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Retraction

Retracted: Metal Oxide Nanomaterials as Rice Transgenic Carriers

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1].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] X. Yang, X. Bai, Z. Zhang, and X. Yu, “Metal Oxide Nanomaterials as Rice Transgenic Carriers,” *Advances in Materials Science and Engineering*, vol. 2022, Article ID 4375986, 15 pages, 2022.

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Research Article

Metal Oxide Nanomaterials as Rice Transgenic Carriers

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For the development of nanotechnology, nanomaterials are in an important position. Due to their special structure and a series of unique properties, nano-metal oxide materials are widely used in nanoelectronics, catalysis, environmental monitoring, electrochemical sensors, and many other fields. Rice, as the most important food crop in the world, has a wide range of planting areas. Therefore, in this paper, the research on the construction of rice transgenic vectors is based on nano-metal oxide materials. In this paper, particle swarm optimization is used to optimize the weights of rice-growing convolutional neural networks. Secondly, it used rice as the test plant to study the effects of seven metal oxide nanomaterials on rice seed germination and root elongation. This sheds light on the toxic effects of metal oxide nanomaterials on rice growth and discusses the factors that affect the phytotoxicity of nanomaterials. The experimental results show that before optimization, the accuracy of the small batch sample test is 87.0456%, the accuracy of the large batch sample test is 93.5876%, and the accuracy of the test is increased by 6.542%. After optimization, the accuracy of the small batch sample test is 93.5876%, the accuracy of the large batch sample test is 99.0133%, and the accuracy of the test is increased by 5.4466%. The inhibition rates of nano-CuO and ZnO on rice root length were 97.28% and 66.75%.

1. Introduction

Since the early 1980s, nanomaterials have been hailed as "the most promising materials of the twenty-first century". Together with information technology and biotechnology, it has become one of the three pillars and strategic commanding heights of social and economic development in the twenty-first century. Nanometal oxides are a class of metal oxide materials with nanostructures. It is currently one of the largest types of nanomaterials produced and has been widely used in catalysts, environmental remediation, infrared absorption materials, composite materials, sensors, fine ceramics and magnetic materials, and other fields.

Nanoparticle (NP) gene vector has the advantages of low or no biological toxicity, no immunogenicity, strong resistance to enzymatic hydrolysis, high transfection efficiency, and stable expression after transfection. It has potential and broad application prospects in gene transduction. And it has been applied in transgenic research of animal and human cells. However, research as a plant transgenic vector is a completely new field, because plant cells have a natural barrier cell wall that prevents nanoparticles from entering the cell. The popularization and application of transgenic rice varieties are beneficial to the sustainable development of modern agriculture. With the development of science and technology and productivity, genetically modified breeding technology has been continuously improved. The research on transgenic technology in the field of rice breeding will be more in-depth and extensive. In the future, it will be able to perform related operations on the target genes in the rice genome, and accelerate the promotion and development of transgenic rice breeding technology in the field of agricultural production.

The innovations of this paper are: (1) The research on metal oxide nanomaterials as rice transgenic carriers is innovative and practical. (2) This paper conducts a preliminary evaluation of the phytotoxicity of metal oxide nanomaterials, to further understand the toxicity mechanism of nanomaterials. It also provides a theoretical basis for the application of nanomaterials in agriculture.

2. Related Work

The twenty-first century is an era of rapid advances in biological and medical research. Many scholars have studied metal oxide nanomaterials. For a highly sensitive acetone sensor, here Chang presented the analgin-assisted surfactant-free Langmuir–Blodgett process. It rapidly assembles monolayer two-dimensional (2D) networks as a suitable percolation strategy for metal oxide semiconductor nanomaterials [1]. Yang reviewed the recent research progress of metal oxides as photoelectrodes and cocatalysts for PEC water splitting. Their performance, limitations, and potential are also discussed. Finally, key challenges and opportunities in the development and implementation of metal oxide nanomaterials for PEC water splitting are discussed [2]. Khandare discussed the application of nanomaterials and composite nanomaterials in the enhanced removal of fluorine-containing wastewater. Various key factors (PH, stirring time, initial fluoride concentration, temperature, particle size, surface area, etc.) that control the effectiveness of different materials in removing fluoride from water are also highlighted [3]. Dontsova discussed nanocomposite metal oxide materials and their ecological applications. Studies have shown that nanomaterials based on them have great application prospects in ecology, especially as sensitive layers for adsorbents, photocatalysts, and gas sensors [4]. Engineered nanomaterials (ENMs) are increasingly used for the remediation of contaminated soils. In this study, Duncan routinely determined the plant availability of pollutants, nutrients, and trace elements in three arsenic- or lead-exposed soils in Australia [5]. Niemuth found that nanomaterials have higher cumulative exposure to sediment organisms than nanomaterials in the water column, which may be a realistic environmental exposure [6]. Anderson reviewed the research progress of metal oxide imaging agents in recent years. The imaging capabilities and properties of these metal oxides are introduced, and new functionalization strategies are proposed. Finally, recommendations are made for future research in this area [7]. Earth-enriched transition metal and metal oxide (EATM&MO) nanomaterials offer many positive properties. Maduraiveeran reviewed various emerging synthetic methods of EATM and MO nanomaterials and their nanocomposites. These methods employ a variety of chemical strategies for state-of-the-art electrochemical applications [8]. However, the shortcomings of these studies are that the model construction is not scientific enough and the data is not well prepared to adapt to more complex situations.

3. Methods of Metal Oxide Nanomaterials

3.1. Nanomaterials

3.1.1. Definition of Nanometer. The definition of nanomaterials (NPS) is usually based on the three-dimensional size of the material. When the size of the material or the constituent unit of the material is in the range of 1–100 nanometers in at least one dimension, the material can be called nanomaterial. There are various classification methods of nanomaterials, which can be divided into different styles according to different sources [9, 10]. It can be divided into natural nanoparticles, such as nanoparticles from volcanic eruptions, sandstorms, and human nanoparticles, such as nanoparticles from factory production, straw burning. According to the existing state of nanomaterials, it can be roughly divided into four categories: nanopowder, nanofilm, nanofiber, and nanoblock. The most common classification is based on the chemical composition of nanomaterials, as shown in Figure 1, [11]. It is classified into carbon nanomaterials, including multi/single-wall carbon nanotubes, fullerenes. Zero-valent metal nanoparticles, such as nano-gold, nano-silver. Organic polymer nanomaterials, such as polystyrene. Quantum dots (ODs) such as CdTe, CdSe. Metal oxide nanomaterials, such as nano CuO, ZnO.

Compared with macroparticles, nanomaterials have structural features such as large specific surface area and surface defects, which lead to a series of effects that are different from macroscopic substances, including surface effects, volume effects, quantum size effects, quantum tunneling effects, and dielectric confinement effects. Thus, it leads to nanomaterials with outstanding properties in melting point, optical properties, chemical reactivity, magnetic properties, etc. The outstanding properties of nanomaterials in physics and chemistry make the development of nanotechnology change with each passing day [12–14]. More and more nanomaterials are integrated into people's daily life in various ways, such as Fe3O4 nanomaterials. It has excellent magnetic properties, biocompatibility, and biodegradability, so it is widely used in the sorting of nonmagnetic materials, the removal and recovery of polluted oil slicks in large areas of water, as well as in medicine, aerospace, etc. Nano-titanium dioxide has good photocatalytic properties and is widely used in environmental pollution treatment and cosmetics [15]. Nano silica is often used as an additive catalyst carrier, decolorizer, plastic filler, etc., and is widely used in various industries.

