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Manufacturing High-Performance Machine Elements for Nanomaterials Using Adaptive Convolutional Neural Networks

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Abstract: With the continuous advancement of science and technology, nanomaterials have made great progress in the manufacturing of high-performance machine elements. With the development of mechanical engineering, the reliability and safety requirements for mechanical components are constantly increasing. Consequently, the application of nanomaterials in this field presents significant challenges. To enhance the reliability and safety of high-performance machine elements, this article analyzes the requirements and manufacturing principles of nanomaterials and such components. It then applies an adaptive Convolutional Neural Network (CNN) to apply nanomaterials to manufacture a high-performance machine element. This article tested the hardness, wear, and fault detection of machine elements, and compared them with two traditional manufacturing methods. The results showed that in terms of fault detection, the average failure rate of high-performance machine elements of ultra-precision reference gears manufactured through adaptive CNN application of nanomaterials was only 0.79%. From the test results, it can be seen that using an adaptive CNN to manufacture high-performance machine elements from nanomaterials has certain feasibility, which can effectively ensure the health status of the parts and promote the healthy development of high-performance machine element manufacturing.

Keywords: High-performance machine element; nanomaterial; adaptive convolutional neural network; part status detection and diagnosis.

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1. Introduction

With technological progress, nanomaterials have made significant achievements in practical applications. In high-performance mechanical manufacturing, their use in key machine elements and part infiltration/coating improves mechanical performance and usage effects. However, as modern machinery becomes more complex with closer part coupling, a single part failure can disrupt the entire equipment. Thus, intelligent fault diagnosis algorithms for online monitoring are crucial for safe operation. With the maturity of deep learning, adaptive Convolutional Neural Network (CNN) algorithms, known for their high accuracy and efficiency, have been widely adopted. Applying these algorithms to nanomaterial-based high-performance machine elements can effectively identify part operating status, enhancing reliability and safety.

As nanotechnology becomes more mature, its application in high-performance mechanical components has also attracted increasing attention from many scholars (Kang et al., 2023; Raduwan et al., 2022). Roh et al. (2024) outlined the nanomaterials used in sensor systems and their components, introduced various methods for manufacturing nanomaterials, and emphasized that nanomaterials used as sensing materials can detect various external environments with high sensitivity and wide detection range, and proposed future research directions for their development as next-generation wireless sensor systems. Saleh et al. (2023) explored the integration of nanostructures and electrochemical systems in economic significance and future applications, outlined the importance of nanomaterials in the development of cost-effective electrochemical energy storage and conversion devices, and emphasized that nanomaterials provide valuable resources for the development of electrochemical devices. Gu et al. (2021) established a constitutive model using nano carbon powder materials as thermal mechanical fillers to endow shape memory polymers with conductivity, and incorporated variable humidity into the framework of the thermal mechanical modeling method to reveal the effect of humidity on thermal viscoelasticity. The effectiveness of the proposed nanomaterial in the wet thermal mechanical constitutive model was confirmed by comparing the model results with uniaxial deformation test data in the literature. Al-Juboori et al. (2019) used finite element analysis software to simulate the effect of nanocoating on mechanical properties. He applied titanium and nickel nanocoating on thin aluminum-walled spherical vessels and compared the results before and after the coating. His results showed that the mechanical properties of thin-walled spherical vessels were significantly improved. Wu et al. (2020) introduced the influence of the selection, production process, grain size, and grain boundary structure of nanoparticles on the mechanical properties of nanomaterials, as well as their applications in medical devices and electronic devices. He believed that nanomaterials have a wider application prospect in future mechanical parts due to their small volume, surface effects, and quantum tunneling effects. Wen et al. (2020) believed that nanomaterials have excellent conductivity, and integration with flexible materials can improve the conductivity of flexible sensor mechanical parts. He reviewed the latest literature on flexible materials and nanomaterials, providing key challenges and opportunities for the future application of nanomaterials in high-performance machine element manufacturing. At present, nanomaterials have made good progress in the manufacturing of high-performance machine elements. However, there are two key gaps in existing research. First, most studies use fixed structure deep learning models, which fail to adaptively adjust the network structure according to the dynamic characteristics of the manufacturing process, resulting in limited model generalization ability. Second, the manufacturing process of nanomaterials involves multi-source heterogeneous data such as process parameters, performance indicators, and image information, and existing methods lack a unified characterization and fusion mechanism for these data. This article proposes an adaptive CNN that combines a dynamic expansion mechanism and an attention module to address the aforementioned gaps. It uses Gram Angular Summation Field (GASF) to encode multi-source data into image input, aiming to improve the online monitoring accuracy and component performance prediction ability of the nanomaterial manufacturing process.

