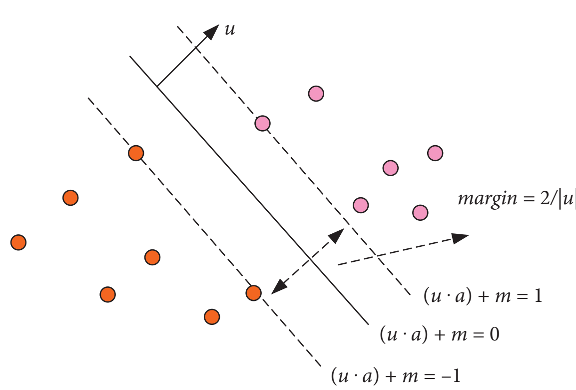

Figure 3: Two types of optimal hyperplanes for linear differentiation.

mathematician Joseph Louis Lagrange) is a method of finding the extreme value of a multivariate function whose variables are restricted by one or more conditions:

$$L(u,m,\phi) = \frac{1}{2}(u \cdot u) - \sum_{k=1}^{n} \phi_k \left[b_k \left(\left(u \cdot a_k \right) + m \right) - 1 \right]. \quad (3)$$

The Lagrangian multiplier in this formula is $\phi > 0$, and u and m at the saddle point of the Lagrangian function are both 0, and we can get the following:

$$\begin{aligned} &\frac{\alpha L}{\alpha u} = u - \sum_{k=1}^{n} \phi_k b_k a_k = 0 \Rightarrow u = \sum_{k=1}^{n} \phi_k b_k a_k, \\ &\frac{\alpha L}{\alpha m} = \sum_{k=1}^{n} \phi_k b_k = 0 \Rightarrow \sum_{k=1}^{n} \phi_k b_k = 0. \end{aligned} \quad (4)$$

According to the Lagrangian multiplier theorem (KK-T), the optimal solution should satisfy the following:

$$\phi_k \left(b_k \left(u \cdot a_k + b \right) - 1 = 0, \quad \forall k. \quad (5)$$

At this time, only the SVM coefficient is not equal to 0:

$$\begin{aligned} &u = \sum_{SV} \phi_k b_k a_k, \\ &\max W(\phi) = \sum_{k=1}^{n} \phi_k - \frac{1}{2} \sum_{k,j} \phi_k \phi_j b_k b_j \left(a_k \cdot a_j \right); \\ &\sum_{k=1}^{n} \phi_k b_k = 0, \quad \phi_k \geq 0, \\ &(u \cdot u) = \sum_{SV} \phi_k * \phi_j * b_k b_j \left(a_k \cdot a_j \right). \end{aligned} \quad (6)$$

At this time, $\phi *$ is regarded as a solution to the quadratic programming problem. Substituting ϕ_k, which is not equal to 0 into formula (5), using an unknown sample a to solve for m, the edge can calculate the support vector category to which a belongs. Most support vector machines do not necessarily have linear separability in practical applications, and incorrectly labeled training sets may also appear. This situation will have a greater impact on the classification of hyperplane. At this time, the relaxation term $\nu \geq 0$ can be added to relax the constraint as follows:

$$b_k \left(u \cdot a_k + m \right) \geq 1 - \nu_k, \quad \nu_k \geq 0, \ k = 1, 2, \ldots, n. \quad (7)$$

At this time, the objective function becomes the following:

$$R(u,\nu) = \frac{1}{2}(u,u) + Z\left[\sum_{k=1}^{n} \nu_k \right]. \quad (8)$$

In the formula, Z is an adjustable parameter, and the degree of punishment for errors can be obtained. At this time, the maximum interval support vector machine constrained in formula (8) is called a soft interval support vector machine. The saddle point of the Lagrangian function of this quadratic programming problem is the optimal solution:

$$\begin{aligned} L(u,m,\phi) = &\frac{1}{2}(u \cdot u) + Z \sum_{k=1}^{n} \nu_k \\ &- \sum_{k=1}^{n} \phi_k \left\{ b_k \left(u \cdot a_k + m \right) + \nu_k - 1 \right\} - \sum_{k=1}^{n} \beta_k \nu_k. \end{aligned} \quad (9)$$