3.1.2. Synthesis of Nanomaterials. The preparation methods of nanomaterials can be roughly divided into physical methods, chemical methods, and other methods. Among them, physical methods include pulverization method, deposition method, sputtering method, etc. Chemical methods include the sol-gel method, precipitation method, evaporative solvent pyrolysis method, redox method, solvothermal method, etc. Figure 2 is a method for preparing nanoparticles.

3.1.3. Characterization of Nanomaterials. To explore the mysteries of the nano-world, the structure and properties of nanoparticles must be characterized. The characterization of nanomaterials is the modern analysis and detection technology and related theoretical knowledge about particle composition, structure, morphology, etc. Usually, we use Inductively Coupled Plasma Emission Spectroscopy (ICP-AES), Scanning Electron Microscopy (SEM), Transmission

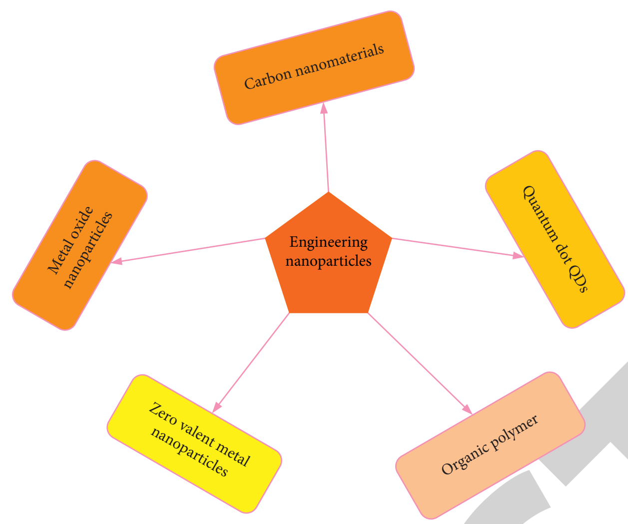


Figure 1: Schematic diagram of nanoparticle classification.

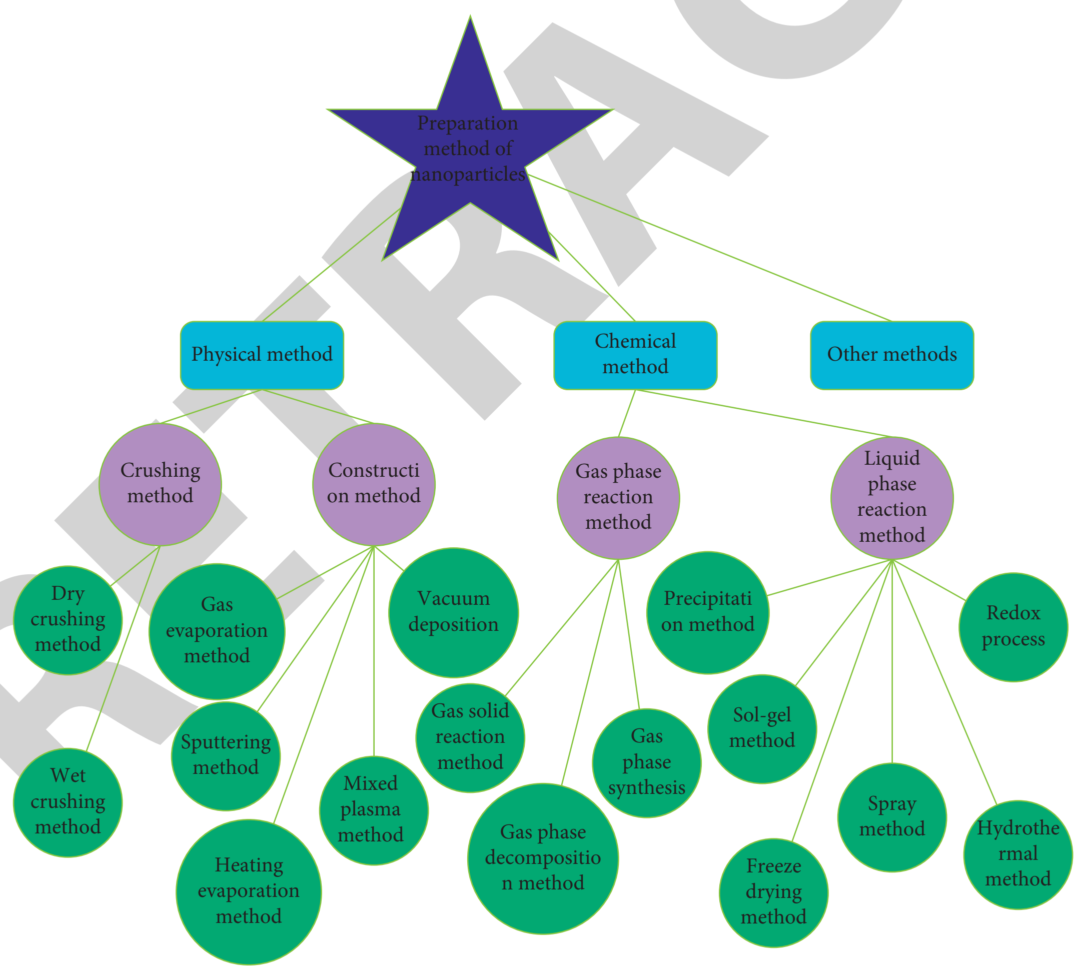


Figure 2: Nanoparticle preparation method.

Electron Microscopy (TEM), Atomic force microscopy (AFM), X-ray diffraction (XRD), and X-ray photoelectron spectroscopy (XPS), etc., to obtain the composition, particle size, morphology, structure, and interface of nanoparticles to characterize the material. The average particle size, particle size distribution, composition, and interface of nanomaterials all affect their physicochemical properties. Figure 3 shows the commonly used characterization methods for nanomaterials [16].

3.1.4. Effects of Nanomaterials on the Growth of Plant Seedlings. Most studies have shown that nanomaterials can inhibit the growth of plant seedlings. Some scholars have studied the effect of nano-Pt on wheat and found that nano-Pt can reduce the elongation and stretching of leaves, resulting in uneven growth of leaves [17, 18]. There are also studies showing that nano-Cu can inhibit the growth of mung beans and wheat. At the same time, nano-Cu was also found to be able to pass through the cell membranes of mung bean and wheat roots and aggregate in the cells. A few studies have shown that nanomaterials are beneficial to plant growth. Carbon nanotubes can promote the germination of tomato seeds, as well as the fresh weight and stem length of tomato seedlings [19, 20]. Anatase nano-TiO2 can promote the growth of spinach by promoting the absorption and transformation of nitrogen salts by spinach. Therefore, different nanomaterials have different plant effects on different plants [21].