The development of science and technology has provided more possibilities for improving the application of nanomaterials in the manufacturing of high-performance mechanical parts (Konstantopoulos et al., 2022; Xie et al., 2023). Ghandehari et al. (2024) used a physics-guided artificial neural network to optimize the design of nanomaterial manufacturing parameters and predicted the filament diameter based on these parameters, combining the basic physical principles of the printing process with experimental data. The results showed that the quality of printed filaments can be classified with an accuracy of 90.44% using the XGBoost classifier. Zhang et al. (2022) proposed a semantic segmentation technology based on deep learning to accurately identify and segment atomic layers in two-dimensional nanomaterials, and applied it to the layer identification and segmentation of graphene and molybdenum disulfide. The results showed that the accuracy of the proposed model was 99.03%, the kappa coefficient was 95.72%, the dice coefficient was 96.97%, and the average cross-merging rate was 94.18%. Francis et al. (2020) discussed the effects of adding nano clay during the pre-treatment, on-site, and post-treatment stages of additive mechanical manufacturing processes, and found that nano particles interact with polymers in different ways, resulting in different structures, morphologies, and microstructures of nano composites. This method can be used to improve material properties for additive manufacturing parts. Subramanian et al. (2021) used nanostructured discrete colloidal silica as an additive to prepare a machine element for digital light projection 3D (three-dimensional) printing. Through experiments, it was found that incorporating nano silica materials into mechanical manufacturing increased the hardness and tensile strength of the parts by 58% and 141%, respectively, providing effective guidance for enhancing the performance of machine elements. With the assistance of science and technology, the application of nanomaterials in the manufacturing of high-performance machine elements has further developed, but most studies have not combined practical problems in the manufacturing process to provide more effective guidance for improving the reliability and safety of high-performance machine elements.

2. Literature Review

2.1. Manufacturing High-Performance Machine Element for Nanomaterials

Nanomaterials refer to ultrafine grains with a nano scale in the microstructure (Gajanan et al., 2018). Its particle size is larger than atomic clusters and smaller than ordinary particles, with a volume ranging from approximately 1 nanometer to 100 nanometers. It mainly consists of two roughly identical volume fractions. One is particles with a particle size of tens of nanometers, and the other is the interface between particles (Bora et al., 2019). Nanomaterials are materials that have at least one dimension within the material boundary scale range of 1 nanometer to 100 nanometers in three-dimensional space or are constructed based on them. Their application forms can be divided into four types: nanoparticles, nanosolids, nanosystem assemblies, and nanocoatings (Bratovcic et al., 2019).

Requirements for high performance machine elements are explained below:

First, consider load and stress conditions in actual use. High-performance machine elements require material selection based on load magnitude and stress. If external forces remain constant, focus on enhancing material brittleness. If loads vary significantly, prioritize impact and vibration resistance.

Second, consider the working environment. For elements exposed to humidity, corrosion and rust resistance are crucial. If temperature limits are strict, consider the linear elastic coefficient and variable temperature stress during temperature changes. In abrasive environments, improve surface hardness to enhance wear resistance and extend service life (Mahmud et al., 2020).

Third, consider part size and weight. Material type, manufacturing method, and strength-to-weight ratio are closely related to these factors. Select materials with high strength-to-weight ratios to reduce part weight.

Currently, nanomaterials are widely used in high-performance machine element manufacturing. Applying nanomaterials to key components improves mechanical, physical, and chemical properties, enhancing effectiveness and lifespan. They also fully utilize elements practical characteristics, such as optoelectronic performance, in micro-machines like switches, speakers, and motors. However, effective safety detection and diagnosis during manufacturing remain lacking.

2.2. Adaptive CNN

With the increasing application of nanomaterials in high-performance mechanical components, the impact of their manufacturing process on the final performance has become increasingly significant. Due to the structural complexity and multi-parameter coupling effects at the nano scale, traditional empirical modeling and physical simulation methods have great limitations in predicting material properties and are difficult to meet the needs of high-precision manufacturing. In recent years, deep learning technology, especially CNN, has demonstrated powerful modeling capabilities in image recognition and feature extraction. However, standard CNNs still have certain limitations when processing nanomaterial images with multi-scale structures and local key areas. Therefore, this paper proposes a two-stage adaptive convolutional neural network (ACNN) framework, which adopts a dynamic expansion mechanism based on convergence rate to achieve network structure adaptation in the training stage, and achieves feature adaptation through integrated channel attention and spatial attention modules in the inference stage.

As the number of neurons increases, the performance of CNN would be enhanced, but the complexity of their operations would also increase (Cong et al., 2019). In the detection of the state of a high-performance machine element, blindly expanding the scale of the network would consume a large amount of training time, and with the increase of network layers, the improvement of its performance is not directly proportional to the increase in computational load. This would cause the accuracy of state recognition of the machine element to occasionally increase and sometimes decrease, presenting instability. Therefore, starting from the actual needs of manufacturing high-performance machine elements using nanomaterials, based on the characteristics of the training data itself, the overall and local adaptive expansion of the network can be combined. Through the overall and local adaptive expansion of the network, the depth of the network is improved, and gradually deepens with the expansion of the network structure. The formation of data-driven ACNN is the focus of improving the performance of algorithmic networks (Wu et al., 2019).

2.2.1. Dynamic Expansion Mechanism during Training Stage

In high-performance mechanical component state detection, blindly expanding the network size will consume a lot of training time, and as the number of network layers increases, the performance improvement is not directly proportional to the increase in computational load. Therefore, based on the practical demand for manufacturing high-performance mechanical components using nanomaterials, this paper proposes a global and local adaptive expansion strategy controlled by convergence rate.

In the manufacturing process of a high-performance machine element, the initial model only consists of a single branch network composed of two convolutional layers (c_1, c_2), two pooling layers (p_1, p_2), and one fully connected layer. When using nanomaterials for machine element manufacturing, this algorithm uses the backpropagation algorithm to learn the state data of the machine element and determines the optimization degree of the current network based on the convergence rate. The convergence rate is expressed in Eq. (1).

$$E_{ie} - E_{ca} \geq R \tag{1}$$

The calculation formula for the current system's true average error E_{ca} is shown in Eq. (2).

$$E_{ca} = \|B - B_s\|^2 = \frac{\sum_{j=1}^{N}\sum_{i=1}^{m}\left(B_i^j - B_s^j\right)^2}{N} \tag{2}$$

The meanings represented by the variables in Eqs. (1) and (2) are shown in Table 1.