According to the Lagrange multiplier theorem, the optimal solution satisfies the following:

$$\begin{aligned} &\frac{\alpha L}{\alpha \nu_k} = Z - \phi_k - \beta_k = 0; \\ &\phi_k \left(b_k \left(u \cdot a_k + b \right) - 1 + \nu_k = 0; \quad \phi_k, \beta_k, \nu_k \geq 0; \ \beta_k \cdot \nu_k = 0. \end{aligned} \quad (10)$$

It turned into a dual quadratic programming problem as follows:

$$\max L(\phi) = \sum_{k=1}^{n} \phi_k - \frac{1}{2} \sum_{k=1}^{n} \sum_{k=1}^{n} b_k b_j \phi_k \phi_j \left(a_k \cdot a_j \right); \quad 0 \leq \phi_k \leq Z. \quad (11)$$

2.2.2. Nonlinear Support Vector Machine. It allows the use of end product operations or it allows the achievement of primitive functions to solve its complexity. At this point, if and when a kernel function satisfies the Messer criterion, it in turn will correspond to the inner product in the space. The motivation for introducing inner product space is to measure vectors in geometric space. We know that in linear space, the linear structure allows us to perform addition and scalar multiplication operations, but other characteristics of the vector are also very important, such as length and angle:

$$\begin{aligned} &\left(a_k \cdot a_j \right); k, \quad j = 1, 2, \ldots, n, \\ &Q\left(a_k \cdot a_j \right); k, \quad j = 1, 2, \ldots, n. \end{aligned} \quad (12)$$

The input variable a is mapped if:

$$Q(a,b) = \lambda(a) \cdot \lambda(b). \quad (13)$$

The Hilbert space is a generalization of the Euclidean space, which is no longer limited to the case of finite dimensions. Similar to the Euclidean space, the Hilbert space is also an inner product space with the concepts of distance and angle (and the concepts of orthogonality and perpendicularity derived from it). Then, the objective function of the maximum interval nonlinear SVM can be transformed into the following:

$$W(\phi) = \sum_{k=1}^{n} \phi_k - \frac{1}{2} \sum_{k=1}^{n} \sum_{j=1}^{n} b_k b_j \phi_k \phi_j Q\left(a_k \cdot a_j \right). \quad (14)$$

The optimization problem of soft interval nonlinear SVM is as follows:

$$\min R(u) = \frac{1}{2}(u \cdot u) + Z\sum_{k=1}^{n} \nu_k. \tag{15}$$

The dual problem is as follows:

$$\max L(\phi) = \sum_{k=1}^{n} \phi_k - \frac{1}{2}\sum_{k=1}^{n}\sum_{j=1}^{n} b_k b_j \phi_k \phi_j Q(a_k, a_j). \tag{16}$$

2.2.3. SVC Macroeconomic Early Warning Principle. The basic idea of SVC macroeconomic forecasting is to predict data based on the laws derived from observational data and construct a hyperplane for decision-making [14]. Compared with the traditional early warning model, it will be improved from the probability model, but it also has certain defects [15]. Need to know in advance the prior probability, conditional probability, or posterior probability, as well as the probability density and the loss of misjudgment. In fact, if these conditions are known, the classification problem is a simple calculation. In addition, the method is based on the progressive theory of statistics, so good promotion ability cannot be guaranteed under the condition of a small sample. Therefore, this section will propose a support vector classification early warning method. The SVC forecasting method does not need to calculate the probability, directly through the problem itself and the sample with the goal of minimizing the structural risk to achieve the purpose of early warning.

