Hindawi
International Transactions on Electrical Energy Systems
Volume 2023, Article ID 9803494, 1 page
https://doi.org/10.1155/2023/9803494

*Retraction*

# Retracted: Impact of Participatory Community Planning on Publicity in Public Space Renewal Based on Machine Learning Algorithm Based on Child-friendly Concept

**International Transactions on Electrical Energy Systems**

Received 12 December 2023; Accepted 12 December 2023; Published 13 December 2023



This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] Y. Dai and J. Li, "Impact of Participatory Community Planning on Publicity in Public Space Renewal Based on Machine Learning Algorithm Based on Child-friendly Concept," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 5903528, 11 pages, 2022.

Hindawi
International Transactions on Electrical Energy Systems
Volume 2022, Article ID 5903528, 11 pages
https://doi.org/10.1155/2022/5903528



*Research Article*

# Impact of Participatory Community Planning on Publicity in Public Space Renewal Based on Machine Learning Algorithm Based on Child-friendly Concept



**Yang Dai and Jiayi Li**

*School of Art and Design, Shanghai University of Engineering Science, Shanghai 201600, China*

Correspondence should be addressed to Jiayi Li; 07170009@sues.edu.cn

Received 1 August 2022; Revised 31 August 2022; Accepted 10 September 2022; Published 29 September 2022

Academic Editor: Raghavan Dhanasekaran



In the existing community planning and implementation, the design concept often does not take into account the needs of children, but only blindly pursues standardization and modernization. This would make the entire community structure unfriendly to children. Factors such as insufficient public play areas, messy traffic network design, and lack of recreational facilities suitable for children would limit children's fun in the community's public spaces. Children's happy growth would be greatly hindered. In order to solve the above problems, this paper has put forward the child-friendly concept and has applied it to community planning, so as to carry out scientific research on the original participatory community planning model based on the support vector machine technology under the machine learning algorithm. And the improved gray wolf optimization algorithm is combined with it for the shortcomings of the technology's algorithm accuracy and other performance, which is not good enough. The final optimization algorithm has played an extremely important role in testing the impact of the participatory community planning model on publicity in the renewal of public spaces. The experimental results have shown that the highest accuracy of the improved gray wolf optimization support vector machine technology can reach 97.88% and the highest Kappa coefficient can reach 96.83%, which greatly improves the feasibility of the research on the impact of public space publicity.

## 1. Introduction

At present, the construction of child-friendly cities and communities has attracted widespread attention from people from all walks of life. Among them, child-friendly communities have been planned and implemented in many places. The purpose is to provide a better and more friendly living environment for children. However, due to the initial stage of the implementation of the plan, the design of child-friendly communities is often too idealistic and unrealistic, which makes the actual build effect less than expected. At the same time, the reason why child-friendly concepts would gradually become a hot topic and be vigorously promoted is because more and more child-unfriendly factors exist in the community. For example, the design of the community transportation network is complex, the public entertainment facilities in the community are not suitable for children to play, and the decorative elements of the community lack interest. These unfriendly factors prevent children from having enough fun in the community. In order to solve the above problems, it is necessary to introduce a child-friendly concept into the existing community planning. At the same time, more people are encouraged to participate in the rectification of the whole process in real time, and the final concept planning needs to be supported by powerful practical application algorithms. In order to reflect the scientific and professional nature of the community planning model, this paper has adopted efficient algorithms under machine learning for system design and research.

In this study, the machine learning algorithm is introduced into participatory community planning under the child-friendly concept, and the original algorithm is improved to meet the high-performance requirements in actual operation. The innovations of this paper are as follows: (1) The concept of participatory community planning is constructed with the concept of child-friendly, so that child-friendly is integrated into the renewal design of public space. (2) The improved gray wolf optimization algorithm is combined with the support vector machine algorithm under machine learning to improve the overall accuracy of the algorithm.

## 2. Related Work

Child-friendly community is a form of community planning that has been vigorously promoted in recent years, which has also attracted many experts and scholars to study it and try to find an effective implementation plan. Among them, scholar Ren K has selected children from a certain community in Hohhot as the research object. A series of behavioral movements, personality preferences, outdoor performance, and other personal characteristics of children of different ages have been recorded and analyzed. And based on the extracted relevant data, the key factors affecting the child-friendly community and the importance of each factor have been summarized [1]. AbeerElshater has reviewed many cities and communities' planning options and actual results. Criticisms have been made for the design issues that ignore children's feelings exposed and a vision for building a child-friendly community has been proposed. Finally, it is called to improve the built environment of the community to strengthen the concept of being child-friendly [2]. Mardiaman has described and discussed the child-friendly community building program implemented in the Jakarta region, and has delved into the cost of building the community and the factors that affect it. Finally, the possible impact of the establishment of child-friendly communities is discussed [3]. Mclean K and his team have analyzed the current situation of the relationship between children and parents in the community, and have established children's play activities in the community to strengthen the connection between parents and children, trying to make the community a child-friendly living environment [4]. The above studies on child-friendly communities have greatly enriched the theoretical knowledge of child-friendly concepts. It has laid a good foundation for the further development of child-friendly communities. However, the above research did not introduce relevant algorithm technology for scientific construction, and lacked data support for practical application.

Aiming at the lack of data support for practical applications in the above research, it can be well solved by using machine learning-related algorithms. Machine learning algorithms have always been a popular research direction in the computer field, so the research efforts in this field are also considerable. Among them, scholar Hu et al. and his team have briefly discussed the development of electric vehicles. And for the battery problem, it chooses to use machine learning-related algorithm to manage it. The algorithm is mainly used to accurately evaluate the state of charge of the battery. Finally, the reliability of the machine learning algorithm is proved through experiments [5]. Buczak and Guven have reviewed the classic literature on the application of machine learning in various fields. And the machine learning methods proposed in these literature are analyzed and described. Based on the above knowledge, relevant suggestions are put forward for the challenges and solutions of machine learning applied to intrusion detection [6]. Jiang et al. and his team have analyzed the development prospects of 5G networks and the related technical support required in the future. They have also briefly outlined the main concepts and technical knowledge of machine learning, thereby exploring the feasibility of machine learning implementation in various application fields of 5G networks [7]. Wang et al. have tried to integrate machine learning methods with data-driven capabilities to solve the inaccurate prediction of RANS modeling. Finally, the scheme is applied to two different training scenarios to demonstrate its practical performance [8]. Baydin et al. have presented the achievements of automatic differentiation techniques and machine learning algorithms in their respective fields and have expounded the related concepts of the two methods. Then, the similarities and compatibility of the two methods are discussed by citing practical application cases of the two methods. Finally, a feasible realization form combining these two methods is proposed creatively [9]. Liu et al. have proposed a scheme that combines interactive techniques with machine learning. This scheme can be used to solve many problems encountered in the field of machine learning applications, and the advantages of this scheme compared with the original algorithm are analyzed. Finally, a feasible experiment to verify the actual effect of this scheme in the future is proposed [10]. The above-mentioned related researches on machine learning algorithms well reflect the operation effect of machine learning in practical applications. However, the algorithms used in the above studies have not been able to perform well enough in terms of main performance such as accuracy and error, and are difficult to meet the high demands of large-scale application environments.

