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The Impact of Short Video Live Broadcast on the Sales of Sports Machinery and Equipment

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ABSTRACT

This paper proposes a neural network model based on deep learning, which can better analyze the impact of short video live broadcast on sports machinery and equipment. Firstly, this paper proposes a U-Net-based convolutional neural network as the backbone network of this paper, which mainly realizes the impact of short video live broadcast on sales. Secondly, this paper proposes a dense residual module based on the Transformer lightweight module, which can effectively improve the global modeling ability of the network model and improve the prediction accuracy of the network model. Finally, through a large number of experiments, it is proved that the convolutional neural network based on U-Net proposed in this paper can be better used for the task of short video live broadcast for the sales of sports machinery and equipment, and achieves better prediction accuracy and reasoning speed.

KEYWORDS

Deep Learning, E-Commerce, Mobile Multimedia, Residual Module, Short Video Live Broadcast, Sports Machinery Sales, Transformer Model, U-Net Network

With the popularization of the concept of national health, the demand for sports machinery and fitness equipment is increasing day by day. However, the sales of sports machinery equipment are constrained by traditional sales channels and methods, making it difficult to fully utilize market potential and diverse sales channels. In the current situation, how to improve the sales of sports machinery equipment has become an urgent problem to be solved. Although the short-video livestreaming method has played a certain promoting role in the sales of sports machinery equipment, sales are greatly affected by the short-video livestreaming method, and there are significant fluctuations within a period of time. Therefore, it is particularly important to find a stable and effective method to increase the sales of sports machinery equipment. To address this issue, this paper proposes a sales prediction method based on deep learning technology, using a U-Net based convolutional neural network (CNN) as the backbone network and a dense residual module based on a lightweight transformer module. Through this model, we aim to improve the global modeling ability of the network model and enhance the sales prediction

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accuracy of the network model. This article verifies through a large amount of experimental data that the proposed neural network method based on deep learning has good predictive performance and can effectively improve the sales of sports machinery and fitness equipment in short-video livestreaming. This study demonstrates the potential application of neural network models based on deep learning technology in improving the sales of sports machinery, providing new perspectives and methods for the sales of sports machinery.

LITERATURE REVIEW

With the rapid development of the economy, people gradually have realized the importance of health (Qu et al., 2024). Health is a precious wealth of people. Without health, there is no colorful life (Huang et al., 2024). With the deepening of the concept of health, people gradually have paid attention to various risk factors that may affect health around people's clothing, food, housing, transportation, birth, old age, sickness, and death (Şenyapar, 2024). At the same time, in the pursuit of a kind of mental, physical, spiritual, and moral health, the concept of health also encourages people to pay for health, which involves various types of health-service organizations and activities (W. Zhang et al., 2024).

The traditional method uses the online sales platform to meet the user's demand for sales equipment, but this method has little effect (Q. Zhang et al., 2024). How to use the current sales platform to increase the sales of sports machinery equipment is still a challenging question. With the continuous development of the mobile internet era, the content of dissemination and the way of live broadcast have changed to a great extent, especially as the short-video live broadcast has become the frontrunner of the standout (Yao et al., 2024). The progress of the information age has broken the enterprise-centered sales, allowing more consumers to participate in the production process. There are many users of short-video platforms, and the profit models of the internet are diverse, making users become viewers of short videos and participants of short-video additions (Yu et al., 2024). Content creators can use the short-video platform to realize video sharing, video creation, content promotion, and other activities. Video creators can push these contents and advertisements to the customer groups in need through data analysis, improved customer faithfulness, and building of a fan economy. In the process of watching, ordinary viewers can make rational purchases according to their own needs for the content of short videos, add-on live broadcasts, and advertisements. At the same time, users feel that the product has certain development advantages and can also carry out secondary promotion and sales (Medjdoubi et al., 2024). Live delivery of goods through short-video live broadcasts on the internet has become a key sales channel at present. In this article, the key way to realize the sales of sports machinery equipment can be realized through short-video live broadcast.

In order to increase the sales of sports machinery equipment, the use of short-video live broadcasts to bring goods has become a key channel for current sales. A large number of merchants and platforms have already participated in this process. The reason is that the low-cost and quick-acting publicity method can quickly fix users (McDonald et al., 2024). Different from traditional online sales platforms, with this new way, people can continuously shorten the distance between merchants and customers in the process of watching videos, potentially motivating customers to buy sports and fitness equipment from merchants, as they are more recognized for this sales method. It has become a key mode of livestreaming (Soliman et al., 2024).