The input pattern set is divided into +1 type points and −1 type points, and the objective function is constructed to distinguish the two types of pattern sets. In the three situations that arise, linearly separable and linearly inseparable can be calculated with Lagrangian multipliers, based on linear functions. Linear inseparability is based on the separation of hypersurfaces in the feature space, the optimal hyperplane is established, and the classifier is used for prediction [16]. The early warning status is divided into alarm and no alarm, and let a_k be the original data vector of the e maintenance alarm indicator. $b_k \in \{\pm 1\}$ is the alert level at the k time point, +1 is no risk, and −1 is risky. The optimal classification function of its training samples and macroeconomic early warning is as follows:

$$\begin{gathered}(a_k \cdot b_k), \quad k = 1, 2, \ldots, n, \\ f(a) = \operatorname{sgn}[u \cdot \lambda(a) + m].\end{gathered} \tag{17}$$

In this formula, $a \in W^i$, the symbolic function is $\operatorname{sgn}[\cdot]$. The macroeconomic early warning is carried out in the second plan, then:

$$\begin{gathered}\max L(\phi) = \sum_{j=1}^{n} \phi_k - \frac{1}{2}\sum_{k=1}^{n}\sum_{j=1}^{n} b_k b_j \phi_k \phi_j Q(a_k, a_j); \quad 0 \le \phi_k \le Z, \\ \sum_{j=1}^{n} b_k \phi_k = 0.\end{gathered} \tag{18}$$

The decision function is as follows:

$$\begin{gathered}f(a) = \operatorname{sgn}\left[\sum_{SV} \phi_k b_k Q(a_k, a) + m\right]; \\ Q(a_k, a_j) = \lambda(a_k) \cdot \lambda(a_j).\end{gathered} \tag{19}$$

The SV in formula (19) represents the support vector.

2.2.4. Support Vector Classification Macroecoanomic Early Warning System. According to the mentioned support vector early warning principle, it is transformed into an optimization problem, that is, a risk minimization problem:

$$\begin{gathered}\min R(u) = \frac{1}{2}(u \cdot u) + Z\sum_{k=1}^{n} \nu_k; \\ b_k((u \cdot a_k) + m) \ge 1 - \nu_k, \quad \nu_k \ge 0.\end{gathered} \tag{20}$$

The dual problem is as follows:

$$\begin{gathered}\max L(\phi) = \sum_{j=1}^{n} \phi_k - \frac{1}{2}\sum_{k=1}^{n}\sum_{j=1}^{n} b_k b_j \phi_k \phi_j Q(a_k, a_j); \quad 0 \le \phi_k \le Z, \\ \sum_{j=1}^{n} b_k \phi_k = 0, \quad k = 1, 2, \ldots, n.\end{gathered} \tag{21}$$

$Q(a_k, a_j) = \lambda(a_k) \cdot \lambda(a_j)$ represents the kernel function. Different kernel functions correspond to different support vector economic early warning methods. Commonly used kernel functions include polynomial kernel, Gaussian radial basis function or RBF kernel, and two-layer neural network kernel. When $Q(a_k, a_j) = a_k \cdot a_j$, it will degenerate into a linear support vector early warning method.

2.3. Macroeconomic Early Warning Method of Neural Network. The application of artificial neural network for the macroeconomic early warning can get rid of the difficulties of traditional early warning models. It is easier to deal with complex algorithms, qualitative indicators, and quantitative indicators of highly nonlinear models [17]. In view of the early warning limits, coordination schemes, time-invariant characteristics, poor adaptive ability, slow self-learning, high consumption, and low efficiency of macroeconomic early warning, researchers have proposed a macroeconomic early warning system that optimizes the BP neural network with genetic algorithms. Genetic algorithm has been widely used in the fields of combinatorial optimization, machine learning, signal processing, adaptive control, and artificial life. Figure 4 is a schematic diagram of indicator warning methods.

The forward three-layer BP neural network appears most frequently in the field of artificial neural networks, as shown in Figure 5.