Table 1. Meaning of formula variables

Sequence	Parameter	Meaning
1	E_{ie}	Expected average error of initial system
2	E_{ca}	Current system true average error
3	R	Expected threshold for convergence speed, set to 0.1
4	N	Total number of training samples
5	m	Categorical data
6	B_i^j	The output of the i-th neuron corresponding to the j -th training sample
7	B, B_s	0, 1 binary matrix of $m \times N$

Eq. (1) is used to determine the necessity of global adaptive expansion. If the formula is valid, it means that the initial network can reach a convergence state. Under this condition, the network needs to continue training to make its overall error close to the expected level, so that the network can reach its optimal state without the need to add new branches and feature maps. If the formula is not valid, it needs to be globally adaptively expanded (Benchao et al., 2020; Gao et al., 2021). This dynamic extension mechanism is only activated during the model training phase to optimize the network structure.

2.2.2. Attention Enhancement Architecture in Reasoning Stage

When the network achieves adaptive expansion as a whole, a new branch o would be expanded based on the initial network ω structure, and before the new branch expansion, the convolution, pooling, and other parameters of the initial network ω as well as the output result f_w of the output layer will be stored. The added new branch structure is similar to the existing branch structure and generates a new output result f_o at the network output layer. Among them, the output result of the output layer activation function is expressed in Eq. (3).

$$f = g(f_w + \omega_o f_o) \tag{3}$$

Among them, f_w and f_o are also $m \times 1$ binary vectors. ω_o is an m-dimensional column vector and also the output weight of branch o. In the training of the network, the structure and related parameters of the initial network remain unchanged. The backpropagation algorithm is used to update only the weights corresponding to the initial network ω. When the overall average error value of the network approaches the expected level, global extended learning can be carried out.

Although the average error value after global expansion is smaller than the expected level, there is still a possibility of not achieving optimal recognition results. At this point, the obtained sample data can be segmented and combined into different training and testing sets. The training set can be used to train the model, and the testing set can be used to evaluate the effectiveness of the model's prediction and diagnosis (Guo et al., 2022). Then, by fusing existing branches, a new branch is constructed to achieve local expansion of the network structure, thereby improving the recognition accuracy of the algorithm.

The weights and outputs contained in the extended global model are stored before the adaptive local extended network structure (Xu et al., 2020). When training local branches, the feature maps of the pooling layer in the extended model are used as inputs to fuse the features as shown in Eq. (4).

$$C_l = g(y_w * k_w + y_o * k_o) \tag{4}$$

Among them, C_l is the feature map of the local branch. y_w and y_o are feature maps of global branches. k_w and k_o are convolutional kernels, and the fusion method uses simple summation operations. Let y_k be the output of the model at the k-th layer, and o_i represent the branch of the i-th node.

During the training process of adaptive convolutional neural networks, the overall structure of each branch remains unchanged, and a backpropagation method is used to update only the local branch weights until the accuracy of the classifier reaches the expected level before terminating (Tian et al., 2019). At this point, the algorithm can achieve the ideal recognition effect on the state of high-performance mechanical parts manufactured from nanomaterials. By using the convergence of neural networks to control the global expansion of the network, and evaluating the model prediction performance of the training and testing sets, it is determined whether to perform local expansion. This achieves self-adaptation adjustment of the depth of the network and the number of feature maps at each level, and transforms all parameters into batch training of multiple parameters at the same time, thereby reducing the difficulty and complexity of training.

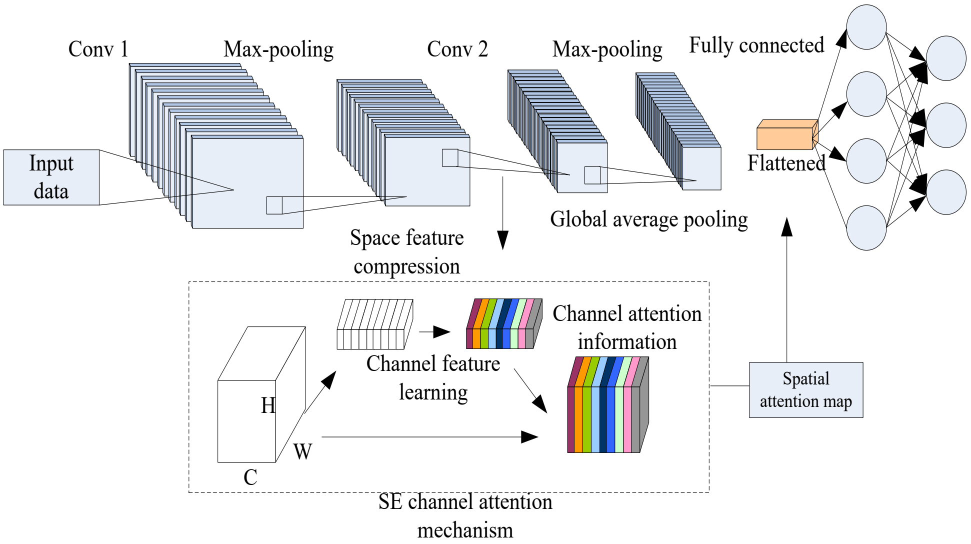


Fig. 1. Model framework

The overall structural framework of the adaptive deep CNN model is shown in Fig. 1. After dynamic expansion is completed, the network forms a stable architecture containing attention modules for actual deployment. This architecture includes an input layer, a multi-scale convolutional layer, a channel attention module, a spatial attention module, a global average pooling layer, and a fully connected output layer. The network structure is shown in Table 2.