Deep learning has become an integral part of various industries, including livestreaming. Huang et al. (2024) discussed the importance of utilizing the best live streaming equipment for optimal video quality. In the sports industry, Na et al. (2024) offered live video production solutions for sports events, emphasizing the use of advanced equipment for broadcasting. Additionally, companies like Singh et al. (2024) provided image recognition software and video analysis tools that incorporated machine learning for automated processes. Cloud computing services from Krasteva et al. (2024) also played a significant role in supporting businesses with data management, hybrid cloud solutions, and artificial intelligence and machine-learning capabilities. Tao et al.(2024) offered a wide range of technology solutions, including software, networking, and cybersecurity services, to empower businesses for the future. Chung (2024) introduced the ATEM Mini switcher for faster video production and livestreaming, highlighting the importance of user-friendly equipment in the industry. Furthermore, Lee et al. (2024) provided video conference room equipment and solutions for seamless collaboration experiences, particularly in hybrid work environments. Live sports streaming services like Srivasstava et al. (2024) have revolutionized the way sports content is consumed, emphasizing the need for advanced video streaming technologies. Overall, the integration of deep learning, short-video livestreaming, and sports equipment sales showcases the continuous evolution of technology in the video streaming industry.

RELATED MATERIALS AND METHODS

Short-Video Live Broadcast Method

In the era of mobile internet, news media and content have undergone earth-shaking changes, and short video has become a leader in the industry in just a few years (Lahiri et al., 2024). With the rapid development of short videos, it has attracted a large amount of traffic and brought huge development prospects (Lee, 2024). With the increasing number of users, new business models and development prospects are gradually emerging (Nair et al., 2024). Similar to short-video platforms like TikTok and Taobao, their users cover a wide range, and the actual number of online users is far more than one million every day. Using this type of platform can well convert mass users into actual shoppers. Diversified content presentation increases desire to read, and traditional text and pictures are more likely to be welcomed by everyone, which can accurately push personal favorite items and ensure user loyalty. At the same time, an operational model based on short videos came into being (Brown et al.,2024). Through third-party placement of advertisements, video embedding, and live delivery of goods, users can enjoy short videos while customizing the purchased products to enrich their material and cultural needs.

With the rapid development of internet technology, short-video live broadcasting has gradually become a TV program that can be watched in real time on the internet, achieving the unity of collective viewing and real-time interaction (Do & Do, 2024). Short-video bloggers share their shopping experience, or help merchants promote products, and provide some key information for customer reference (Alsawy et al., 2024). Through the short-video live-broadcast platform, customers can live broadcast or share their shopping experience, bypassing the layer-by-layer overweight of middlemen, selling their products to the public, and allowing users to buy genuine, high-quality and inexpensive products, while reducing the cost of merchants' cost of promoting a product. The short-video industry has gradually transformed from a user-increasing type to a profitable growth model. By continuously promoting products and increasing revenue, short-video livestreaming gradually has become a key channel for sales. New e-commerce models such as short video plus e-commerce and short video plus advertising have become the focus. Faced with the new business model, merchants also need to explore, improve, and keep up with the trend of the times (Sah, 2024).

Short-video platforms such as TikTok have risen rapidly. In the past few years, the number of users has increased exponentially, and the number of users has exceeded hundreds of millions. Through the sharing of video-creation content on the short-video platform, tens of thousands of likes are obtained at every turn, allowing many businesses to see business opportunities from short videos. After initial attempts, many merchants found that selling products through this short-video live broadcast can reduce costs, achieve fast results, and quickly attract new users. With the popularity of short-video platforms, a large number of merchants have settled on this platform and continuously increased the sales of their products. The way of bringing goods through live broadcast is different from the traditional way of software shopping. The traditional way is to require users to search, find the items they need, and then buy them. The way to bring goods through live broadcast is to let users relax and watch videos, while narrowing the distance between people, and subtly influence customers to choose and buy. It is an active sales method. At the same time, this model takes effect quickly, which brings positive influence and constantly attracts merchants to participate in these kinds of activities. In this article, in order to increase the sales of sports machinery and fitness equipment, livestreaming with goods or short-video live broadcasting can effectively increase the range of influence of products. Therefore, an analysis of short-video live-broadcasting platforms is carried out in this article.