The test set is used to evaluate the effect of learning and training, and each level connects with each other and transmits information. It evolves the initial features enough to characterize the characteristics of the input mode and extracts the features. Assuming that the trained neural

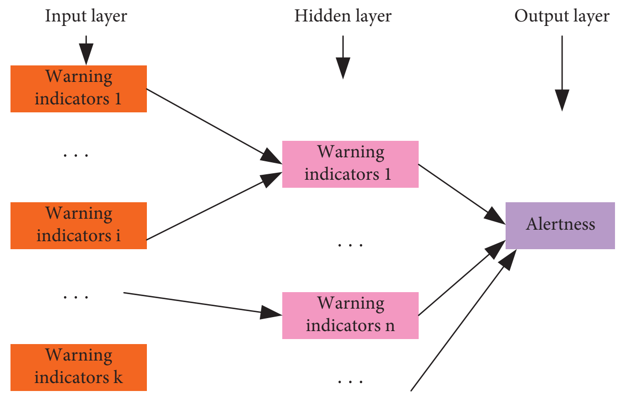

Figure 4: Macroeconomic early warning of indicators under neural network.

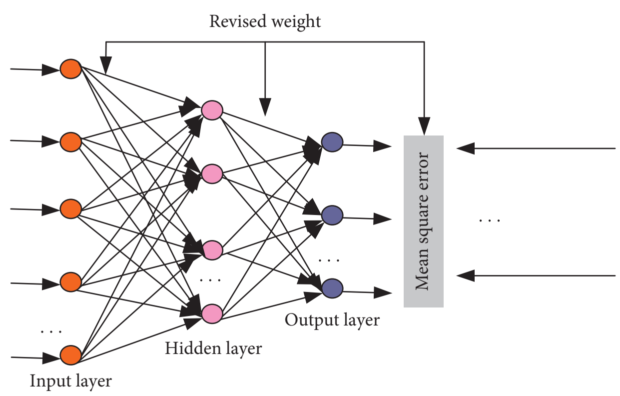

Figure 5: Forward three-layer BP network.

network is not enough to make a good evaluation of its learning and training process [18], the alertness here can be used as a feature extraction medium for alert signs, so the class of alertness indicators can be used as the lowest value of the number of hidden nodes in the neural network [19].

3. Experimental Analysis and Results

Model Based on Support Vector Machine and Multi-Sensor Data Fusion: the trust level of the sensor is used as the output, the trust level of each sensor is accurately predicted, and the weight of the sensor data fusion is optimally divided. The multi-sensor system based on SVM is shown in Figure 6:

At this time, this article will experiment with 60 sets of sensors. At this time, this article will experiment with 60 sets of sensors. The trained neural network is used to predict the trust degree of the sensor, and the fusion knowledge base is used to predict the trust degree globally. It compares the traditional weighted least-squares filtering. The fit of the two algorithms is shown in Figure 7.

It can be seen that the SVM-based multi-sensor algorithm obviously has the better predictive performance. At this time, the weighted least-squares filtering algorithm and the fusion algorithm are compared, and Figure 8 can be obtained.

It can be seen that the position estimation based on the support vector machine is more accurate, the error is smaller, and the superiority is higher, and the prediction accuracy and convergence of the weighted least-squares filtering algorithm are better.

Application and Analysis of Results Based on Support Vector Machine and Multi-Sensor Data Fusion Model in the Early Warning of Economic Crisis of Listed Companies: both the SVM multi-sensor data fusion model and the traditional model have their own limitations and advantages. Therefore, in this article, the training parameters and test data in the sample data will be randomly selected, and different early warning samples will be used to obtain the economic early warning results, so that the algorithm model proposed in this article is more representative. In order not to be affected by factors such as economic cycles in the macroeconomic environment, the sample will select 48 of the 80 listed companies that have undergone special treatment as training samples and 32 as test samples. To ensure the timeliness of the data, the data uniformly adopt the statistics of the previous year, and the samples cover industries, service industries, tourism, and housing industries. A primary screening and a secondary screening were performed. a1 is set as a company with normal operations is identified as a company with a financial crisis, and a2 is set as a situation where a company with a financial crisis is recognized as a normal company. 8 experiments are conducted to ensure the versatility of the experiment. Table 1 shows the prediction results of the SVM multi-sensor data fusion model on the original data.

It can be seen that the accuracy is high, with an accuracy value of 0.88. Table 2 shows the first screening index prediction results of the data through the SVM model.