Table 2. Network structure description

Classification	Parameter
Input layer	Input size: 128×128×3
Convolutional layer 1 (Conv1)	64 convolution kernels, size (3,3), stride = 1
Maximum pooling layer (MaxPool1)	Pooling window: (2,2), stride = 2
Convolutional layer 2 (Conv2)	128 convolution kernels, size (3,3), stride = 1
Channel Attention Module (SE)	Global average pooling + fully connected layer + feature recalibration
Spatial attention module	Maximum pooling and average pooling along the channel dimension + 7 × 7 convolution
Global average pooling layer	Output size: 128 channels
Fully connected layer	256 neurons, Dropout ratio = 0.5
Output layer (Softmax)	Number of categories: N

After normalization, the input data is fed into the first convolutional layer, which contains 64 convolution kernels of size (3,3) with a stride of 1 and ReLU activation function. Subsequently, a MaxPooling layer is connected with a pooling window size of (2,2) to reduce feature dimensionality and enhance translation invariance.

In the second layer of convolution, 128 (3,3) convolution kernels were used, and an SE (Squeeze and Excitation) module was introduced as the channel attention mechanism. Channel statistical information was obtained through global average pooling, and channel weights were generated using fully connected layers to perform weighted fusion on the original features.

In the inference stage, the SE module obtains channel statistical information through global average pooling, generates channel weights, and performs weighted fusion on the original features. The spatial attention module generates spatial attention maps through a 7 × 7 convolution to enhance the expression of key region features. These two attention mechanisms work together to achieve adaptive enhancement of features.

After global average pooling, the final features are input into a fully connected layer consisting of 256 neurons. Dropout (with a ratio of 0.5) is used to prevent overfitting, and finally, the prediction results are output by a Softmax classifier.

3. High Performance Machine Element Testing

To verify the practical effect of adaptive convolutional neural networks in the manufacturing of high-performance mechanical parts in nanomaterials, this paper takes the manufacturing of ultra-precision standard gear mechanical parts as an example, and tests the mechanical parts manufactured using this method from three aspects: hardness, wear, and fault detection. The data was collected from the nanocomposite gear production line of a precision machinery manufacturing enterprise from March to June 2024, with a total of 6208 valid samples obtained. Each sample contains 23 dimensional manufacturing process parameters (nanomaterial spraying temperature, spraying pressure, spraying time, heat treatment temperature, insulation time, cooling medium temperature) and corresponding 5-dimensional finished product performance indicators (hardness, wear coefficient, surface roughness, density, porosity. The results are compared with those manufactured using standard CNN models with Long Short-Term Memory (CNN-LSTM) models. To adapt to the two-dimensional convolution architecture of ACNN, this paper uses GASF to transform one-dimensional multivariate time series into two-dimensional images. Specifically, normalize the 28-dimensional features of each sample to the polar coordinate system, calculate the sum of angles between each feature, and generate a 128 × 128 pixel pseudo color image as the network input. The three channels of the image correspond to the sum field, difference field, and original value field of different feature combinations. The cross-entropy loss function is used as the objective function in the model training process. Adam is selected as the optimizer, the initial learning rate is 1e-4, and weight_decay is set to 1e-5 to alleviate the problem of model overfitting. At the same time, in order to improve the convergence efficiency of the model, the cosine annealing learning rate scheduler is introduced, and the cycle is set to 50 epochs. The training data is divided into training set, validation set, and testing set in a ratio of 7:2:1, with a total of 6208 samples, all of which are collected from the actual manufacturing process of nano composite gear workpiece parameters and performance indicators. Among them, there are 4346 training sets, 1241 validation sets, and 621 testing sets. Each batch is set to 64, and the maximum number of training rounds (epochs) is set to 200. The early stopping mechanism monitors the validation set loss. If there is no obvious improvement for 10 consecutive epochs, the training is terminated.

3.1. Data Card

To enhance the reproducibility of the research, this article provides a detailed description of the data. The data is sourced from the nanocomposite gear production line of a precision machinery manufacturing enterprise that requested anonymity, and was collected from March 1, 2024, to June 30, 2024.

In terms of data collection equipment, the Siemens S7-1500 PLC control system is used for process parameter collection, with a sampling frequency of 1Hz. The hardness test uses a Vickers microhardness tester (HVS-1000) that meets the ISO 6507-1:2018 standard. The wear test adopts a friction and wear testing machine (UMT-3) that meets the ASTM G99-17 standard. The fault detection adopts acoustic emission sensors combined with a vibration analyzer (NI PXIe-4499) that complies with the ISO 13379-1:2022 standard.

In the labeling process, each gear product needs to undergo 72 hours of continuous operation testing. Three senior quality inspection engineers independently label the health status (normal/abnormal) according to the ISO 1328-1:2013 gear accuracy standard, with a consistency of 95.3%. Inconsistent samples are labeled after discussion, and consensus is reached.

The data fields include process parameters (23 dimensions, such as spray temperature and spray pressure), performance indicators (5 dimensions, such as hardness and wear coefficient), and labels (1 dimension: health status; 0 indicates normal, 1 indicates abnormal). All physical quantities are measured in the International System of Units (SI) and anonymized, removing identifiable information such as product batch numbers, operator IDs, production timestamps, and retaining only process parameters and performance indicators.