Sales of Sports Machinery and Fitness Equipment

With the spread of the concept of health, people's health awareness also has been greatly expanded. Moreover, personal health has received a lot of attention. The use of fitness equipment to improve people's physical condition has become a key way to enhance people's sense of participation and enthusiasm for participating in activities, so that fitness has been fully popularized, corresponding to the growth of sports machinery equipment. The demand is also increasing. In order to better integrate with the market and at the same time increase the sales volume of sports machinery equipment, we conduct a comprehensive analysis of the development strategy of fitness equipment from the perspective of health.

Sports machinery equipment is an auxiliary means to promote the development of physical health. Through sports equipment, the enthusiasm of the public can be improved and, at the same time, the further transformation of the industrial structure can be realized, so that the sports cause has gradually received more attention from participants. In order to increase the sales of sports equipment, we should improve in the following aspects. (a) Improve the competitiveness of the fitness equipment market. (b) Enhance the core competitiveness of enterprises. (c) Expand the sales channels and methods of sports machinery equipment to continuously adapt to the development of the modern digital information age.

Sports machinery equipment is a key auxiliary means for the development of sports. The use of sports machinery equipment can further mobilize people's enthusiasm for work and also can influence more people to participate in fitness activities. In order to promote the healthy development of sports, we should enhance the core competitiveness of sports machinery equipment and build a complete production and sales model from various issues in the entire stage of design, production, sales, and after-sales. The sales of sports machinery equipment must take into account the actual situation of the public. The design pricing and sales price must conform to the actual economic conditions at that time and, at the same time, the public must be given some opportunities to try. For example, we can set up various types of fitness equipment in public facilities and then count the opinions or suggestions used in a period of time, collect relevant data on fitness equipment, and provide a large amount of data for the design and development of fitness equipment in the future. At the same time, we can truly understand the needs of users, make some improvements and adjustments to the equipment, and increase the conditions of use. The preliminary research and testing can truly reveal the actual needs of users, be used to improve the products according to the needs of customers, help us meet the needs of people's physical and psychological health, and begin to create a good social environment.

Compared with the world's advanced development speed, the attention based on sports health has a certain lag. Therefore, it is necessary to improve the core competitiveness of enterprises and continuously promote and publicize health equipment. Under the premise of pursuing physical health, it is important to continuously consider people's physical and psychological characteristics and further improve the rationalization of using sports machinery equipment. At the same time, we should pay more attention to different groups of users, such as elderly, youth, and disabled fitness, among other groups, and make targeted designs and improvements to meet the needs of the public.

Deep Learning Model

With the continuous development of deep learning technology, artificial intelligence technology based on neural networks gradually has replaced the traditional method and has become one of the most common and extensive technologies at present. Deep learning technology has far-reaching influence. From the initial perceptron, linear model, backpropagation model, activation function, and so on, to the later general basic network structures such as ResNet, simplebaseline, HRNet, among others, deep learning has continuously refreshed the neural network prediction accuracy ranking list. These deep learning techniques are widely used in target detection, target tracking, face recognition, face generation, pose estimation, and many other computer vision tasks, and the techniques have bright application prospects. In the short-video live-broadcast method of this article, we use the deep learning network to learn the mapping from the live-broadcast method to the sales volume of sports equipment, learn and analyze through experimental data, and provide reasonable information for subsequent sales tasks.

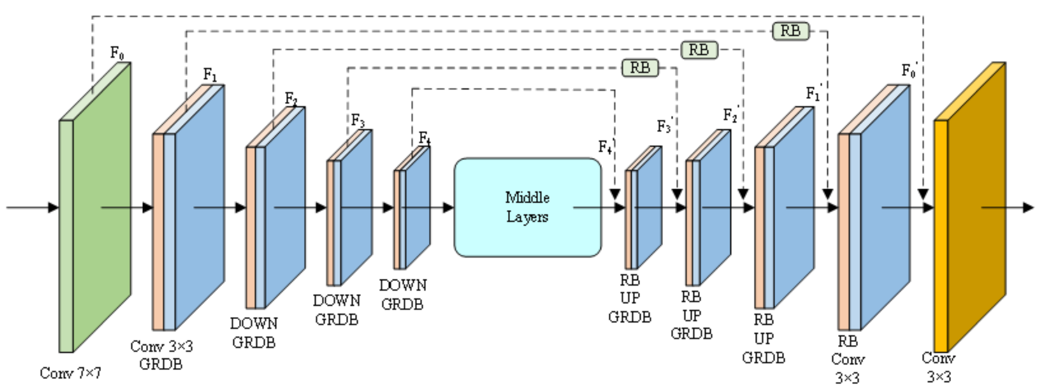
The main task of this paper is to explore the impact of short-video live broadcast on the sales of sports machinery equipment. In order to solve this problem, this paper proposes a neural network structure based on video processing. The first step is to analyze the input video and determine whether the input video is a type of short-video live broadcast. Then, the category of the video is connected and analyzed with the sales volume of sports machinery equipment through the fully connected layer. Finally, the sales volume of sports machinery equipment is reasoned and predicted through live video.