The accuracy at this time is still high, reaching 0.89. Table 3 shows the second screening index prediction results of the data through the SVM multi-sensor data fusion model.

The prediction accuracy of the model shown in the above three table data is as high as 87% or more, and the standard deviation is also small. It can be seen that the performance of this model is relatively stable, and the predicted value has a certain balance. The multi-sensor data fusion economic early warning model based on support vector machine has the early warning test accuracy value, standard deviation, and accuracy change in the three sample data as shown in Figure 9.

Comparison of Multi-Sensor Data Fusion Model Based on SVM and Traditional Model: this article compares the SVM multi-sensor data fusion model with the traditional model to verify its superiority in macroeconomic early warning. Comparison models include traditional support vector machine, BPN, and GA-SVM. The above experimental data are also tested, and the accuracy comparison is shown in Figure 10.

It can be seen that its average accuracy is 5.63% higher than the average accuracy of the highest precision early warning model in the traditional model. The performance is extremely superior, and the economic prediction performance of BPN is the worst. It can be seen that the SVM

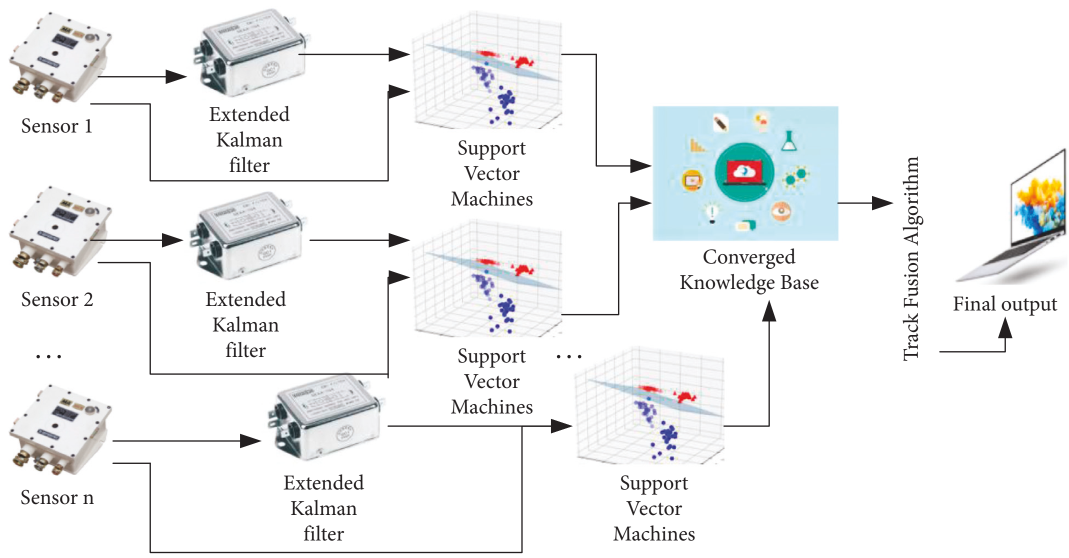

Figure 6: Multi-sensor fusion algorithm based on support vector machine.

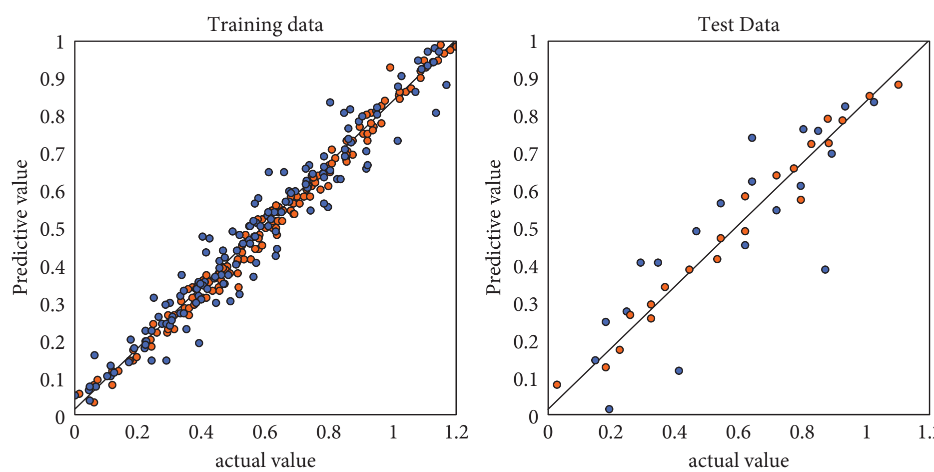

Figure 7: Comparison of the degree of fit between the SVM-based multi-sensor algorithm and the traditional weighted least-squares filtering algorithm.