The dataset is randomly stratified in a ratio of 7:1.5:1.5 to ensure that the proportion of samples in each category is consistent in each subset. After partitioning, there are 4346 training sets, 931 validation sets, and 931 test sets, with no cross-sample data leakage.

3.2. Preparation of Machine Element

Under specific process conditions, this article adopted coating treatment, placing nanomaterials into the spraying equipment, and applying pressure atomization to evenly coat the substrate surface. After spraying, the nano coating was formed by standing still. Then, using a heat treatment method, the gear workpiece was heated to a temperature close to or above its critical temperature, maintained for a specific time, and then cooled in a certain medium to reduce internal stress and brittleness. Traditional methods used traditional manufacturing and testing processes to obtain a set of six different types of nano high-performance machine elements with different structures. The method in this article was to use ACNN to real-time detect the state of machine elements under nanomaterial manufacturing, thereby obtaining a set of 6 types of high-performance nano machine elements with different structures.

3.3. Performance Testing

(1) Hardness testing

Hardness testing is an important component of the quality control process. For ultra-precision reference gear machine elements, their local resistance to hard objects pressing into their surfaces is crucial for ensuring safe use. This article randomly selects 10 different structured mechanical parts prepared by three methods as samples. The mean values and standard deviation (SD) results of each model under hardness testing are shown in Table 3.

Table 3. Mean and SD of hardness

Model	Mean	SD
CNN	47.2	3.5
CNN-LSTM	47.4	3.8
ACNN	54.4	3.8

In Table 3, it can be seen that the hardness values of ultra precision standard gear parts show different results under the three methods. Among them, the highest hardness value of the parts manufactured using the CNN model is 49.6, and the average hardness value is about 47.2; The highest hardness value of the parts manufactured using the CNN-LSTM model is 49.3, with an average hardness value of approximately 47.4. There is no significant difference in the hardness test results between the two methods. The highest hardness value of ultra precision reference gear machine elements manufactured through adaptive CNN application of nanomaterials reached 57.6, with an average hardness value of about 54.4. From the comparison of results, it can be seen that using adaptive CNN to manufacture ultra precision reference gear machine elements with nanomaterials has significant advantages in terms of hardness performance. With the support of adaptive CNN method, the hardness feature detection requirements of high-performance machine elements based on nanomaterials in the manufacturing process are relatively strict. It mainly determines the status of parts based on specific usage needs. Under this standard, the hardness of machine elements would be effectively guaranteed and controlled.

Affected by internal and external factors, high-performance machine elements often require strong wear resistance, which specifically refers to the continuous loss of performance on the surface of the material during the friction process of machine elements. This article took the wear factor as the indicator, set the wear time to 3600 seconds, and calculated the wear factors of 10 machine elements randomly selected from three different types of machine elements sets using three methods. The mean and SD results of each model under wear testing are shown in Table 4.

In Table 4, it can be seen that the wear factor of ultra precision reference gear mechanical parts manufactured by adaptive CNN using nanomaterials is at a lower level, while the wear factors of the other two methods are at a higher level. Among them, the maximum wear factor of mechanical parts under the CNN model reaches 0.612, and the average wear factor is about 0.494; The maximum wear factor of mechanical parts under the CNN-LSTM model reaches 0.498, and the average wear factor is about 0.457. The maximum wear factor of machine elements under this method was only 0.253, while the average wear factor was about 0.205. In terms of wear factors, ultra precision reference gear machine elements manufactured through adaptive CNN application of nanomaterials can maintain ideal results, and their reliability can be greatly improved in practical use.

Table 4. Mean and SD of wear coefficient

Model	Mean	SD
CNN	0.494	0.052
CNN-LSTM	0.457	0.047
ACNN	0.205	0.055

In order to gain a deeper understanding of the wear resistance performance of high-performance machine elements of ultra precision reference gears manufactured through adaptive CNN application of nanomaterials, this article analyzed the wear thickness changes of machine elements under different time series (wear times of 1200 seconds, 2400 seconds, and 3600 seconds) using the friction surface method. The results are shown in Fig. 2.

In Fig. 2, it can be seen that the wear thickness of machine elements under different time series produced different results, and the wear thickness of high-performance machine elements of ultra precision reference gears would change in the same direction as the wear time increases. From the specific thickness variation results, when the wear time was 1200 seconds, the wear thickness of high-performance machine elements remained basically within the range of 2.0 micrometers to 3.0 micrometers. When the wear time was 2400 seconds, the wear thickness of machine elements remained within the range of 2.9 microns to 4.1 microns. When the wear time was 3600 seconds, the wear thickness of high-performance machine elements of ultra precision reference gears manufactured through adaptive CNN application of nanomaterials remained within the range of 4.0 micrometers to 5.5 micrometers. Although the wear thickness value of machine elements continues to increase with time, overall, the change in wear thickness is not very significant and is basically stable within a better level range. From this point, it can be seen that with the support of an adaptive CNN, the wear resistance of high-performance machine elements is relatively stable.