3.2. Nanoparticles

3.2.1. The Meaning of Nanoparticles. Nanoparticles can be used as embedded delivery vehicles for active substances and as stabilizers at two-phase interfaces. It is prepared from natural source macromolecular materials. Nanoparticles have gradually become a research hotspot in the field of food science. Nanoparticles, as the name suggests, refer to solid particles with a particle size between 1 and 1000 nm. Compared with micron-sized particles, which are difficult to disperse and suspend in the bulk phase due to gravity, the smaller particle size of nanoparticles endows them with good bulk stability. In the test of the intestinal model of nanoparticles, it was found that the absorption rate of particles around 100 nm in the intestine is 15–250 times higher than that of particles of 1–10 μm. This is because its nanoscale size can penetrate the submucosal layer for better intestinal absorption. The micron-sized particles can only stay in the mucous *epidermis*. Therefore, nanoparticles have obvious advantages in improving the stability and bioavailability of bioactive components [22, 23].

There are two main types of nanoparticles: inorganic and organic. Inorganic nanoparticles are mainly nanoparticles prepared from inorganic materials, mainly including SiO_2、$CaCO_3$、Fe_3O_4、Al_2O_3, clay and montmorillonite. Organic nanoparticles are generally derived from biological macromolecules such as proteins (milk protein, soy protein and zein, etc.), carbohydrates (starch and cellulose, etc.), oils or fats, and other organic substances such as flavonoids and spores. Inorganic nanoparticles cannot be digested and absorbed by the human body, and their safety in the food system cannot be guaranteed, which limits their application in the food system. Therefore, natural sources of biological macromolecules such as proteins, lipids, and carbohydrates are increasingly favored by researchers due to their relative safety, especially natural macromolecules derived from proteins.

3.2.2. Preparation Method of Nanoparticles. There are various methods for preparing nanoparticles. There are two types: "top-down" and "bottom-up". The "top-down" approach mainly uses macro-scale solid materials as raw materials. It uses certain means (such as pulverization, grinding, X-rays, high pressure homogenization or ultrasound) to reduce its lateral size to obtain nanoscale small particles. This method has the characteristics of long time, high energy consumption, low efficiency, and easy entry of metal debris into the product [24].

3.2.3. Stabilization of Nanoparticles at the Oil-Water Interface. At present, some inorganic nanoparticles (such as A particles) are often used to prepare Pickering emulsions. However, these particles are generally only suitable for theoretical research and chemical production due to their biosafety, and cannot be applied to the food industry. Therefore, food-grade nanoparticles prepared from natural biomolecular materials are increasingly favored by researchers. The edible nanoparticles with Pickering stabilization effect that have been found are mainly cellulose nanocrystals, modified starch particles, chitosan particles, solid liposome particles, Zein particles, whey protein particles and soy protein nanoparticles, etc. [25]. Among them, protein-based nanoparticles have obvious advantages over food-grade nanoparticles due to their excellent nutritional value and functional properties. Nanoparticles prepared from biological macromolecules (such as proteins, polysaccharides, starch) have the advantages of good biodegradability and compatibility, low cytotoxicity, effective controlled release in the body, and prolonged action time of active ingredients. It is widely used for the embedding and delivery of biologically active ingredients and poorly soluble drugs.

3.3. Metal Oxide Nanomaterials

3.3.1. Application of Metal Oxide Nanomaterials. There are many kinds of metal oxide nanomaterials with different properties and diverse functions. It is currently the most widely used nanomaterials. According to statistics, the annual production volume of titanium dioxide nanomaterials is about 3,000 tons, which are widely used in the cosmetics industry. Nano-cerium oxide has excellent optical and catalytic properties and is widely used in the fields of polishing and fuel cell energy. Fe_3O_4 has magnetic properties and is widely used in medicine, electroacoustic devices, aerospace, and other fields. In addition, some nanomaterials are even directly used in agricultural production, such as nano-silica, which is directly used in nano-fertilizers. Nano-zinc oxide is added to pesticides. Therefore, its toxicity research has received great attention.

Figure 3: Nanomaterials characterization techniques.

3.3.2. Phytotoxicity of Metal Oxide Nanomaterials. As can be seen from Table 1, most of the metal oxide nanomaterials are harmful to the growth of plants. Current research on the phytotoxicity of metal oxide nanomaterials usually focuses on one or two nanomaterials. And the research methods are diverse and lack of comparison. Therefore, it is necessary to use the same method to evaluate the phytotoxicity of a class of nanomaterials [26]. In addition, it can also be seen from the figure that the current research on the effects of metal oxide nanomaterials on phytotoxicity mostly focuses on phenotypic changes. Physiological and molecular mechanisms have been poorly studied.

3.4. Modeling Principle of Rice Insect Situation Prediction Based on BP Neural Network

3.4.1. Introduction of Artificial Neural Network

(1) Development of Neural Networks. The historical summary of neural network development can be divided into four stages, namely the enlightenment period from 1891 to 1968, the low tide period from 1968 to 1981, the revival period from 1981 to 1985, and the occurrence period of the new era from 1985 to the present.

(2) Classification of neural networks. Neural networks have experienced several periods of development and continuous improvement. At present, there are more than 40 kinds of neural network models. Among them, the more typical neural networks are Adaptive Resonance Theory networks, back propagation neural networks (BP neural network), cellular neural networks, multilayer forward propagation networks (BOP network), and so on. Based on the connection mode of the neural network, the neural network can be divided into two categories:.

(i) Forward network

The forward network model is shown in Figure 4. The neurons in each layer come from the input of the previous neuron. Each neuron is independent of each other without any feedback relationship [27]. Neurons are arranged hierarchically according to the input layer, hidden layer, and output layer. The input layer under the regularity of each layer is finally output in the output layer.

(ii) Feedback network

As shown in Figure 5, in the feedback network structure, there is feedback between the input layer and the output layer for the association. But it takes a while to reach a plateau.

(iii) Self-organizing network

As shown in Figure 6. Among many self-organizing networks, Kohonen network is the most typical one [28]. It believes that when the outside world is input to the network, the network will be

TABLE 1: Phytotoxic effects of different metal oxide nanomaterials.

nanometer material	Tested plant	Toxic effect
CuO	Rice	CuO can inhibit the growth of rice seedlings
CuO、ZnO	Wheat	Both CuO and ZnO can inhibit the growth of wheat roots, but there are great differences in root morphology, and both can produce genotoxicity to early wheat
CuO、ZnO	Cucumber	CuO and ZnO can inhibit the growth of cucumber
Fe_3O_4	Pumpkin	Fe_3O_4can be absorbed by pumpkin and transported to the aboveground part
CeO_2	Corn	CeO_2can not affect the phenotypic growth of maize, but can cause a series of physiological indexes of maize to change, and the contents of APX, cat, and HSP70 increase
TiO_2	Spinach	0.25%TiO_2can enhance the light cooperation of spinach Use it to promote its growth
TiO_2	Corn, peas	TiO_2can inhibit the germination of maize seeds in the first 24 hours and can significantly inhibit the elongation of maize roots under the treatment of 4‰ concentration
TiO_2	Corn	200 mg/kg TiO_2did not affect the growth of maize
TiO_2	Onion, tobacco	TiO_2can cause DNA damage in onion and tobacco
SiO_2、TiO_2	Soybean	SiO 2 and TiO 2 can promote the germination and growth of soybean, improve its root activity, antioxidant capacity, and stress resistance

divided into different regions with different response characteristics. Each area responds in the best possible way, resulting in a topological organizational diagram. At the same time, because this is a kind of nonlinear adaptation, it is also called self-organizing network.