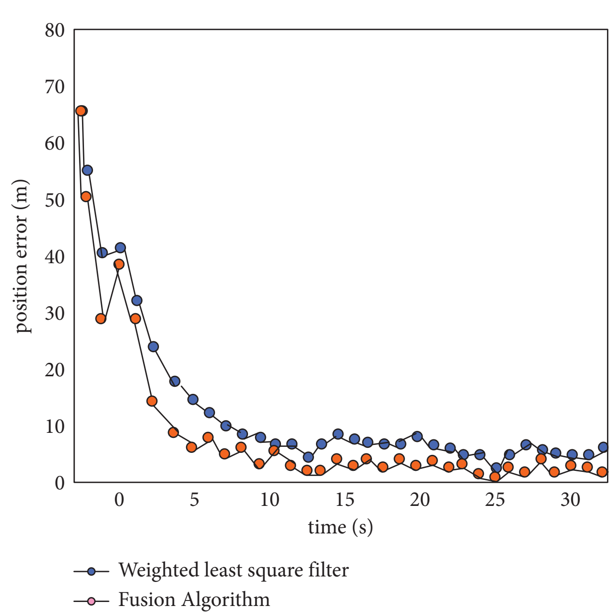

Figure 8: SVM-based multi-sensor algorithm and traditional weighted least-squares filtering algorithm position estimation error curve.

Table 1: Prediction results of SVM multi-sensor data fusion model on the original data.

Experiment/result	a1	a2	Accuracy
1	0.025	0.1	0.875
2	0.0125	0.025	0.9625
3	0	0.1	0.9
4	0.075	0.05	0.875
5	0.05	0.125	0.825
6	0.075	0.075	0.85
7	0.025	0.1	0.875
8	0.05	0.05	0.9

Table 2: SVM multi-sensor data fusion model predicts the results of the first screening index.

Experiment/result	*a*1	*a*2	Accuracy
1	0	0.1	0.9
2	0.025	0.025	0.95
3	0	0.075	0.825
4	0	0.125	0.875
5	0.05	0	0.95
6	0.075	0.025	0.9
7	0.075	0.05	0.875
8	0.05	0.1	0.85

Table 3: SVM multi-sensor data fusion model predicts the results of the second screening index.

Experiment/result	*a*1	*a*2	Accuracy
1	0.175	0.025	0.8
2	0.025	0.025	0.95
3	0	0.075	0.925
4	0.025	0.05	0.925
5	0.05	0.05	0.9
6	0.1	0	0.9
7	0.125	0.1	0.775
8	0.1	0.1	0.8