The network structure based on video processing proposed in this paper is mainly divided into four parts, namely, the backbone network structure, residual dense block, middle layer, and transformer attention mechanism. These aspects will be described in detail next.

Backbone Network Structure

The network model structure of this paper is shown in Figure 1. The entire network structure is mainly composed of four blocks, which are encoder, decoder, skip connection, and intermediate layer. In the encoder structure, the function of down-sampling is implemented using convolution. Since the image size of the input network structure is large, and the calculation amount of the network structure is proportional to the square of the input image size, with the continuous increase of the number of channels, the network model parameters and calculation amount far exceed the calculation provided by the computing hardware. Therefore, in the down-sampling stage, convolution is used to continuously reduce the size of the image and, at the same time, the increase of the number of image channels is controlled by hyperparameters to reduce the feature loss in the process of image size reduction. In the decoder, deconvolution layers and 1×1 convolution layers are used to increase the size of the image, while reducing the number of channels in the image, and continuously generate new image features. The skip connection means that the image features saved in the down-sampling process and the image features generated in the up-sampling process are integrated, and the feature loss of the image in the convolution is avoided through the joint action. The middle layer is mainly composed of transformer

Figure 1. Overall Network Structure



modules, which mainly learn the high-dimensional features extracted by the convolution layer, so that the neural network model can better learn the features we need, filter out those irrelevant and interfering features, and improve the network model's overall performance. The number of feature channels used by the encoder in 1, 2, 3, and 4 global residual dense blocks are 32, 64, 128, and 256, respectively. The feature channels used by the decoder in 1, 2, and 3 global residual dense blocks are the numbers 128, 64, 64, and 32, respectively. The ReLU activation function is used in the entire network model, mainly because its operation speed is fast, and the calculation value is suitable for the network structure of this paper. At the end of the network model, a fully connected neural network is used, which is mainly to analyze and organize the output features semantically.

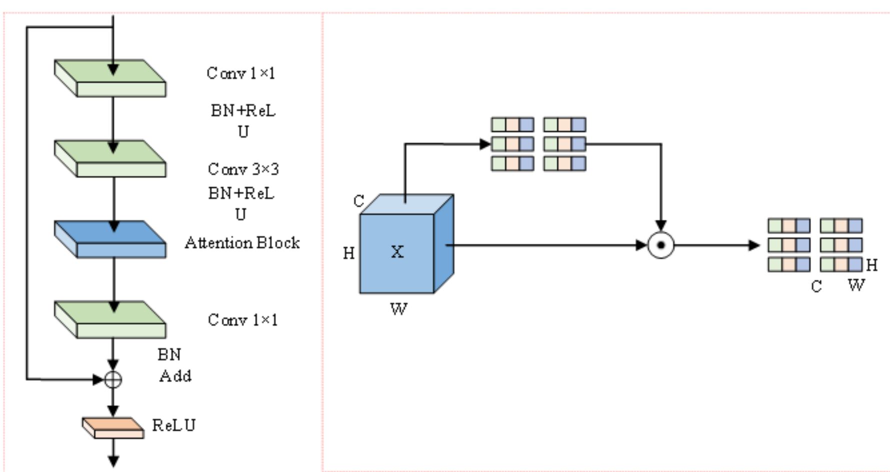
Residual Dense Block

In this paper, a simple convolutional layer is used in the neural network structure, so the structure of the network model is relatively simple, and the depth of the network is not enough, resulting in limited learned features of the network model. In order to achieve higher prediction accuracy and faster inference speed, this paper improves on the bottleneck module of the SimpleBaseline network structure. And in order to improve the prediction accuracy of the model and make the network model pay more attention to the area of interest, we also added an attention mechanism module.