3.4.2. Feedforward Calculation of BP Network. There are N practice samples. In the training phase of the training network, it first selects the input/output mode of a certain sample p to operate on $\{A_p\}$ and $\{T_p\}$ and on the BP network. The input of the neuron of the uth hidden layer under the action of p is as follows:

$$\mathrm{net}_u^p = \sum_{v=1}^{R} K_{uv} H_v^p - \alpha_u = \sum_{v=1}^{R} K_{uv} A_v^p - \partial \,(u = 1, 2, \cdots, n). \tag{1}$$

In the formula, A_v^p and H_v^p are the output and input of the input node v when the sample p acts, respectively. Relative to the input node, the difference between the two is not much. K_{uv} is the corresponding value. ∂_u is the threshold value, which is located in the hidden layer. R is the number of nodes, that is, the number of input layers. The output of the uth monomer in the hidden layer is as follows:

$$H_v^p = g\left(net_u^p\right)(u = 1, 2, \cdots, n). \tag{2}$$

Nonlinear action function for neurons—activation function

$$g(A) = \frac{1}{1 + \exp\left[-(A + \partial_1)/\partial_0\right]}. \tag{3}$$

The d and y in the hidden layer $g(\mathrm{net}_u^p)$ (activation function) are

$$g\left(net_u^p\right) = g\left(net_u^p\right)\left[1 - g\left(net_u^p\right)\right] = H_v^p\left(1 - H_v^p\right)(u = 1, 2, \cdots, n). \tag{4}$$

The output H_v^p of the uth monomer in the hidden layer will be used as the input to the next monomer (in the output layer). The total input is as follows:

$$\mathrm{net}_s^p = \sum_{u=1}^{n} K_{su} H_u^p - \partial_s \,(s = 1, 2, \cdots, F). \tag{5}$$

The real output of the next monomer obtained by the output layer is as follows:

$$H_s^p = g\left(net_s^p\right)(s = 1, 2, \cdots, F). \tag{6}$$

The differential function of the activation function $g(net_s^k)$ of the output layer is as follows:

$$g\left(net_s^p\right) = g\left(net_s^p\right)\left[1 - g\left(net_s^p\right)\right] = H_s^p\left(1 - H_s^p\right)(s = 1, 2, \cdots, F). \tag{7}$$

Adjustment rules---BP network weight coefficient.

The output corresponding to the input mode of a single different sample p is as follows:

$$T_p = \frac{1}{2} \sum_{s=1}^{F} \left(C_s^p - H_s^p\right)^2. \tag{8}$$

Summing the errors of all samples, the total error function is given by:

$$T = \sum_{p=1}^{M} T_p = \frac{1}{2} \sum_{p=1}^{M} \sum_{s=1}^{F} \left(C_s^p - H_s^p\right)^2. \tag{9}$$

Adjustment of weight coefficients—output layer.

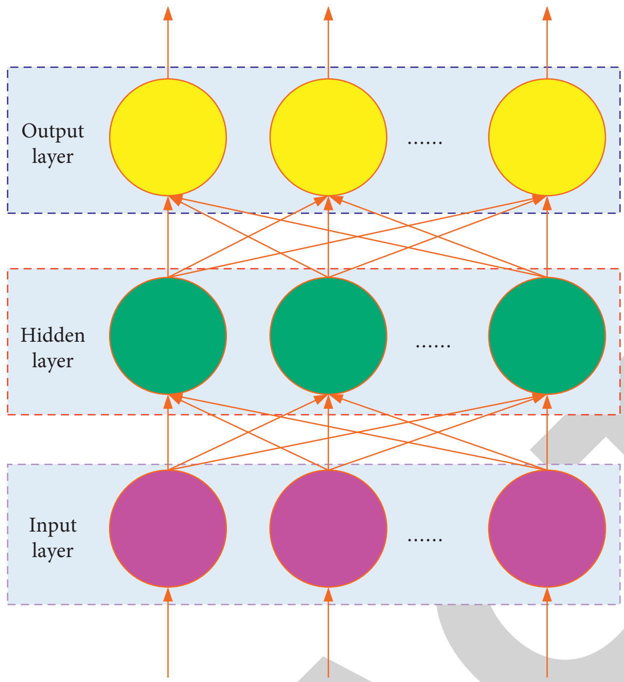


FIGURE 4: Forward neural network model.

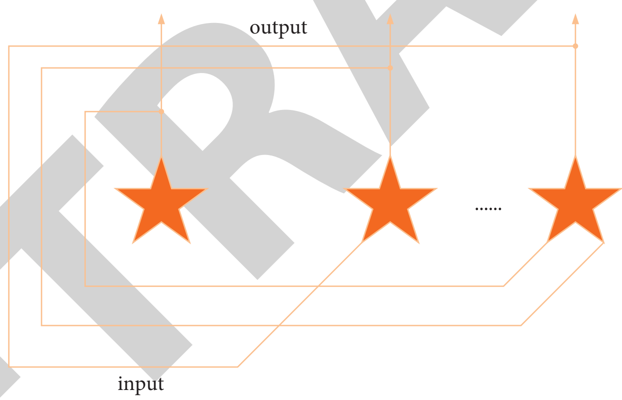


FIGURE 5: Feedback neural network.

In the principle of the gradient method, the correction formula (coefficient output layer of each neuron) is as follows:

$$\begin{aligned}\Delta K_{\mathrm{su}} &= -\eta \frac{\partial T_p}{\partial K_{su}} = -\eta \frac{\partial T_p}{\partial net_s^p} \bullet \frac{\partial net_s^p}{\partial K_{su}} \\ &= -\eta \frac{\partial T_p}{\partial net_s^p} \bullet \frac{\partial}{\partial K_{su}} \left(\sum_{u=1}^{n} K_{su} H_u^p - \alpha_s \right) = -\eta \frac{\partial T_p}{\partial net_s^p} \bullet H_u^p.\end{aligned} \tag{10}$$

In formula 10, η is the learning efficiency and $\eta > 0$. Definition

$$\begin{aligned}\delta_s^p &= -\frac{\partial T_p}{\partial net_s^p} = -\frac{\partial T_p}{\partial H_s^p} \bullet \frac{\partial H_s^p}{\partial net_s^p} = (C_s^p - H_s^p) \bullet g\left(net_s^p\right) \\ &= (C_s^p - H_s^p) H_s^p \left(1 - H_s^p\right).\end{aligned} \tag{11}$$

Therefore, the output layer correction formula is as follows:

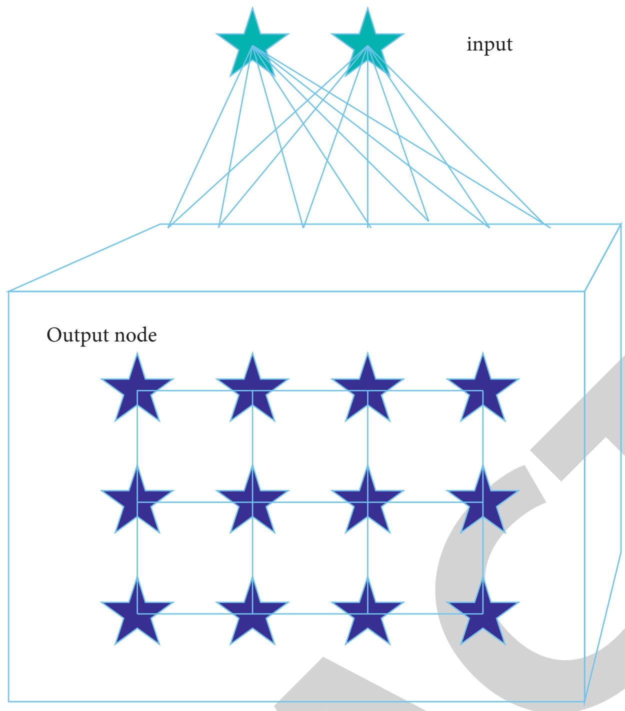


Figure 6: Self-organizing neural network.

$$\Delta K_{su} = \eta \delta_s^p H_u^p = \eta H_s^p (1 - H_s^p)(C_s^p - H_s^p) H_u^p. \tag{12}$$

Adjustment of weight coefficients—hidden layer.