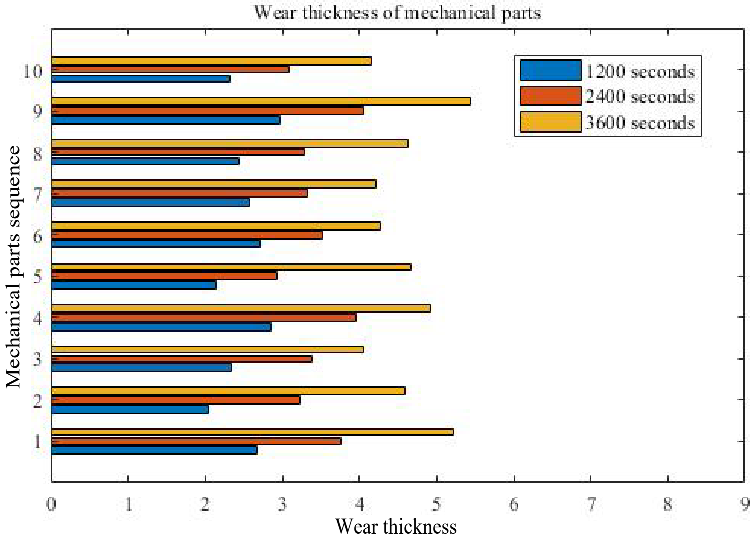


Fig. 2. Wear thickness results

(2) Fault detection

Fault detection aims to determine the health status of high-performance machine elements during use using different methods. This article evaluated the set of high-performance machine elements under three different types of methods using fault rate as an indicator. The higher the fault rate, the less ideal the performance of the machine elements. The mean and SD results of each model under fault testing are shown in Table 5.

Table 5. Mean and SD of wear coefficient

Model	Mean	SD
CNN	1.96	0.32
CNN-LSTM	1.43	0.37
ACNN	0.89	0.26

The failure rate of high-performance machine elements of ultra precision reference gears during use should not exceed 3%. From the test results in Table 5, it can be seen that the mechanical parts under all three methods meet the standards. However, from the specific comparison results, the failure rate under both control methods is higher than that of the method proposed in this paper. Among them, the average failure rate of high-performance mechanical parts of ultra precision standard gears under CNN is about 1.96%, and the average failure rate of high-performance mechanical parts of ultra precision standard gears under the CNN-LSTM model is about 1.43%. However, the average failure rate of high-performance machine elements of ultra precision reference gears manufactured through adaptive CNN application of nanomaterials was less than 1%, with a specific result of only 0.79%. It can be seen that under the adaptive CNN algorithm, the state of machine elements during the manufacturing process can be well identified and detected, thereby achieving a lower failure rate and a healthy state during use.

In order to comprehensively evaluate the prediction and classification capabilities of the model in this paper in the manufacturing of high-performance mechanical components of nanomaterials, this paper further designs comparative experiments and introduces support vector machine (SVM), random forest (RF), standard CNN, ResNet-18, and CNN-LSTM models for comparative analysis: accuracy, recall rate, and F1 value indicators are used for comparison. The indicator results are calculated based on the binary classification results (such as whether the expected strength or fracture toughness is achieved). As shown in Table 6.

Table 6. Comparison of model results

Model	Accuracy (%)	Recall (%)	F1 score
SVM	76.4	74.1	0.752
RF	79.8	77.6	0.785
CNN	83.2	81.5	0.823
ResNet-18	85.6	84.0	0.847
CNN-LSTM	86.9	85.3	0.860
ACNN	90.3	88.7	0.895

In Table 6, the model in this paper has the most ideal results, with an accuracy of 90.3%, a recall of 88.7, and an F1 score of 0.895. The effectiveness of the attention mechanism significantly improves the model's ability to focus on key features. The manufacturing process of nanomaterials involves complex multi-scale structures and interactions with process parameters. Models such as SVM and RF are difficult to effectively capture locally important areas. ACNN introduces a channel attention mechanism that can dynamically adjust the weights of different feature channels, thereby more accurately identifying key factors that affect material properties, such as lattice defect distribution and stress concentration areas.

To evaluate whether the differences among the three methods (CNN, CNN-LSTM, and ACNN) in terms of hardness, wear coefficient, and failure rate are statistically significant, this paper conducted a one-way analysis of variance (ANOVA) and Tukey's Honestly Significant Difference (HSD) post-hoc multiple comparisons. The results are shown in Table 7.

Table 7. Results of one-way ANOVA

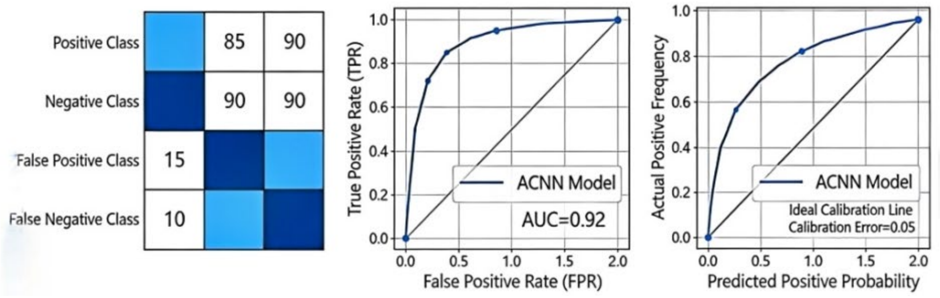
Indicator	F-value (2,27)	p-value	η^2	Significance
Hardness	12.47	<0.001	0.48	Extremely significant
Wear coefficient	18.23	<0.001	0.57	Extremely significant
Failure rate	15.86	<0.001	0.54	Extremely significant