## 3. Child-Friendly Participatory Community Planning Based on Machine Learning

*3.1. Child-Friendly Participatory Community Planning Model.* At present, the public spaces and public facilities in most cities and their communities are standardized and too monotonous, which are more suitable for most teenagers and adults to use. It makes it difficult for young children to gain experience and satisfaction in public spaces. In view of the lack of relatively child-friendly design scenarios in public spaces, the voice of building child-friendly cities and communities has grown louder in recent years. Relevant child-friendly policies are also being vigorously implemented, which makes the concept of child-friendliness gradually enter the public's field of vision.

In Figure 1, the child-friendly concept is divided into five parts, namely social policy, development environment, growth space, rights protection, and public services. The aim is to start from all aspects that can enhance child-friendliness, and strive to create a comprehensive child-friendly environment that provides the most comfortable conditions and treatments for children to grow up. The child-friendly concept can be widely used in urban and community construction, providing a comfortable growth environment for children living in it, and laying a good foundation for the

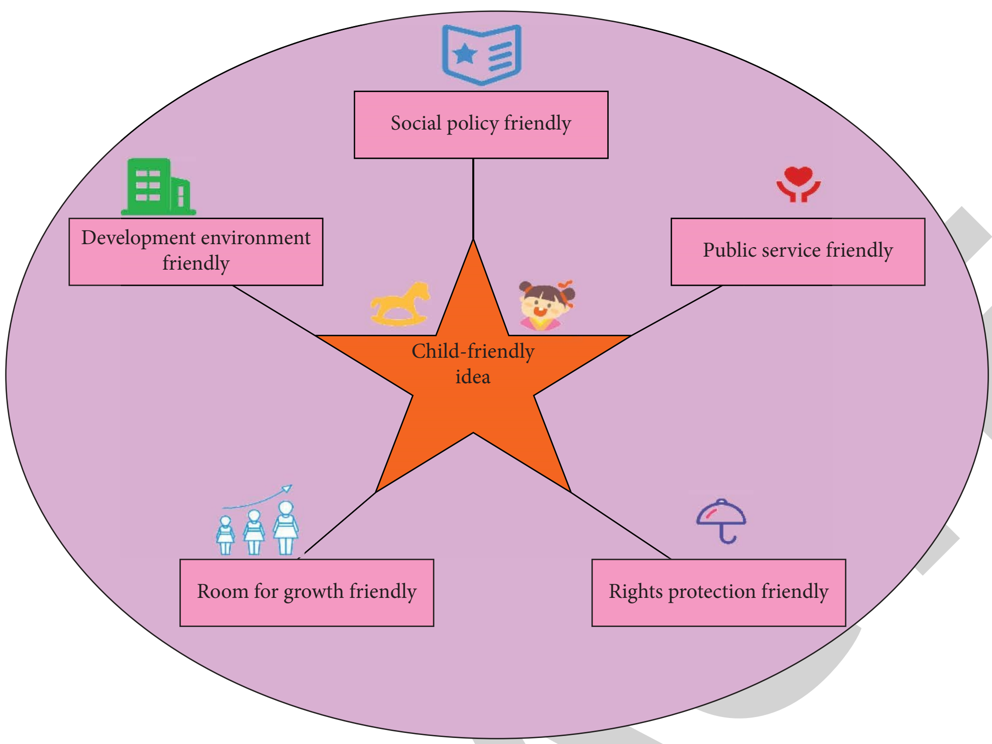


Figure 1: Child-friendly concept design.

Table 1: Activity area survey of children's daily play.

| Activity venue | Votes | Voting percentage (%) |
|---|---|---|
| Activities at home | 452 | 91.9 |
| City Square | 229 | 46.5 |
| Shopping mall | 355 | 72.2 |
| Amusement park | 106 | 21.5 |
| City park | 249 | 50.6 |
| Outdoor event venues within the community | 63 | 12.8 |
| Community service center | 22 | 4.4 |

future development of children. The reason why the child-friendly concept has been vigorously promoted in recent years. The main reasons are: the public activity space of the existing community is too limited; the community structure design is biased towards an adult-friendly environment; the transportation network is complicated, the public facilities and equipment are outdated or not suitable for children; the community element design is too simple and other factors, which make it impossible for most children to play safely in the community. This paper has selected a community with a large population as the survey object, and interviewed a total of 500 community residents with children for the questionnaire survey. The content of the questionnaire is the choice of activity area for parents to lead their children to play in daily life. Each person can choose three items in the questionnaire, and 492 valid questionnaires were recovered. The results of the survey are as follows.

It can be seen from Table 1 that most of the 492 parents chose public areas outside the community for the choice of activity areas for children to play. Among them, there were 452 votes for the option of staying at home, accounting for 91.9%. This means that most people would prefer their children to play at home rather than in community common areas, with shopping malls and city park options closely followed with 72.2% and 50.6% of the votes, respectively. The total number of votes for the two options of community public activity space is only 85, which also intuitively reflects that the current community public environment is not friendly to children's entertainment, and the application of child-friendly concepts in the community urgently needs to be strengthened.

To this end, this article combines community planning with child-friendly concepts. And more community residents are encouraged to participate in the overall planning of the community and express their opinions and opinions. It aims to create a child-friendly participatory community that caters to most people's perceptions [11]. According to the actual situation, this paper has summarized the problems found in many community surveys and found corresponding solutions. It has also proposed six original ideas for improvement to create a new model of child-friendly participatory community planning. The specific composition structure of this mode is shown in Figure 2.