According to the gradient method, the correction formula is as follows:

$$\begin{aligned}\Delta K_{\mathrm{su}} &= -\eta \frac{\partial T_p}{\partial K_{su}} = -\eta \frac{\partial T_p}{\partial net_s^p} \bullet \frac{\partial net_s^p}{\partial K_{su}} \\ &= -\eta \frac{\partial T_p}{\partial net_s^p} \bullet \frac{\partial}{\partial K_{su}} \left(\sum_{u=1}^{n} K_{su} H_u^p - \alpha_s \right) = -\eta \frac{\partial T_p}{\partial net_s^p} \bullet H_u^p \\ &= \eta \delta_{\mathrm{u}}^p H_v^p.\end{aligned} \tag{13}$$

In the formula, η is the learning efficiency, and $\eta > 0$.

$$\delta_{\mathrm{u}}^p = -\frac{\partial T_p}{\partial net_u^p} = -\frac{\partial T_p}{\partial H_u^p} \bullet \frac{\partial H_u^p}{\partial net_s^p} = -\frac{\partial T_p}{\partial H_u^p} \bullet g(net_u^p) = -\frac{\partial T_p}{\partial H_u^p} H_u^p (1 - H_s^p). \tag{14}$$

The output units of the hidden layer are connected. A single change will cause changes in all related units, that is

$$-\frac{\partial T_p}{\partial H_u^p} = \sum_{s=1}^{F} \delta_s^p K_{su}. \tag{15}$$

Therefore, the correction formula is as follows:

$$\Delta K = \eta H_u^p (1 - H_u^p) \left(\sum_{s=1}^{F} \delta_s^p K_{su} \right) H_v^p. \tag{16}$$

In the formula, H_u^p is the output of the implicit node u when the sample p acts. H_v^p is the input of input node j, that is, the output of input node v when sample p acts [29].

When the sample p acts, the improved formula is as follows:

$$K_{uv}(s+1) = K_{uv}(s) + \eta \delta_u^p H_v^p. \tag{17}$$

When the sample p acts, the improved formula of the k weighting coefficient of different neurons in the output layer is as follows:

$$K_{su}(s+1) = K_{su}(s) + \eta \delta_s^p H_u^p. \tag{18}$$

It can be known from formula 17 and formula 18 that for a certain sample p of any given point, the requirement can be achieved by maintaining the weighting coefficient of the network.

$$\begin{aligned} K_{su}(s+1) &= K_{su}(s) + \eta \sum_{p=1}^{M} \delta_s^p H_u^p, \\ K_{su}(s+1) &= K_{su}(s) + \eta \sum_{p=1}^{M} \delta_{\mathrm{u}}^p H_{\mathrm{v}}^p. \end{aligned} \tag{19}$$

In the formula, δ_{s}^p and δ_{u}^p are calculated in the same way as above, namely

$$\begin{aligned} \delta_{\mathrm{s}}^p &= H_s^p (1 - H_s^p)(C_s^p - H_s^p), \\ \delta_{\mathrm{u}}^p &= H_u^p (1 - H_u^p) \left(\sum_{s=1}^{F} \delta_s^p \bullet K_{su} \right). \end{aligned} \tag{20}$$

When there are many samples, it can be ensured that the development of the total error F in the decreasing direction is completed by batch correction. Online learning converges slower than batch learning [30].

3.5. Judgment of the Advantages and Disadvantages of Rice Growth Stage Based on Convolutional Neural Network. Convolutional Neural Network (CNN for short) is mainly developed based on artificial neural networks. The difference between the weight-sharing network structure and the biological neural network is that it reduces the parameter scale and the complexity of the network model. The network performs particularly well when images are used as input. For convolutional neural networks, image data can be fed directly into the model. Unlike traditional neural networks, it avoids the process of manually extracting image features. The structure of the convolutional neural network can adapt to the scale, position change, rotation, or deformation of the two-dimensional image. The deep convolutional neural network structure is shown in Figure 7 [31].

Convolutional Neural Networks are a basic framework for deep learning. It is a deep learning method specially designed for image classification and recognition, and it is developed by simulating the mechanism of the human brain. It evolves into deeper features by combining low-end features, avoiding explicit feature extraction, and implicitly learning from training data. Especially multi-dimensional image data can be directly used as the feature of network input. The theoretical basis of deep learning, namely convolutional neural network, is an advanced computer vision technology. Judging from the current research popularity of convolutional neural networks, this research has been applied in different fields and there is still some room for improvement in improving network performance. And it lays the foundation for the development of intelligence and automation in future field applications [32, 33].

This chapter firstly understands and learns the theoretical knowledge of convolutional neural networks, and finds that its network structure is closer to the human brain's visual system. Therefore, the convolutional neural network is more suitable for processing images. It lays a theoretical foundation and provides a theoretical basis for the subsequent discriminant analysis of images of rice growth stages based on convolutional neural networks.

4. Experiment of Metal Oxide Nanomaterials as Rice Transgenic Carriers

4.1. Particle Swarm Optimization of Rice Growth Potential Convolutional Neural Network Weight Test

4.1.1. Particle Swarm Optimization Network Weights. At present, network weight, network structure, and learning rule optimization are the three main directions of particle swarm optimization in neural network optimization. To optimize the network weights, many neural networks use the back-propagation algorithm to increase the network weights. This is a powerful algorithm with local search capabilities, so the algorithm is prone to getting stuck in local optima.

In this experiment, the particle swarm algorithm is mainly used to optimize the network weights of the convolutional neural network, rather than the back propagation algorithm. Convolutional neural networks are usually trained using the backpropagation algorithm, which is a gradient descent algorithm. The algorithm can easily get stuck in a local optimum, and the solution depends on the initial position.

4.1.2. Small Batch and Large Batch Test Results and Comparative Analysis. The particle finds the individual optimal solution P_{id} and the global optimal solution P_{gd}, and sets the solution as the particle's historical optimal solution. Then it finds out the global optimal solution of the particle and sets it as a column, and calculates the global optimal fitness value and the specific position of the optimal particle. It updates the particle's velocity and position parameters. Then, by setting the structural parameters of the convolutional neural network and the parameters of the particle swarm, the training set samples are input into the convolutional neural network model of the advantages and disadvantages of the rice growth stage optimized by the particle swarm for training. The comparison chart of the test results of small batch samples before and after optimization is shown in Figure 8(a). The training samples and test samples in a large batch of target databases are respectively input into the particle swarm optimization convolutional neural network for training. The relationship between the number of iterations and the error rate of the optimized large batch of samples in the training process is shown in Figure 8(b).