The ANOVA results indicate that there are extremely significant differences ($p < 0.001$) among the three methods for all three indicators, and the effect sizes (η^2) are all greater than 0.14, suggesting that the method factor accounts for over 40% of the variance in the indicators, which falls within the range of a large effect. Tukey's HSD post-hoc tests revealed the following: For hardness, ACNN (M = 54.4, SD = 3.8) was significantly higher than CNN (M = 47.2, SD = 3.5, $p < 0.001$, Cohen's d = 1.96) and CNN-LSTM (M = 47.4, SD = 3.8, $p < 0.001$, d = 1.84); there was no significant difference between CNN and CNN-LSTM (p = 0.89). For the wear coefficient, ACNN (M = 0.205, SD = 0.055) was significantly lower than CNN (M = 0.494, SD = 0.052, $p < 0.001$, d = 5.36) and CNN-LSTM (M = 0.457, SD = 0.047, $p < 0.001$, d = 4.98). For the failure rate, ACNN (M = 0.79%, SD = 0.26%) was significantly lower than CNN (M = 1.96%, SD = 0.32%, $p < 0.001$, d = 4.02) and CNN-LSTM (M = 1.43%, SD = 0.37%, $p < 0.001$, d = 2.11). The above results demonstrate that the ACNN method yields statistically significant improvements in the performance of mechanical components, with effect sizes indicating a large effect.

To comprehensively evaluate the predictive capability of the model proposed in this paper in the manufacturing of high-performance mechanical components from nanomaterials, a binary classification task was defined: predicting whether the hardness of finished gears meets the ISO 54 HRC standard (≥54 HRC is considered compliant, labeled as 1; <54 HRC is non-compliant, labeled as 0). A 5-fold cross-validation was employed to assess model performance, ensuring that the sample ratio of each category remained consistent in each fold. The evaluation metrics included accuracy, recall, F1 score, ROC-AUC, and PR-AUC, with the average results and standard deviations from the 5 folds reported. The comparison models included Support Vector Machine (SVM), Random Forest (RF), standard CNN, ResNet-18, CNN-LSTM, and the ACNN proposed in this paper. The results are shown in Table 8.

Table 8. Comparison of model classification performance (5-fold cross-validation, mean ± standard deviation)

Model	Accuracy (%)	Recall (%)	F1 Score	ROC-AUC	PR-AUC
SVM	76.4±2.1	74.1±2.5	0.752±0.023	0.812±0.019	0.763±0.025
RF	79.8±1.8	77.6±2.2	0.785±0.019	0.845±0.016	0.801±0.021
CNN	83.2±1.5	81.5±1.9	0.823±0.016	0.876±0.014	0.839±0.018
ResNet-18	85.6±1.4	84.0±1.7	0.847±0.014	0.894±0.012	0.862±0.016
CNN-LSTM	86.9±1.3	85.3±1.6	0.860±0.013	0.905±0.011	0.878±0.015
ACNN (This paper)	90.3±1.1	88.7±1.4	0.895±0.011	0.934±0.009	0.912±0.012



(a) Confusion matrix (b) ROC curve (c) Calibration curve

Fig. 3. Classification Performance of ACNN

Fig. 3 presents the confusion matrix, ROC curve, and calibration curve of ACNN on the test set (using a typical fold as an example). From Table 8 and Fig. 6, it can be observed that ACNN outperforms the comparison models across all metrics, with an accuracy of 90.3% and an ROC-AUC of 0.934, indicating its excellent discriminative ability. The PR-AUC of ACNN is 0.912, significantly higher than that of other models, suggesting that it can maintain high precision even when there are fewer positive samples. The calibration curve shows that the predicted probabilities of ACNN are close to the true probabilities (Brier score = 0.087), demonstrating good probability calibration and making it suitable for risk decision-making in the manufacturing process.

Fig. 4 shows a physical comparison of ultra precision reference gears before and after treatment with nanomaterial coating. The left side is the untreated gear substrate, with a metallic luster on the surface; On the right is the finished gear optimized by nano coating and ACNN process, with a uniform gray black nano composite coating on the surface, without obvious color difference or sagging phenomenon. The coating thickness was measured to be 3.2 ± 0.3 μ m.

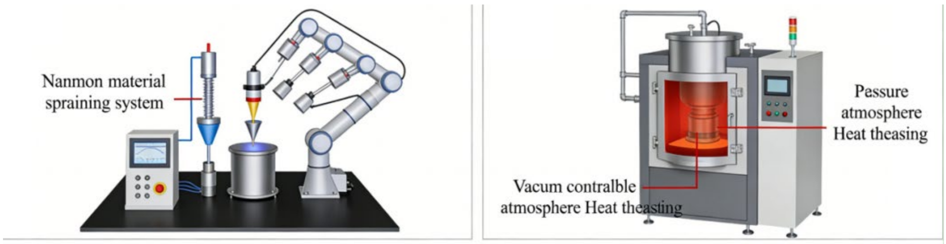
Fig. 5 shows the experimental equipment used in this study: (a) a nanomaterial spraying system (equipped with a pressure atomizing nozzle and a six axis robotic arm), (b) a heat treatment furnace (vacuum controlled atmosphere), (c) a Vickers microhardness tester (HVS-1000), (d) a friction and wear tester (UMT-3), (e) a vibration analyzer (NI PXIe-4499), and the installation position of acoustic emission sensors.

4. Multi-Dimensional Value Evaluation of ACNN Method in Manufacturing Decision-Making

When evaluating the practical value of the ACNN method for manufacturing decisions, analyzing five key dimensions of quality, cost, delivery cycle, safety, and environmental impact can provide a comprehensive and in-depth insight into its overall benefits in production management.