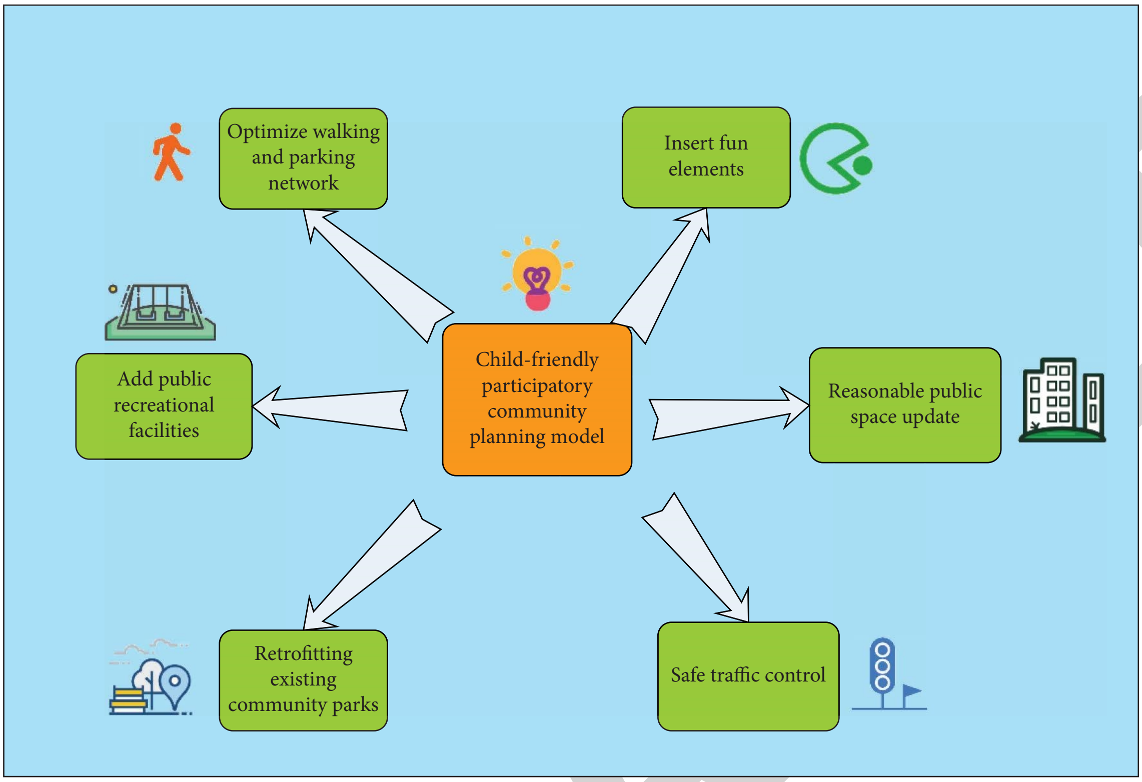


Figure 2: Child-friendly participatory community planning model.

Figure 3: Plan for building a child-friendly community.



Figure 2 shows the six major improvements to the child-friendly participatory community planning model proposed in this paper. The following is a specific introduction to the six programs: the network structure of pedestrian and vehicle traffic is improved to ensure children's safe travel; fun elements are added to improve children's play interest; reasonable public space updates are carried out to expand children's play areas; safe traffic control is carried out to ensure the basic safety of children; existing community parks are renovated and public recreational facilities are added to enrich children's recreational life [12]. These six improvement programs are proposed to strengthen the concept of child-friendly and build a more advanced and integrated child-friendly participatory community. In order to make a more vivid description of the child-friendly participatory community planning model, it would give the viewer a more intuitive impression. This paper designs a planning map corresponding to this model, trying to restore the actual display effect of the child-friendly participatory community planning model to the greatest extent. The planning map is shown in Figure 3.

Figure 3 shows the general structure of a child-friendly community in line with popular expectations (a bird's-eye view of the community on the left, and a rendering of the renovation of the park in the community on the right) and the overall structure in the community is very reasonable. There are more green areas, and the transportation network design is scientific and reliable. At the same time, in response to the above model requirements, many public activity spaces have been added to reflect the child-friendly concept. Among them, the design of community parks is very delicate, reflecting child-friendly elements everywhere, and the entertainment facilities are also suitable for children to play. At the same time, the environment is very beautiful, and the child-friendliness of the whole community has been greatly enhanced.

*3.2. Support Vector Machine Algorithm.* For the data classification problem of the above-mentioned participatory community planning model, this paper would adopt the support vector machine algorithm under machine learning to solve it. A support vector machine is a classification technology used to minimize the risk [13, 14]. It mainly seeks the hyperplane with the best classification performance that meets the classification criteria from the entire data to ensure the best classification accuracy performance. At the same time, all the empty spaces near the hyperplane are maximized, so that the entire data classification can reach the best state. The hyperplane with the best classification performance has the following constraints:

$$\max_{\varphi,c} \frac{2}{\|\varphi\|}, \tag{1}$$

$$t.g z_i\left[(\varphi \times y_i) + c\right] - 1 \geq 0, \quad i = 1, 2, \ldots, m. \tag{2}$$

In Formula (1), $2/\|\varphi\|$ represents the range of the interval selected in the classification process. In order to obtain the hyperplane with the best classification performance, it is usually necessary to study the upper limit of the classification interval, which would also make the classified region robust. In Formula (2), $z_i\left[z_i(\varphi \times y_i) + c\right]$ is the distance between the classification area and the selected sample position, and the value of the distance should not be less than 1. Figure 4 shows the schematic of the support vector machine algorithm.

The diamond-shaped crystal and the green four-leaf clover in Figure 4 represent the samples corresponding to two different types of data classified respectively, and the solid line is the classification area. The length separated by the dashed lines on both sides of the solid line represents the classification interval [15].

The kernel function has a great influence on the derivation of the support vector machine algorithm. If the kernel function is different, the application of the corresponding support vector machine algorithm is also different. Effective use of the kernel function enables the algorithm to be used in more than four dimensions. There are three commonly used kernel functions, and the corresponding formulas are as follows:

$$J(y_i, z_i) = (y_i \times z_i + 1)^p. \tag{3}$$

Formula (3) represents the representation of the polynomial kernel function, and Formula (4) represents the formulation of the radial basis kernel function:

$$J(y_i, z_i) = \exp\left[\frac{|y_i - z_i|^2}{\gamma^2}\right], \tag{4}$$

$$J(y_i, z_i) = \tan r\left[d_1(y_i \times z_i) + d_2\right. \tag{5}$$

Formula (5) is the kernel function expression applied to the neural network correlation model.

$\varepsilon_1$ is the error representation of the algorithm. The best way to minimize the structural risk is to use $\varepsilon_1$ as an important parameter of the loss function. The optimization problem of the algorithm can be described as follows:

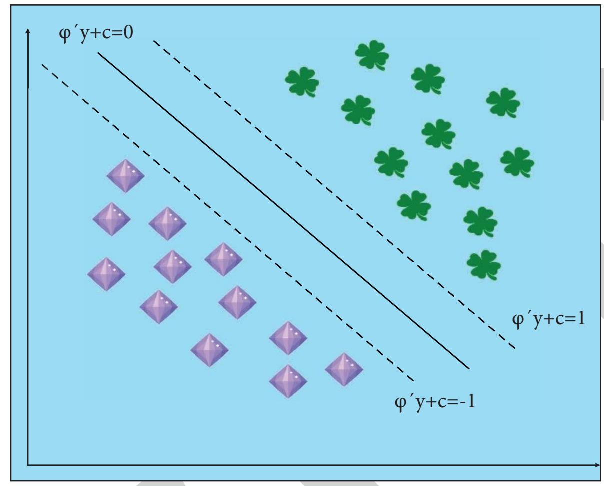


Figure 4: Schematic diagram of the support vector machine algorithm.

$$\min H(\varphi, \varepsilon) = \frac{1}{2}\varphi \times \varphi + d\sum_{i=1}^{k} \varepsilon_i, \tag{6}$$

$$t.g \begin{array}{l} z_i\left[(\chi(y_i) \times \varphi + c\right) \geq 1 - \varepsilon_i, \\ \varepsilon_i \geq 0, \quad i = 1, 2, \ldots, k. \end{array} \tag{7}$$

In this paper, the Lagrangian method is used to solve the optimization problem embodied by Formulas (6) and (7), which can be transformed as follows [16]:

$$\max U(b) = -\frac{1}{2}\sum_{i,h=1}^{k} b_i z_i J(y_i, u_h) b_h + \sum_{i=1}^{k} b_i, \tag{8}$$

$$t.g \begin{array}{l} \sum_{i=1}^{k} b_i z_i = 0, \\ 0 \leq b_i \leq d, \quad i = 1, 2, \ldots k. \end{array} \tag{9}$$

The performance of the above SVM algorithm is not good enough in terms of accuracy and control error, and the global search capability also needs to be strengthened.