It can be seen from the comparison of the small batch test results before and after optimization in Figure 8(a) that the optimized model starts to converge before the 20th iteration. And the convergence speed is much faster than the convergence speed before optimization. At the same time, the optimized model oscillates less and is smoother, showing good stability. The unoptimized accuracy was 87.0456% on a small batch sample experiment. The accuracy of the optimized model is 93.5876%, an increase of 6.542%. Experiments show that the particle swarm optimization has good performance in the optimization of small batch samples, which pave the way for particle swarm optimization experiments in large batches.

Similarly, the large-batch optimization results perform similarly to the small-batch optimization process. As can be seen from Figure 8(b), in the comparison chart of the large-scale test results before and after optimization, the optimized model starts to converge before the 10th iteration. And the convergence speed is faster than that before optimization. Compared with the model before optimization, the vibration and instability effects are much better, and the model after optimization shows good stability. At the same time, in the large-scale sample test, the accuracy rate of the unoptimized model was 93.5936%, and the accuracy rate of the optimized model was 99.0342%, an increase of 5.4466%. Experiments show that the particle swarm optimization has high

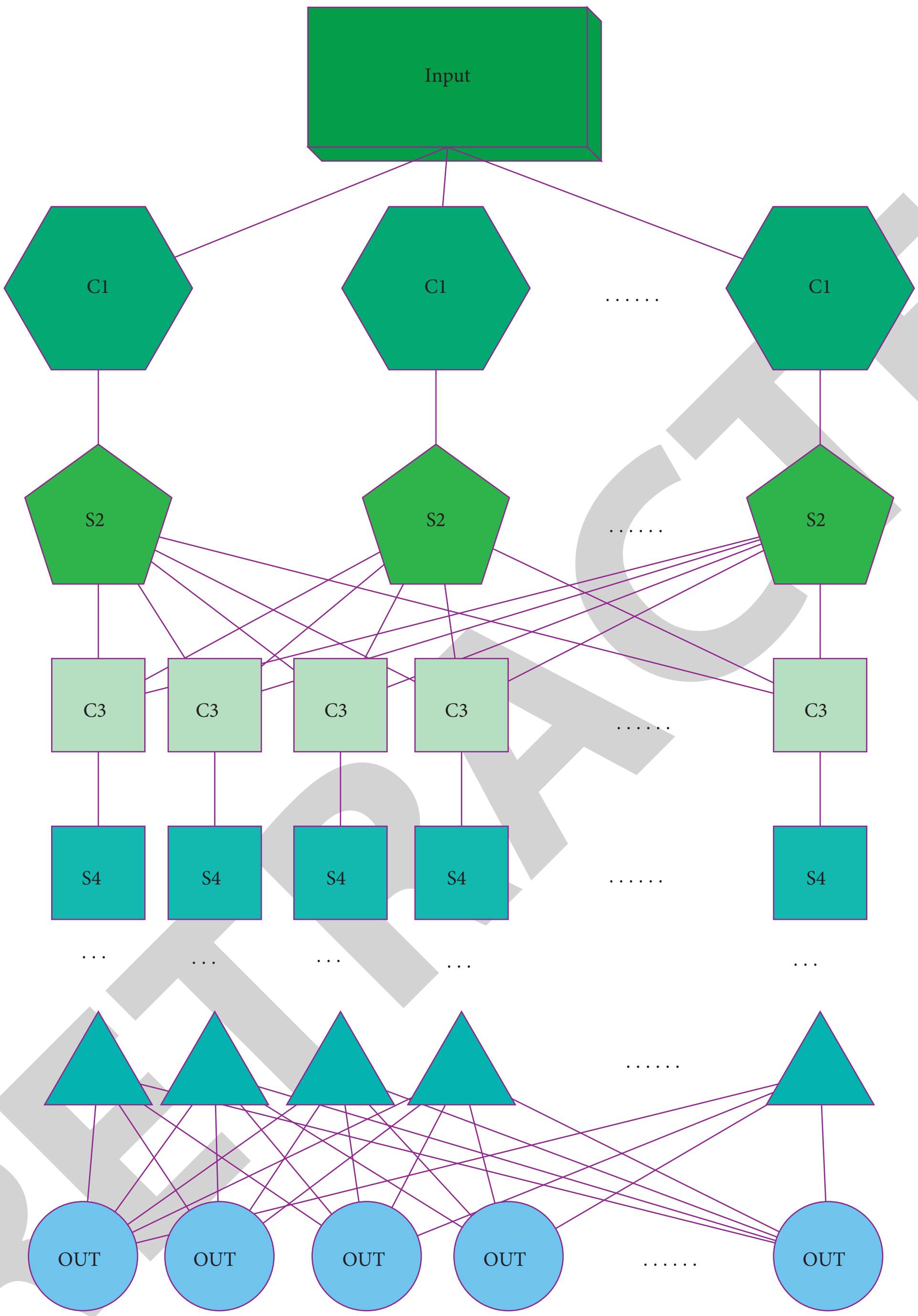
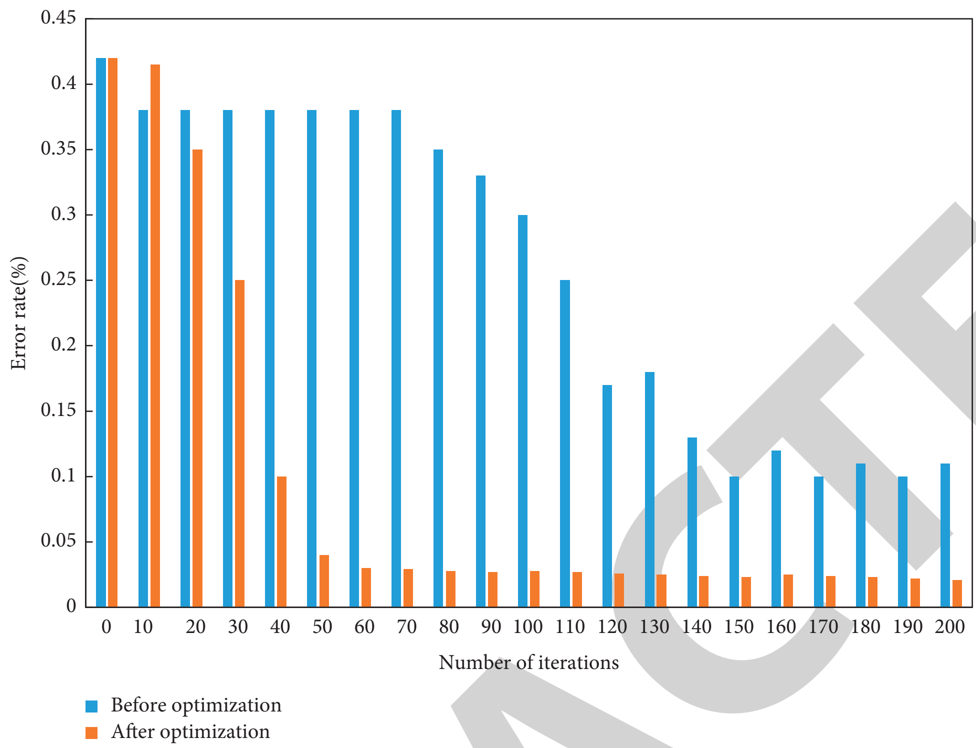


Figure 7: Deep convolutional neural network architecture.