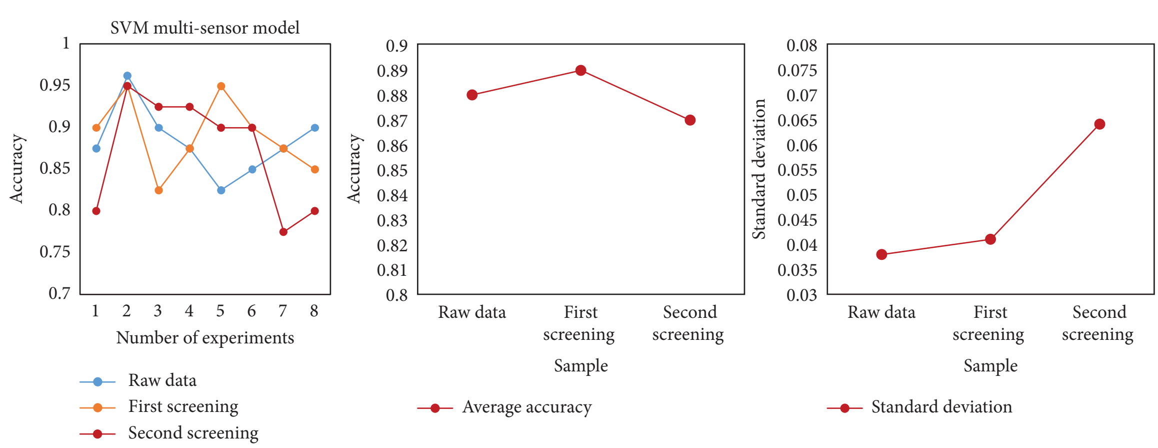

Figure 9: Accuracy and standard deviation of the SVM-based multi-sensor data fusion model under three samples.

multi-sensor data fusion model has the most stable prediction of each group of data, and the performance is better, except for its high accuracy. The standard deviation of the macroeconomic forecast results is estimated here, as shown in Figure 11.

Only the multi-sensor data fusion model of BPN and support vector machine has more stable changes in the macroeconomic early warning results, while the other two models have larger changes; that is, the stability of the algorithm is crossed. On the whole, the macroeconomic early

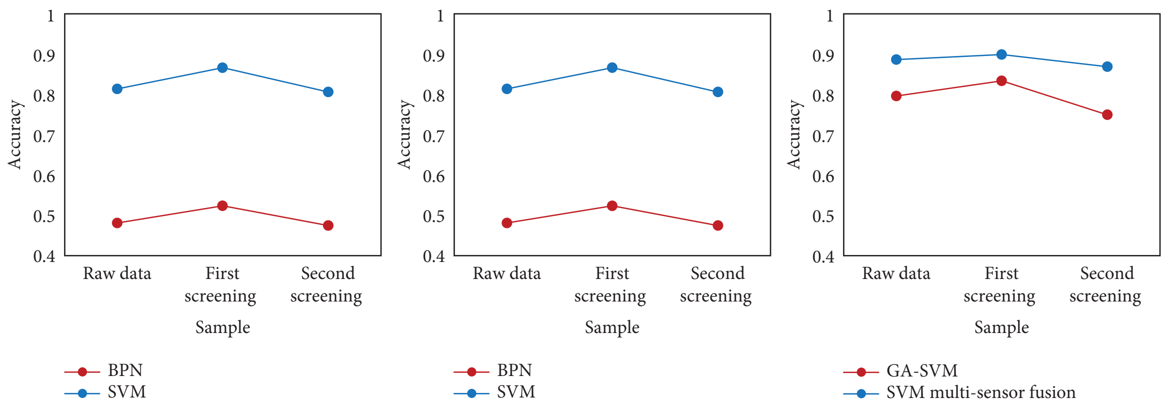

Figure 10: Comparison of economic early warning accuracy of each model.

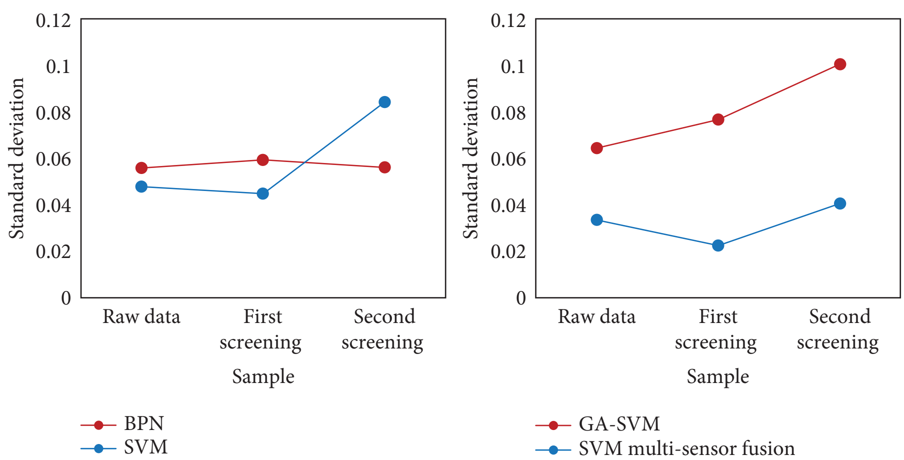

Figure 11: Comparison of economic early warning standard deviations of various models.