*3.3. Improved Grey Wolf Optimization Support Vector Machine Algorithm.* Although the above support vector machine algorithm greatly improves the performance of the participatory community planning model under the child-friendly concept of this paper, there is still room for optimization in terms of parameter configuration, global search capability, and algorithm accuracy. Therefore, this paper integrates the improved gray wolf optimization algorithm with this algorithm to further improve the overall performance of the algorithm. Although the gray wolf optimization algorithm has the advantage of accurate search in a very short period of time when searching for the target, its overall strategy still has major defects in the search process. Therefore, the algorithm is further improved in this paper. The levels of wolves are still divided into four categories as before. Among them, compared with wolves, wolves are more capable of searching for target prey [17]. The behavior of gray wolves when searching for prey is expressed as follows:

$$
\begin{aligned}
\overrightarrow{A} &= \left|\overrightarrow{D} * \overrightarrow{Y}_q(s) - \overrightarrow{Y}(s)\right| \\
\overrightarrow{Y}(s+1) &= \overrightarrow{Y}_q(s) - \overrightarrow{B} * \overrightarrow{A} \\
\overrightarrow{B} &= 2\overrightarrow{b} * \overrightarrow{g}_1 - \overrightarrow{b} \\
\overrightarrow{D} &= 2\overrightarrow{g}_2.
\end{aligned}
\tag{10}
$$

In Formula (10), $\overrightarrow{B}$ and $\overrightarrow{D}$ are the synergy coefficients, and $s$ represents the number of repeated feedbacks at the current stage. $\overrightarrow{Y}_q$ represents the area where the current prey is hiding, and $\overrightarrow{Y}$ represents the area where the gray wolf is searching. During the whole search process, $\overrightarrow{Y}$ gradually decreases from 2 to 0, and $\overrightarrow{g}_1$ and $\overrightarrow{g}_2$ are variables that combine multiple random factors. The random range is $[0, 1]$. In the improved gray wolf optimization algorithm, the competitive cooperation between wolf leaders is incorporated to improve the overall search performance [18]. The division and update of the wolf leader level would be determined by the real-time error evaluation value, and the active area of the wolf group would be determined by Formulas (11)–(13):

$$
\begin{cases}
\overrightarrow{A}_\beta = \left|\overrightarrow{D}_1 * \overrightarrow{Y}_\beta - \overrightarrow{Y}\right|, \\
\overrightarrow{Y}_1 = \overrightarrow{Y}_\beta - \overrightarrow{B}_1 * \overrightarrow{A}_\beta,
\end{cases}
\tag{11}
$$

$$
\begin{cases}
\overrightarrow{A}_\delta = \left|\overrightarrow{D}_2 * \overrightarrow{Y}_\delta - \overrightarrow{Y}\right|, \\
\overrightarrow{Y}_2 = \overrightarrow{Y}_\delta - \overrightarrow{B}_2 * \overrightarrow{A}_\delta,
\end{cases}
\tag{12}
$$

$$
\begin{cases}
\overrightarrow{A}_\sigma = \left|\overrightarrow{D}_3 * \overrightarrow{Y}_\sigma - \overrightarrow{Y}\right|, \\
\overrightarrow{Y}_3 = \overrightarrow{Y}_\sigma - \overrightarrow{B}_3 * \overrightarrow{A}_\sigma.
\end{cases}
\tag{13}
$$

In the above formula, $Y$ represents the active area of the wolf pack, and $\overrightarrow{A}_\beta$, $\overrightarrow{A}_\delta$, and $\overrightarrow{A}_\sigma$ represent the relative distances between the currently pending candidate wolves and the three best-performing wolves, respectively. When $|B| > 1$, the wolves move independently to search for their prey. When $|B| < 1$, wolves would act collectively to capture the searched prey [19]. At the same time, the whole process would make the selected wolf always have the best quality searchability. From time to time, the current best wolf is updated and re-selected based on the advancement of the number of repeated feedbacks. In this way, the status of wolves in all wolf packs can be continuously improved, and the specific improvement measures are given as follows:

$$
\begin{cases}
\overrightarrow{Y}_1^\beta = \overrightarrow{Y}_1 + \left(\dfrac{E_{\text{error}}^{\max} - E_{\text{error}}^s}{S}\right) \times s, \\[2ex]
\overrightarrow{Y}(s+1)^{\beta-\text{gwo}} = \dfrac{\overrightarrow{Y}_1^\beta + \overrightarrow{Y}_2 + \overrightarrow{Y}_3}{3}.
\end{cases}
\tag{14}
$$

$s$ is used to represent the number of repeated feedback at the current stage. $E_{\text{error}}^{\max}$ represents the upper limit of error in all classification results. $E_{\text{error}}^s$ represents the difference between the current classification result and the actual result. $S$ represents the total number of repeated feedbacks.

In addition, this paper also adds feature selection operations to further improve the gray wolf optimization algorithm [20]. In this operation, the set of parameters that describe the relationship of mathematical functions to time would be represented by $\{z_i\}$, $\quad i = 1, 2, \ldots, m$, $z_i$ is a vector of $n * 1$, and the above parameters exist in any $z_i$ vector. The calculation of the kernel matrix can be expressed as:

$$
J_{\lambda\tau} = \left(\psi(z_v) \times \psi(z_\tau)\right). \tag{15}
$$

Based on this, the new kernel matrix can be obtained by the following formula:

$$
J_{\lambda\tau} \longrightarrow J_{\lambda\tau} - \frac{1}{N}\left(\sum_{\rho=1}^{N} J_{\lambda\rho} + \sum_{\rho=1}^{N} J_{\rho\tau}\right) + \frac{1}{N^2}\sum_{\rho,\varpi}^{N} J_{\rho\varpi}. \tag{16}
$$

This article would use the Jacobian matrix to find the kernel matrix $\eta_1, \eta_2, \ldots, \eta_m$. In vector calculus, a Jacobian matrix is a matrix in which the first-order partial derivatives are arranged in a certain way and this matrix can also be used to calculate the vector $w_1, w_2, \ldots, w_m$ with eigenvalue information. The eigenvalues are arranged in order from large to small. Then, the above vectors are processed and obtained by Schmitt orthogonalization, and the final transformation matrix can be calculated by the corresponding extraction of the above vectors:

$$
\widetilde{w}^S = \left[\widetilde{w}_1^T, \widetilde{w}_2^T, \ldots, \widetilde{w}_m^T\right]^S, \tag{17}
$$

$$
\widetilde{w}^S x' = KLx' = \widetilde{y}. \tag{18}
$$

In Formula (18), $\widetilde{y}$ is obtained by operating $w_1, w_2, \ldots, w_m$ by the transformation matrix, which represents the extracted principal component vector. $\widetilde{y} = \{\widetilde{y}_1\widetilde{y}_2, \ldots, \widetilde{y}_m\}^T$ represents the extracted principal component vector.