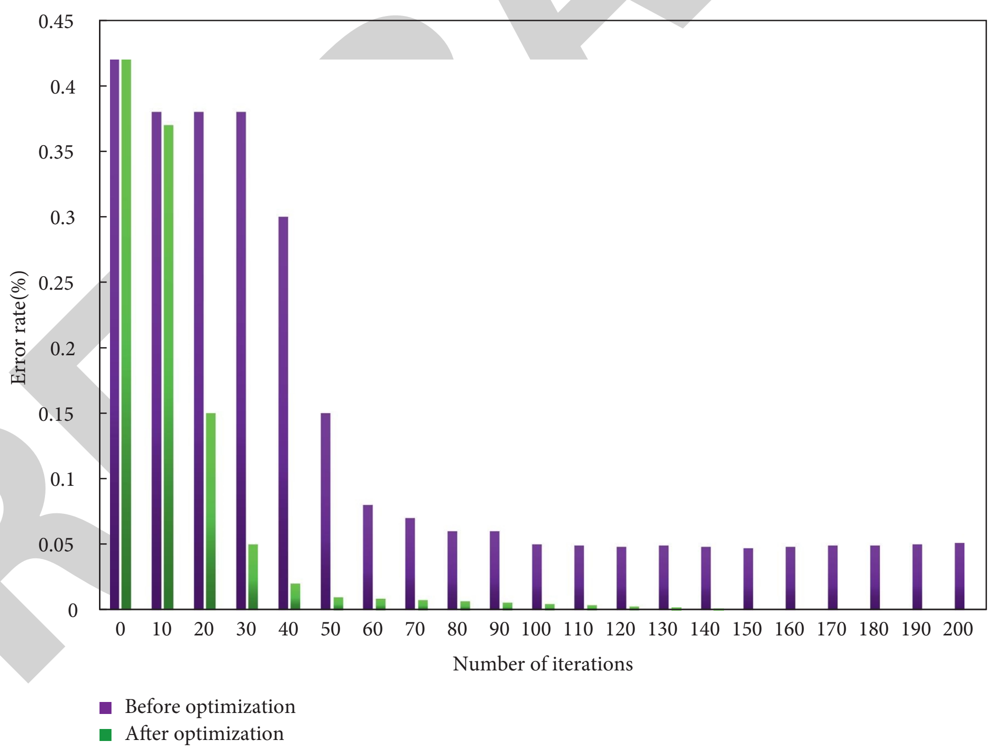
accuracy, convergence speed and model stability in the optimization of large batches of samples.

4.2. Comparison and Summary. Table 2 is a summary table of the relationship between the small batch sample test, the large batch sample test, the optimized small batch sample test, the optimized large batch sample, and the accuracy rate:

By constructing a convolutional neural network model, the accuracy rate of the advantages and disadvantages of rice growth stages of small batch samples is 87.0456%. The improved convolutional neural network model of particle swarm optimization has an accuracy rate of 93.5876% for the advantages and disadvantages of rice growth stages of small batch samples. The test was optimized to improve by 6.542%. In the same way, for the comparison before and after optimization of the large-scale sample test, it is 93.5876% before optimization, 99.0342% after optimization, and the test is improved by 5.4466% after optimization. This shows that the particle swarm algorithm greatly improves the network weights in the convolutional neural network model during training. And the optimization method is reasonable,



(a)



(b)

Figure 8: Comparison of test results of small/large batch samples before and after optimization. (a) Comparison of test results of small batch samples before and after optimization. (b) Comparison of test results of large batches of samples before and after optimization.

Table 2: Summary of test types and accuracy.

Test type	Accuracy (%)	Test type	Accuracy (%)	Percentage increase in size and batch (%)
Small batch sample test	87.0456	Mass sample test	93.5876	6.542
Optimize small batch sample test	93.5876	Optimize mass sample test	99.0342	5.4466
Percentage increase before and after optimization	6.542		5.4466	

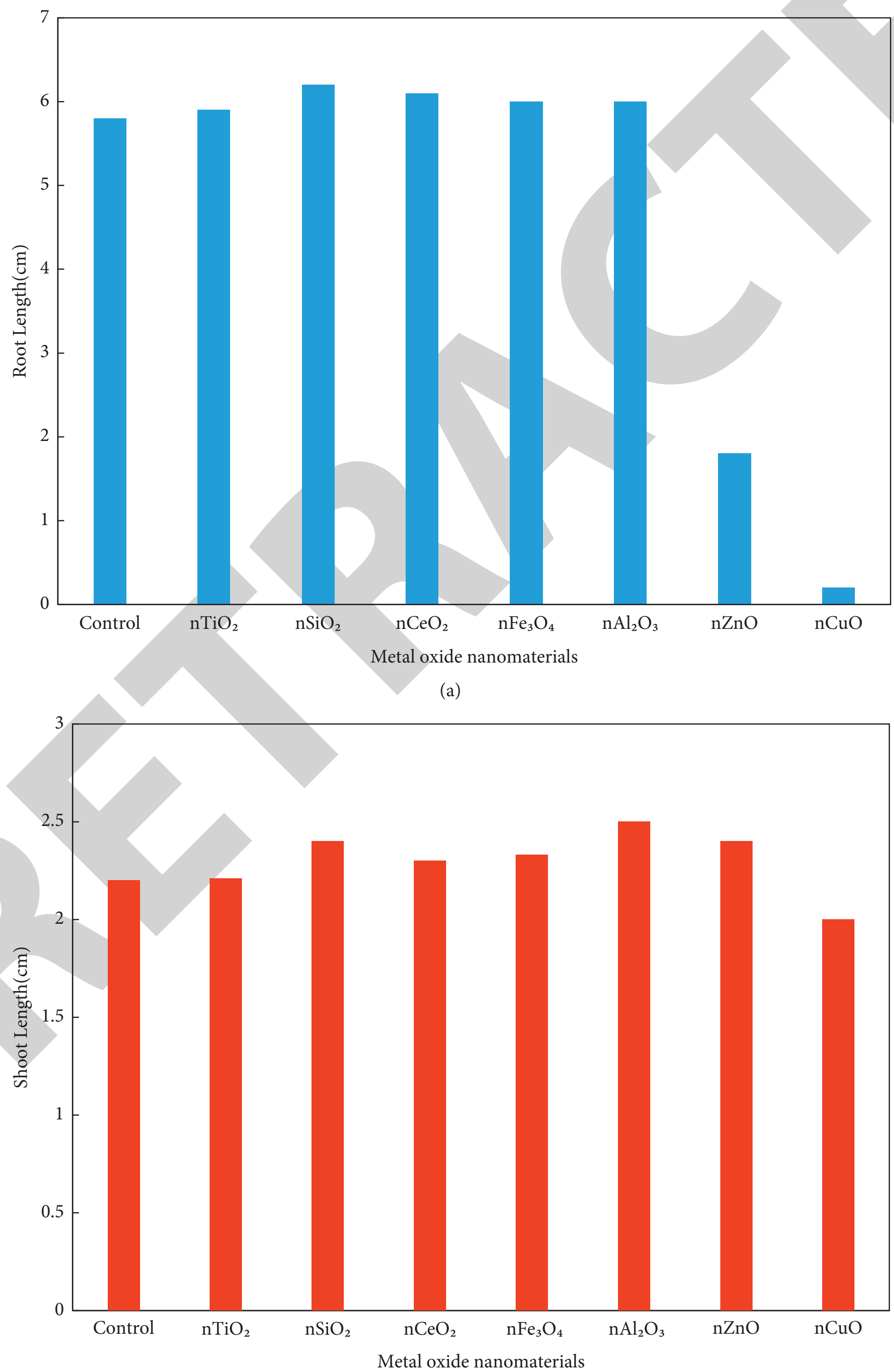


Figure 9: Effects of seven metal oxide nanomaterials on root and shoot growth in rice ((a), (b)).