The traditional attention mechanism block is mainly divided into channel attention mechanism and spatial attention mechanism, but this attention mechanism has limited use conditions and provides limited accuracy. Therefore, on the basis of referring to the traditional attention mechanism, this paper adopts a three-dimensional spatial attention mechanism, which can obtain a more refined attention weight map and better guide the tasks involved. In this paper, a dense residual module is proposed by combining the three-dimensional attention mechanism with the residual module. The dense residual module in this paper is mainly composed of a 3D attention mechanism and three convolutional layers. The ReLU activation function is used at the end of the module to control the output of the module. The network structure is shown in Figure 2. The input feature map of each convolutional layer is shown in Equation 1.

$$\mathrm{X}_i = \sigma(W_i[X_0, X_1, \ldots, X_{i-1}]) \quad (1)$$

Figure 2. Residual Dense Block



The output feature map is shown in Equation 2.

$$\mathrm{X}_{out} = W_{1\times 1}(\phi([X_0, X_1, ..., X_{i-1}, X_i])) + X_0 \tag{2}$$

The 3D attention layer mainly fuses the input feature map, multiplies the attention feature map with the 3D weight, and finally realizes the fusion of feature channels and channel compression through 1×1 convolution. At the same time, skip connections are added to improve the information flow characteristics. The final output of the 3D attention feature fusion layer is shown in Equation 3.

$$\phi(X) = \psi(\frac{(X-\mu)^2}{4\times(\frac{\nu(X-\mu)^2}{w\times h-1}+\lambda)+0.5}) \odot X \tag{3}$$

The global residual dense module is used as the basic convolution module, and the dense connection and residual learning mechanism are used to improve the performance of the network model. The calculation formula is shown in Equation 4.

$$Y_{out} = W_{1\times 1}([Y_0, Y_1, ..., Y_i]) + Y_0 \tag{4}$$

Middle Layer

A neural network is used to map the vectorized 2D spatial features into a linear space. In order to encode the spatial position of the 2D feature block, additional position information needs to be embedded into the input matrix. The middle layer contains many cascaded transformer modules. A single transformer layer contains a multi-head self-attention mechanism and a multilayer perceptron feed-forward neural network. In Equation 5, r represents the calculation of the multi-head attention mechanism. In Equations 5 and 6, Q, K, and V represent the query matrix, key matrix, and value matrix of the ith head attention mechanism of the multi-head self-attention mechanism, respectively.

$$\tau(Q,K,V) = W^0[h_1, h_2, ..., h_i] \tag{5}$$

$$h_i = soft\max(\frac{Q_i K_i^T}{\sqrt{d}})V_i \tag{6}$$

In addition, in order to make the network model better fit the data loss, this paper proposes multi-scale reconstruction loss, multi-scale similarity loss function, and perceptual loss. By introducing these new structures and functions, the network model is more uncertain during the training process, effectively suppressing the gradient disappearance and gradient explosion problems during the training process, accelerating the convergence of the network model, and improving the prediction of the network model effect. The multi-scale reconstruction loss is a loss function of the L2 norm established to accurately recover image details while capturing different moderate contextual information. The introduction of the structural pixel loss is to increase the stability of the training of the network model and increase the visual effect of the network model due to the influence of data outliers in the training process. Perceptual loss is to increase the quality of image generation and encoding, and to improve the effect of network model processing and generation.

Transformer Attention Mechanism

The traditional vision-based transformer network structure has a huge amount of parameters and computation, and it is difficult to directly apply it in the network. Therefore, lightweight CNNs are more useful in vision tasks, and their spatial inductive bias allows them to learn representations with fewer parameters in different vision tasks. However, these networks can only be locally modeled in space, and a transformer module based on a self-attention mechanism is required to learn global representations. In general, based on the combination of CNN convolution module and transformer mechanism, a model based on CNN and ViT is constructed to build a lightweight and low-latency network for vision tasks.