Essentially, the mathematical model of a multiclass SVM is a convex quadratic programming problem. The key step is to determine the appropriate kernel function coefficients and penalty factors. This paper constructs the objective function of convex quadratic programming to model the support vector machine:

$$
\begin{aligned}
&\min P(\beta) = \frac{1}{2}\sum_{i,h=1}^{M} \beta_i\beta_h z_i z_i J(Y_i, Y_h) - \sum_{i=1}^{M}\beta_i \\
&R.s. \sum_{i,h=1}^{M} \beta_i z_i = 0 \\
&\quad 0 \le \beta_i \le D, \quad i = 1, 2, \ldots, M.
\end{aligned}
\tag{19}
$$

$\beta_i$ represents the Lagrange multiplier. $Y_i$ and $Y_h$ are the vector representation in the input process. $z_i$ represents the variable used to label the type. $J(Y_i, Y_h)$ is the representation of the kernel function. In most cases, the integrity of the data after separation cannot be guaranteed, so the data loss during separation needs to be incorporated into the entire calculation process:

$$\min_{\rho,c,\phi_i} \frac{1}{2}\|\alpha\|^2 + D\sum_{i=1}^{n}\phi_i$$
$$r.s. \begin{cases} z_i\left(\alpha^T y_i + c\right) \geq 1 - \phi_i \\ \phi_i \geq 0, \quad i = 1, 2, \ldots, M. \end{cases} \tag{20}$$

In Formula (20), $\alpha$ represents the effective vector perpendicular to the plane. $\phi_i$ is the slack variable. There is one $\phi_i$ in each sample. It represents the degree to which the sample does not conform to the existing constraints. $D$ represents the constraint factor, and the function used for data classification is expressed as follows:

$$f(y) = \operatorname{sgn}\left\{\sum_{i=1}^{M} \beta_i^{\wedge} z_i J(y, y_i) + c^{\wedge}\right\}. \tag{21}$$

Among them, $c^{\wedge}$ represents the offset constant. In this paper, the prominent Gaussian kernel function is used in the kernel function to improve the operation ability of the support vector machine algorithm on nonlinear problems:

$$J(y, x) = \exp(\xi\|y - x\|). \tag{22}$$

Combining Formulas (20) and (22), $D$ and the kernel function parameter $\xi$ profoundly affect the classification performance of the improved algorithm. Among them, $D$ determines the similarity between the classification results and the actual situation, and $\xi$ determines the action range of the support vector machine, thereby greatly improving the generalization ability of the algorithm.

In this way, the optimization of the support vector machine algorithm through the improved gray wolf optimization algorithm can greatly improve the classification accuracy and enhance the global search ability.

## 4. Machine Learning Applied to Child-Friendly Participatory Community Planning

*4.1. Application of Child-Friendly Participatory Community Planning Model.* In order to verify the feasibility and professionalism of the participatory community planning model under the child-friendly concept proposed in this paper in practical application, this paper applies the model to the actual community environment. The various design aspects of the mode are discussed. At the same time, the influence of the mode on the publicity in the renewal of public space is explored, and the public performance under the mode is analyzed from different angles. This paper first interviews five experts who have deeply researched the field of child-friendly communities, and presents the relevant design of the proposed participatory community planning model to the five experts. From a professional point of view, the impact of the community planning model proposed in this paper on the publicity of public space renewal is studied.

Table 2: Five experts' evaluation of influencing factors on public space renewal.

| Influencing factors | P1 | P2 | P3 | P4 | P5 | Mean |
|---|---|---|---|---|---|---|
| Participatory community planning | 5 | 4 | 4 | 5 | 5 | 4.6 |
| Community demographic changes | 5 | 5 | 4 | 5 | 5 | 4.8 |
| Economic level around the community | 5 | 4 | 5 | 4 | 5 | 4.6 |
| Community culture building | 4 | 3 | 4 | 4 | 4 | 3.8 |

Table 3: Investigation of public impact of participatory community planning model on public space renewal.

| Question Expert | Q1 | Q2 | Q3 | Q4 | Q5 | Mean |
|---|---|---|---|---|---|---|
| A expert | 10 | 9 | 9 | 8 | 9 | 9 |
| B expert | 9 | 9 | 10 | 9 | 9 | 9.2 |
| C expert | 9 | 9 | 8 | 10 | 8 | 8.8 |
| D expert | 9 | 9 | 8 | 8 | 7 | 8.2 |
| E expert | 10 | 9 | 8 | 8 | 7 | 8.4 |
| Mean | 9.4 | 9 | 8.6 | 8.6 | 8 | |

The evaluation results of five experts on the four influencing factors of public space renewal are shown in Table 2.

As can be seen from Table 2, in the comparison with the main influencing factors of the other three public space renewal areas, the influence degree of participatory community planning has reached an excellent level. In the professional vision of five experts, participatory community planning plays an important role in the renewal of public space. Its average score was 4.6, second only to the 4.8 for the community demographic change factor. The scores of the two influencing factors were not significantly different. This can prove that the participatory community planning model proposed in this paper has the same level of influence as the commonly used measurement factors affecting public space renewal.

In addition, an important goal of the original participatory community planning model designed in this paper is to enhance the publicity of public space renewal in a child-friendly manner, in order to conduct a professional evaluation of the above goals. This paper invited the above-mentioned five experts to score five questions about the impact of the participatory community planning model on the publicity of public spaces. The specific questionnaire results are shown in Table 3.

Table 3 shows that the average score of each question is above 8, and the highest score is 9.4 points for question 1. The five experts gave high scores to the five questions related to public influence. Among them, the highest average score of Expert B is 9.2 points, and the lowest average score is 8.2 points of Expert D. In all the related questions about whether the participatory community planning model in this paper can improve the publicity of public space, the score is not lower than 7 points. This also shows that the participatory community planning model under the child-friendly concept can influence the publicity of public space renewal to a large extent, and this influence is also comprehensive.