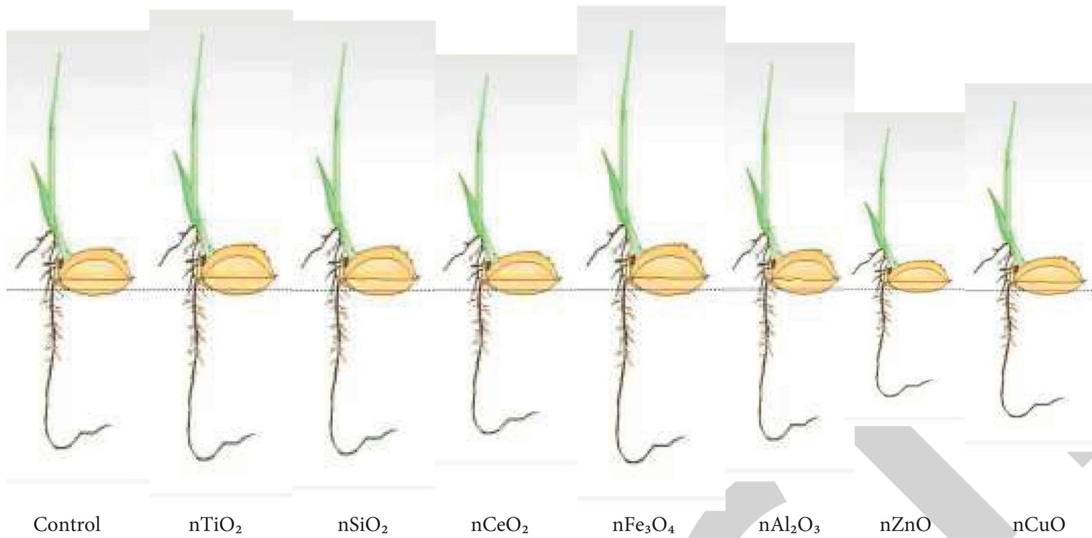


Figure 10: Comparison photos of root elongation on the 5th and 7th day of germination of rice seeds under different nanomaterial treatments.

which can improve the accuracy of the model and make the model have good usability.

It can be shown that after comparing the test results of small batch samples and large batch samples, the accuracy of the small batch sample test is 87.0456% before optimization. The accuracy of the large batch sample test is 93.5876%. The accuracy of the test is improved by 6.542%. After optimization, the accuracy of the small batch sample test is 93.5876%. The accuracy of the large batch sample test is 99.0133%. The accuracy of the test is improved by 5.4466%. The sample size of the database has a positive correlation with the recognition rate of the test results when using the convolutional neural network for deep learning. The larger the sample size of the data set, the more detailed and comprehensive the feature extraction in the machine training process, so the higher the recognition rate.

4.3. Effects of Metal Oxide Nanomaterials on Seed Germination and Root Growth of Maize and Rice. Seed germination experiments are widely used in phytotoxicity tests due to their advantages of rapidity, sensitivity and simplicity. However, the germination of seeds is susceptible to environmental influences such as soil pressure, air permeability, microorganisms. Therefore, plate germination was selected as the research method in this study to exclude the interference of these factors, and it uses the guidelines published by the United States Environmental Protection Agency as a standard for measuring whether nanomaterials are phytotoxic. It investigated the effects of 7 metal oxide nanomaterials ($nCeO_2$、nFe_3O_4、$nSiO_2$、$nTiO_2$、nAl_2O_3、$nZnO$、$nCuO$) on the germination and growth of 1 crop (rice) seeds at a concentration of 2000 mg/L. (Figure 9).

It can be seen from Figure 10 that different metal oxide nanomaterials have different effects on the growth of rice roots and shoots. Compared with the blank control, Nano CeO_2、Fe_3O_4、SiO_2、TiO_2 did not inhibit the growth of rice roots and shoots at a concentration of 2000 mg/L. Nano Al_2O_3、ZnO、CuO inhibited the growth of rice roots and shoots to varying degrees. The inhibition rates of nano-CuO and ZnO on rice root length were 97.28% and 66.75%. Alumina is less toxic and has no obvious inhibitory effect on the growth of rice roots and shoots.

Among the above seven metal oxide nanomaterials, only Al_2O_3、ZnO、CuO showed phytotoxicity, and the toxicity was $Al_2O_3 < ZnO < CuO$.

5. Discussion

To actively respond to the notice issued by the General Office of the Ministry of Agriculture of the People's Republic of China, the agricultural and rural big data practice case is studied with the image of the rice growth stage as the starting point. The growth state of rice in each period directly affects the yield and quality of rice. Therefore, the timely identification of normal rice and abnormal rice in the growth stage of rice has become the top priority of agricultural development.

Nanoparticles, as a nanomaterial, have a high surface area. They are not fully coordinated on the particle surface, thereby increasing the active centers of the surface. Nanotechnology and biotechnology are combined to produce nanobiotechnology and use nanotechnology to solve biological problems. Various sensors based on nanomaterials have been widely used in the biological field.

Regarding the optimization of the convolutional neural network model of rice growth based on particle swarm optimization, this paper constructs a convolutional neural network model of the advantages and disadvantages of rice growth stages. On this basis, this paper uses a particle swarm optimization algorithm to improve the weights in the network. The algorithm greatly improves the convergence speed and accuracy of the model during the whole network training process. It makes the model have good generalization ability and practicality, and the accuracy rate of this test is above 93.5936%.

6. Conclusions

This experiment investigated the effect of metal oxide nanomaterials on rice seed germination and growth. It was found that the seven metal oxide nanomaterials exhibited different toxic effects on rice. Among them, nCuO is the most phytotoxic. At a low concentration (25 mg/L), it showed a significant inhibitory effect, and the concentration-response curve showed an "*L*" shape. The phytotoxicity of nZnO is second, and it has no inhibitory effect at low concentrations. As the concentration increases, the toxicity effect is more significant, and the concentration-response curve shows an "*S*" shape. The toxicity of Al_2O_3 is the weakest, and it only has an inhibitory effect on the growth of maize at 2000 mg/L. $nCeO_2$、nFe_3O_4、nSiO_2、nTiO_2 did not show phytotoxicity. The toxicity of metal oxide nanomaterials comes from the nanomaterials themselves and is related to the species of plants tested, exposure concentration, size and other factors. The ions they release in aqueous solutions are not sufficient to affect plant growth.

Data Availability

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

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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