warning model based on support vector machine-based multi-sensor data fusion not only has strong stability but also has high prediction accuracy, superior performance, and good versatility. Therefore, the support vector machine parameters based on multi-sensor data fusion have better classification accuracy. According to the abovementioned position estimation of the support vector machine-based multi-sensor data fusion algorithm, it can be known that the convergence effect is good and the error is small. The average accuracy is optimized by 5.63% compared with the average accuracy of the highest precision warning model in the traditional model.

4. Discussion

Since this article is about the early warning methods of support vector machines and multi-sensor data fusion for macroeconomics, this article discusses the algorithm process of support vector machines and the design of multi-sensor data fusion system models. It also uses machine learning BP neural network to analyze the application of economic early warning and finally integrates the three to generate a certain connection. Whether it is relevant, whether the proposed model is feasible, and whether the feasibility is high are explored. Due to the meticulousness of the experiment, this study analyzes and designs support vector machines and multi-sensor data fusion systems before making the three connections. During the design process, fusion and knowledge base were also used to predict the trust degree globally. To show the effect of this model more clearly, the relationship between training parameters and test samples is 4 : 1. Obviously, even if there are more training parameters, its fitting effect is equally good. This system design is relatively intuitive and not complicated. It can be seen that if there is a more in-depth design, it may have better results. After that, this article not only used the economic conditions of listed companies to conduct a separate performance test on the support vector machine multi-sensor data fusion macro-warning model but also used traditional models to compare them. It is found that in the individual test process, the standard deviation is small and the test accuracy is high, which is stable at above 87%. The model compares them and finds that in the individual testing process, the standard deviation is small and the testing accuracy is high, stabilizing above 87%. In the comparative experiment, the accuracy and standard deviation performance are the best. The values used in the figure are obtained from the average and standard deviation of the values in the table. The standard deviation of the BPN model is relatively stable, but the accuracy is the worst. The accuracy of the GA-SVM model is considerable, but the prediction is unstable [20]. The support vector machine multi-sensor data fusion macro-warning model has the best effect in two aspects. This verifies the feasibility of the experiment and the better application prospects.

5. Conclusions

In this study, in the multi-sensor data fusion macroeconomic early warning model experiment based on support vector machines, the algorithm system framework is first designed. It uses sensors, filters, and support vector machines to form a system and uses 60 groups of sensors to be divided into test samples and training parameters. The traditional multi-sensor data fusion model of weighted least-squares filtering and support vector machine was carried out to do data fitting result experiments to test its trustworthiness prediction performance. It is concluded that the SVM-based multi-sensor algorithm obviously has the better prediction performance, and the position estimation is more accurate, the error is smaller, the superiority is high, and the convergence is fast. Then, the listed company is taken as an example, and based on the SVM and multi-sensor data fusion model to predict the company's economic situation, the experimental sample is 80 listed companies of various types. It is also divided into training samples and test samples, multiple experiments to test the accuracy and standard deviation of the multi-sensor data fusion model of the support vector machine. Finally, the accuracy is as high as 87%, and the stability is good. Finally, three traditional models of GA-SVM, BPN, and SVM are compared with the multi-sensor data fusion macroeconomic early warning model of support vector machine. For the experimental samples, refer to 3.2. It is concluded that this model is very suitable for macroeconomic forecasting. It not only has good convergence and strong stability but also has small errors and high accuracy. On average, the accuracy of GA-SVM, the most accurate prediction model mentioned in the traditional model, is optimized by 5.63%. Therefore, in the field of macroeconomic forecasting, the machines studied in this paper have a good application prospect.

Data Availability

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

Conflicts of Interest

The authors declare no conflicts of interest.

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