In order to more practically test the feasibility of the child-friendly participatory community planning model

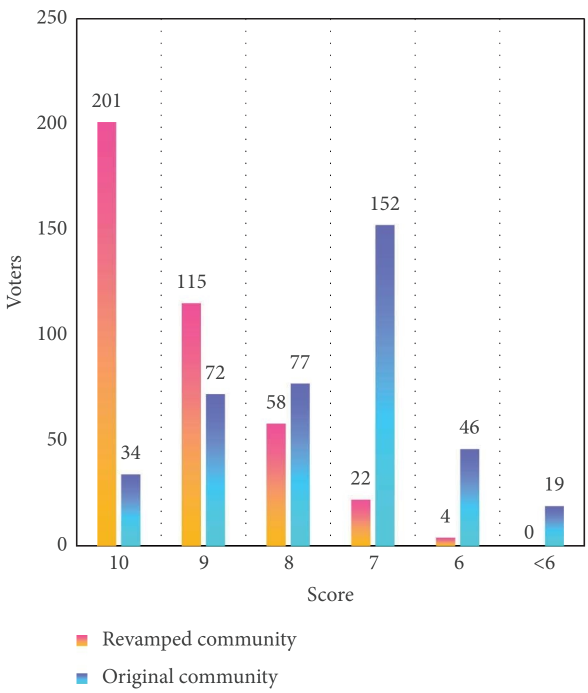


Figure 5: Residents' satisfaction survey on the Community before and after renovation.

proposed in this paper, this paper selects a community to be transformed as the experimental object, and applies the model to the construction of child-friendly communities. Residents can participate in community planning, aiming to design a benign community environment that is child-friendly and friendly to all residents, aiming to design a benign community environment that is both child-friendly and friendly to all residents. After the community reconstruction, this paper randomly selects 400 resident users in the community to participate in the satisfaction survey before and after the community reconstruction, so as to explore the intuitive image of child-friendly participatory community planning in the minds of residents. The comparison results are shown in Figure 5.

It can be clearly seen from Figure 5 that the satisfaction of the 400 community residents for the community after the transformation of the model optimized in this paper has been greatly improved compared to before. More than half of the residents gave full scores, and the number of voters in the corresponding score segment also dropped significantly as the score decreased. No resident rated the renovated neighborhood a 6 or below. This means that the community after the transformation is generally in line with the expectations of all the people, and the transformation effect is obvious.

In addition, this paper launched a targeted questionnaire survey of 312 parents with children in the community on the impact of child-friendly participatory community planning on public spaces. The purpose is to measure the role of participatory community planning in affecting publicity from the intuitive feelings of occupants. The survey results are mentioned as follows.

It can be seen from Table 4 that, after feeling the changes before and after the community reconstruction, 312 respondents gave a very high evaluation of the impact of the model proposed in this paper on the publicity of community public spaces. The affirmative rate on the 4 issues related to the degree of influence exceeds 83%. And it is concluded that most parents affirmed the child-friendly manifestation of participatory community planning; their tendency to bring their children to the public areas of the community increased significantly; they were also satisfied with the renovated community environment. These all demonstrate the greater influence of bringing child-friendly concepts into participatory community planning on the publicity of public spaces.

Finally, this paper analyzes the child-friendly performance of the participatory community planning model in this paper from the perspective of children, considering that there may be differences in behavioral styles and psychological factors between young and old children. In this paper, 100 children of two age groups in the experimental community were selected for interviews, and the children were asked to evaluate the reconstructed community in their impressions. The results are shown in Figure 6.

In Figure 6, there is not much difference in community satisfaction among children of the two age groups, and both account for more than 90% in the evaluation range of 8 to 10 points. Among them, the number of votes with full scores of community satisfaction is the largest, with 56 votes and 61 votes respectively. This also fully reflects that the community after the transformation of the participatory community planning model in this paper has an excellent degree of friendliness to children, and almost meets the entertainment needs of children of all ages.

*4.2. Improved Application of SVM Algorithm for Grey Wolf Optimization.* In order to test the main performance of the combination of the support vector machine algorithm based on machine learning technology and the gray wolf optimization algorithm proposed in this paper, this paper would conduct a number of scientific and feasible experimental evaluations of the improved algorithm. The main influencing factors of the algorithm on the participatory community planning mode of this paper, such as accuracy, error control, etc., would be compared and tested. The advantages of this algorithm are highlighted by comparison with other classical algorithms. First, the classification error performance of this algorithm is compared with the traditional SVM algorithm which is not improved by the gray wolf optimization algorithm. In this paper, the relevant samples of the participatory community planning model are selected as the experimental objects, and the error control results are shown in Figure 7.

The data results in Figure 7 show that the classification error of the improved gray wolf optimization SVM algorithm in the initial stage is roughly the same as that of the traditional algorithm, and the subsequent error control performance is better. After the $10^{\text{th}}$ repetition of the feedback, the error gap with the traditional algorithm

Table 4: Residents' evaluation of the impact of the renovated community on the publicity of community space.

| Question Satisfaction level | Great (vote) | General (vote) | Dissatisfied (vote) |
|---|---|---|---|
| Does the transformed community embody child-friendliness? | 282 | 23 | 7 |
| Are you more willing to bring your children to play in the public spaces of the community? | 261 | 40 | 11 |
| Satisfaction of the renovated community environment | 277 | 26 | 9 |
| The influence of participatory planning model on community publicity | 289 | 18 | 5 |

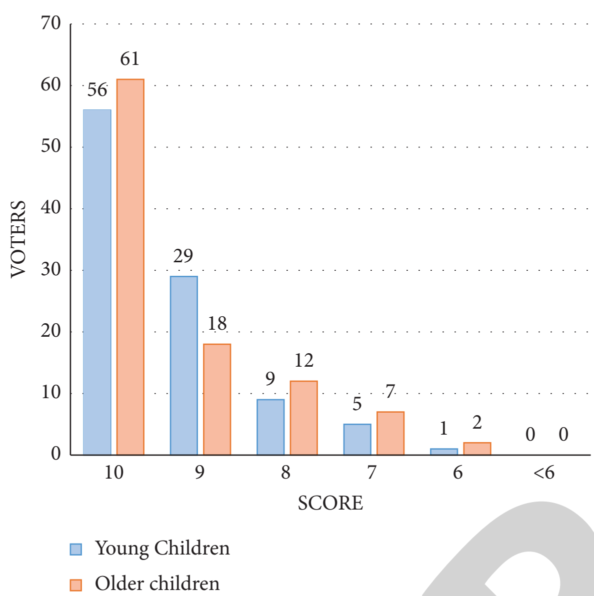


Figure 6: Children of different age groups are satisfied with the renovated community.