(a) Before coating treatment (b) After nano coating treatment

Fig. 4. Actual ultra precision reference gear



(a) Spray coating system (b) Heat treatment furnace

(c) Hardness tester (d) Wear testing machine (e) Vibration analysis system

Fig. 5. Experimental equipment

From the perspective of quality, the ACNN method has demonstrated excellent performance improvement effects. Compared with the CNN method, the hardness compliance rate of gears manufactured using ACNN has significantly increased from 72.3% to 89.6%, while the wear coefficient has decreased by 58.5%. This significant change directly indicates a qualitative leap in product quality. A higher hardness compliance rate means that gears have stronger stability and reliability when subjected to high-intensity work, while a decrease in wear coefficient extends the service life of gears, reduces production interruptions and cost increases caused by frequent gear replacement, and provides a solid guarantee for the long-term stable operation of products.

In terms of cost, the real-time monitoring function of ACNN has played a huge role. The defect rate has decreased from 11.2% to 4.7%. Calculated based on a production cost of 350 yuan per gear and an annual output of 100000 pieces, the annual cost savings are as high as approximately 2.275 million yuan. In addition, the reduction in failure rate has also brought considerable economic benefits, and it is expected that the annual maintenance cost can be reduced by about 450000 yuan. The reduction of these costs directly enhances the profit margin of enterprises, strengthens their competitiveness in the market, and enables them to invest more resources in research and innovation, further promoting their development.

Delivery cycle is an important indicator for measuring production efficiency, and ACNN's online monitoring technology performs outstandingly in this regard. It has shortened the quality inspection time from an average offline sampling time of 45 minutes per piece to real-time online inspection, reducing the overall production cycle by about 18%. This means that companies can bring products to market faster, meet customer needs, and improve customer satisfaction. In today's fiercely competitive market environment, fast delivery capability is one of the key factors for enterprises to win market share, and the ACNN method provides strong support for enterprises.

Safety is an important aspect that cannot be ignored in the production process of enterprises, and the ACNN method also performs well in this regard. The failure rate of gears is only 0.79%, far below the industry average threshold of 3%, and it is expected to reduce equipment downtime caused by gear failures by about 76%. This not only significantly improves the operational safety of the production line and reduces the risk of accidents caused by equipment failures, but also avoids production losses due to downtime, ensuring the continuity and stability of production.

The environmental impact dimension reflects the social benefits of the ACNN method. The decrease in defect rate means a reduction in raw material waste. By saving 6.5% of raw materials annually, it is expected to reduce the consumption of nanomaterials by about 230kg and reduce carbon emissions by about 4.8 tons of CO_2 equivalent. This meets the requirements of today's society for green manufacturing and sustainable development, helps companies establish a good social image, fulfill social responsibilities, and also makes positive contributions to addressing global climate change.

In summary, the ACNN method not only achieves significant improvements in technical performance but also brings significant benefits in production management decision-making, covering both economic and social benefits. It provides comprehensive solutions for enterprises in terms of quality improvement, cost control, efficiency improvement, safety assurance, and environmental friendliness, and is a powerful tool for enterprises to achieve sustainable development and enhance comprehensive competitiveness.

5. Conclusion

Advances in nanotechnology, nanomaterials and their application in the manufacture of high-performance machine elements are becoming more and more sophisticated. Compared with traditional materials, nanomaterials have the characteristics of high controllability and high flexibility, which can effectively improve the performance of machine elements. However, in the face of the complexity and diversified development of unloading equipment in industrial systems, the role and status of safety and reliability of component equipment in the manufacturing process are becoming increasingly significant. To effectively improve the safety of high-performance machine elements made of nanomaterials, this article applies ACNNs to manufacture high-performance machine elements using nanomaterials. It not only improved the basic performance of parts, such as hardness and wear resistance, to a certain extent, but also significantly reduced their failure rate, effectively ensuring the health of the parts. The research results of this article provide the following decision-making basis for managers of high-performance mechanical component manufacturing enterprises.

First, production process decision-making: Managers should consider embedding an online quality monitoring system based on ACNN into existing production lines to replace the traditional post-inspection mode. This transformation can transform quality inspection from "offline and lagging" to "online and real-time", enabling timely detection of process deviations and adjustment of parameters, reducing the occurrence of defective products.

Second, equipment investment decisions: When updating equipment or building new production lines, priority should be given to selecting intelligent spraying and heat treatment equipment that supports data interfaces, laying the data foundation for implementing artificial intelligence algorithms such as ACNN. Although the initial investment may increase by 10% -15%, according to the cost analysis in this article, it is expected that the investment can be recovered within 1.5-2 years by reducing the defect rate and maintenance costs.

Third, personnel training decision-making: Managers need to organize process engineers and quality management personnel to receive basic training in data analysis and artificial intelligence, so that they can understand the warning information output by ACNN and convert it into specific process adjustment instructions, achieving human-machine collaborative decision-making.

Fourthly, supply chain management decision-making: The ACNN method can more accurately predict the performance and failure rate of finished products. Managers can share this predicted information with downstream customers, optimize spare parts inventory management and preventive maintenance plans, and improve the overall efficiency of the supply chain.

In summary, the ACNN method proposed in this article is not only a technical tool but also a catalyst for promoting the transformation of manufacturing enterprises towards data-driven decision-making.

This article focused on the application of ACNNs in the manufacturing of high-performance machine elements using nanomaterials. Although it provided specific guidance for promoting the intelligent development of machine elements manufacturing, there are still some issues that need to be addressed for improvement in the research process. In future research, one would continue to expand the research scope and perspectives and consider applying ACNNs to nanomaterials to manufacture more types of high-performance machine elements.

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