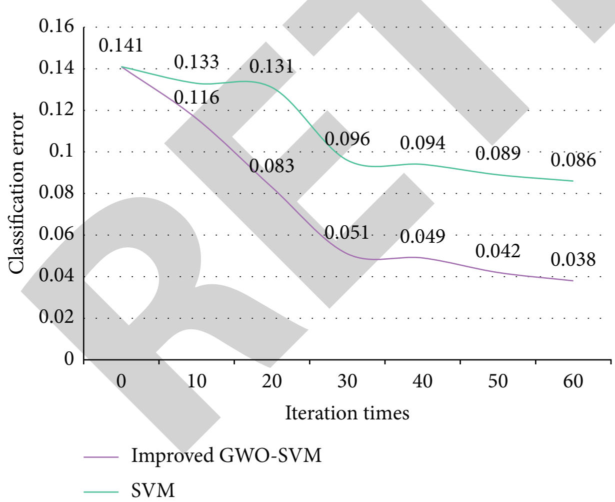


Figure 7: Classification error results for both algorithms.

gradually widens. The optimal error of the algorithm is 0.038. In contrast, the minimum error of the traditional SVM algorithm is only 0.086. In terms of the worst error performance of the algorithm, the improved gray wolf optimization SVM algorithm and the traditional algorithm are both 0.141. Obviously, in the aspect of error control, the improved algorithm proposed in this paper has absolute advantages.

In addition, this paper conducts an analogy test on the accuracy and Kappa coefficient of the algorithm to further evaluate the reliability of the improved algorithm proposed in this paper. The Kappa coefficient represents the correlation between the test results and the sample types in the actual environment, which is also an important factor to measure the performance of the classification results. In order to strengthen the comparison and professionalism of the experiment, this paper selects the relevant samples of the participatory community planning model as the experimental object and adds another APSO-SVM algorithm, which has successfully improved the support vector machine algorithm, as a comparison. At the same time, the Kappa coefficients before and after the feature selection operation were recorded to explore the effect of feature selection on the actual classification effect. And two comparative experiments under the same environment were carried out to enhance the reliability of the experimental data. The experimental results of the Kappa coefficients of the three algorithms are as follows:

In Figure 8, the Kappa coefficient of the optimization algorithm proposed in this paper is higher than the other two algorithms in both experiments, and the highest value of the Kappa coefficient can reach 96.83%. The highest values of support vector machine algorithm and APSO-SVM algorithms are only 83.38% and 89.93%, respectively. This shows that the classification effect of the optimization algorithm proposed in this paper is better. At the same time, there is a large difference in the Kappa coefficients of the three algorithms before and after feature selection. After the feature selection operation, the Kappa coefficients are significantly improved compared with the previous ones. This shows the effectiveness of the feature selection operation in improving the classification performance.

In the experimental test of accuracy, the experimental environment is consistent with the above Kappa coefficient experiment, but the sample size is increased to better evaluate the real accuracy of the algorithm. The final accuracy is shown in Figure 9.

Figure 9 shows that in the two accuracy comparison experiments, the improved gray wolf optimization SVM algorithm proposed in this paper occupies an absolute leading edge in the experimental accuracy. The highest accuracy is 97.88% after feature selection. At the same time, the accuracy of the algorithm also reaches 93.96% before the feature selection operation. This is higher than the accuracy of the other two algorithms after the feature selection

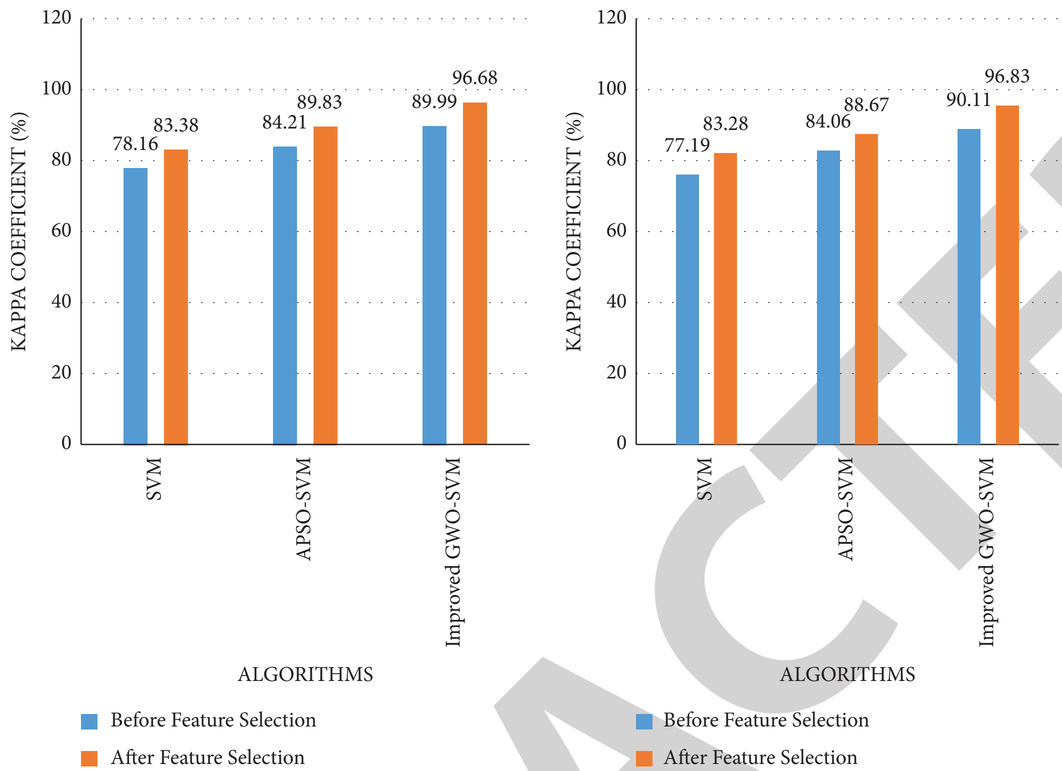


FIGURE 8: Two comparisons of the Kappa coefficients of the three algorithms.

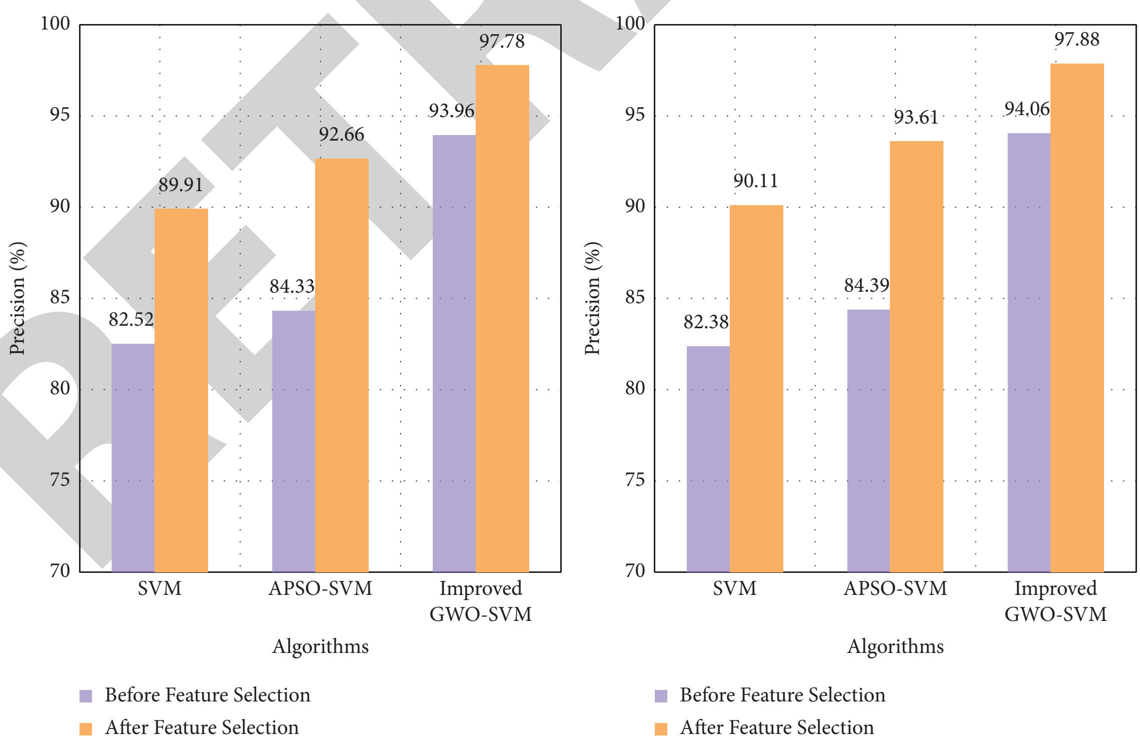


FIGURE 9: Comparison of two accuracy of three algorithms before and after feature selection.

operation. Therefore, it can be concluded that the improved gray wolf optimization SVM algorithm has the best accuracy performance among the three algorithms, and the feature selection operation plays an important role in improving the accuracy performance of the algorithm.

## 5. Conclusions

How to combine community planning with public participation and child-friendly concepts to create a beautiful and harmonious community has become a topic of concern to many people. This paper has skillfully integrated the child-friendly concept into participatory community planning, and formed a professional model to better reflect child-friendly in practical application. Algorithmically, according to the characteristics of this mode, the support vector machine algorithm based on machine learning algorithm has been used to construct. In order to solve the problem of insufficient algorithm performance, an improved gray wolf optimization algorithm has been introduced. Finally, the actual operation of this model has verified the influence of participatory community planning on the renewal of public space. And through the comparative experiments, the powerful advantages shown in the main performance such as the accuracy of the algorithm are detected. The highest accuracy is 97.88% after feature selection, and the algorithm is 93.96% accurate before feature selection. Finally, this paper has room for improvement in performance such as accuracy, and follow-up work would focus on maximizing the average accuracy of the algorithm throughout the process.

## Data Availability

The data that support the findings of this study can be obtained from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## References


[1] K. Ren and L. Xu, "Dataset on energy efficiency assessment and measurement method for child-friendly space in cold residential area," *Data in Brief*, vol. 14, pp. 148–155, 2017.

[2] A. Elshater, "What can the urban designer do for children? Normative principles of child-friendly communities for responsive third places," *Journal of Urban Design*, vol. 23, no. 3, pp. 432–455, 2018.

[3] Mardiaman and A. Mubarok, "The cost risk implementation on design-build project of integrated public spaces child friendly in capital of Jakarta," *AIP Conference Proceedings*, vol. 1903, no. 1, pp. 1–15, 2017.

[4] K. Mclean, S. Edwards, and H. Morris, "Community playgroup social media and parental learning about young children's play," *Computers & Education*, vol. 115, pp. 201–210, 2017.

[5] X. Hu, S. E. Li, and Y. Yang, "Advanced machine learning approach for lithium-ion battery state estimation in electric vehicles," *IEEE Transactions on Transportation Electrification*, vol. 2, no. 2, pp. 140–149, 2016.

[6] A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion detection," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 2, pp. 1153–1176, 2016.

[7] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. C. Chen, and L. Hanzo, "Machine learning paradigms for next-generation wireless networks," *IEEE Wireless Communications*, vol. 24, no. 2, pp. 98–105, 2017.

[8] J. X. Wang, J. L. Wu, and H. Xiao, "Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data," *Phys.rev.fluids*, vol. 2, no. 3, pp. 034603–034622, 2017.

[9] A. G. Baydin, B. A. Pearlmutter, A. A. Radul, and J. M. Siskind, "Automatic differentiation in machine learning: a survey," *Journal of Machine Learning Research*, vol. 18, no. 153, pp. 1–43, 2018.

[10] S. Liu, X. Wang, M. Liu, and J. Zhu, "Towards better analysis of machine learning models: a visual analytics perspective," *Visual Informatics*, vol. 1, no. 1, pp. 48–56, 2017.

[11] D. C. Read, *Book review: building together: case studies in participatory planning and community building KatanRogerShiffmanRonald. 2014. building together: case studies in participatory planning and community building*, New Village Press, New York, NY, USA, 2017.

[12] M. Ward, A. J. Schulz, B. A. Israel, K. Rice, S. E. Martenies, and E. Markarian, "A conceptual framework for evaluating health equity promotion within community-based participatory research partnerships," *Evaluation and Program Planning*, vol. 70, pp. 25–34, 2018.

[13] P. Bouboulis, S. Theodoridis, C. Mavroforakis, and L. Evaggelatou-Dalla, "Complex support vector machines for regression and quaternary classification," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 6, pp. 1260–1274, 2015.

[14] C. Kyrkou, C. S. Bouganis, T. Theocharides, and M. M. Polycarpou, "Embedded hardware-efficient real-time classification with cascade support vector machines," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 1, pp. 99–112, 2016.

[15] W. Hu, W. Zhang, Y. Min, L. Chen, and L. Wang, "Real-time emergency control decision in power system based on support vector machines," *Proceedings of the Csee*, vol. 37, no. 16, pp. 4567–4576, 2017.

[16] T. Tanino, R. Kawachi, M. Akao, and K. Tatsumi, "Performance evaluation of multiobjective multiclass support vector machines maximizing geometric margins," *Numerical Algebra, Control and Optimization*, vol. 1, no. 1, pp. 151–169, 2011.

[17] M. Kohli and S. Arora, "Chaotic grey wolf optimization algorithm for constrained optimization problems," *Journal of Computational Design and Engineering*, vol. 5, no. 4, pp. 458–472, 2018.

[18] Z. Xu, H. Yang, J. Li, X. Zhang, B. Lu, and S. Gao, "Comparative study on single and multiple chaotic maps incorporated grey wolf optimization algorithms," *IEEE Access*, vol. 9, no. 24, pp. 77416–77437, 2021.

[19] Y. Han and X. Tong, "Multi-step short-term wind power prediction based on three-level decomposition and im-proved grey wolf optimization," *IEEE Access*, vol. 8, no. 1, pp. 67124–67136, 2020.

[20] A. Routray, R. K. Singh, and R. Mahanty, "Harmonic reduction in hybrid cascaded multilevel inverter using modified grey wolf optimization," *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 1827–1838, 2020.