Usually for vision-based transformer modules, the first is to resize the input into a series of patches, then project them into a fixed spatial dimension, and finally learn the feature representation between patches through a set of transformer modules.

$$X \in \mathbb{R}^{H \times W \times C} \tag{7}$$

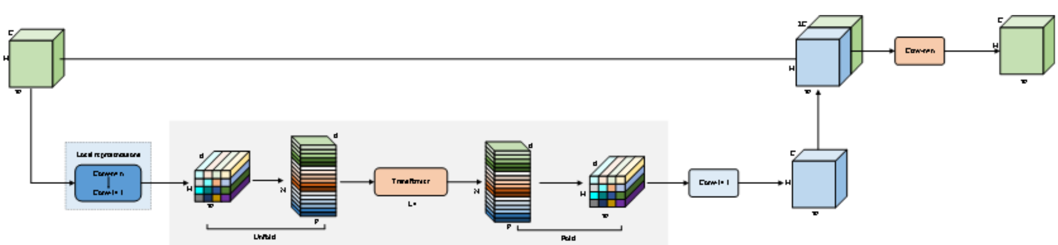
$$X_f \in \mathbb{R}^{N \times PC} \tag{8}$$

$$X_p \in \mathbb{R}^{N \times d} \tag{9}$$

where C, H, and W represent the channel, height, and width of the tensor, respectively, P represents the number of pixels in the patch, and N is the number of patches. Since these models ignore the spatial inductive bias inherent in CNNs, more parameters are required to learn representations of vision. At the same time, these models have weaker optimization capabilities and require a large amount of data to enhance the learned features and avoid overfitting.

The module structure of MobileViT is shown in Figure 3. By inputting a small number of parameters, local modeling and global modeling can be performed. First, through the input tensor, the MobileViT module will first operate on the input tensor using n×n and 1×1 convolutions to obtain. The n×n convolution is used to learn local spatial features, and the 1×1 convolution is used to project the input features into a high-dimensional space. In order to obtain longer-distance spatial relationships, a visual transformer module with multi-head self-attention mechanism is used for vision tasks. To enable MobileViT to learn a global representation with spatial inductive biases, this

Figure 3. Lightweight Transformer Block



paper first expands to N non-overlapping patches. Where p=wh, N=HW/P is the number of patches. Unlike ViT, which loses pixel order, MobileViT neither loses patch order nor the spatial position of each pixel in each patch. The last n×n convolution of the module is used to fuse local and global features. The local information of the convolutional n × n region is used to encode, while the global information of the p-th position in the p patches is encoded, so the global information in the input feature map can be sensed.

$$X_L \in \mathbb{R}^{H \times W \times d} \tag{10}$$

$$X_U \in \mathbb{R}^{P \times N \times d} \tag{11}$$

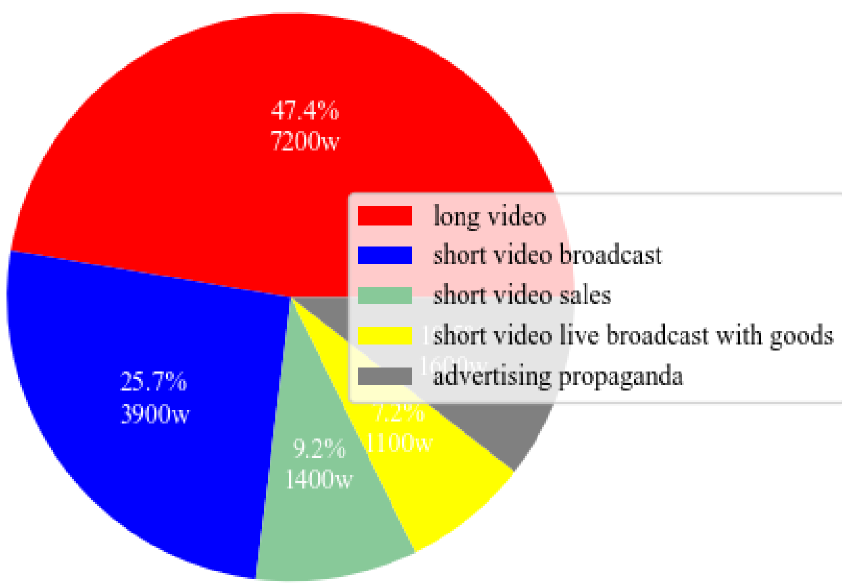
$$P = wh, N = \frac{HW}{P} \tag{12}$$

$$X_G(p) = Transformer(X_U(p)), 1 \leq p \leq P \tag{13}$$

RESULTS AND ANALYSIS

Figure 4 shows the comparison results of the sales volume of machinery and equipment. As can be seen from the figure, a total of five types of sales methods have been selected, namely, long video

Figure 4. Comparison of Sales Volume Across Multiple Channels



(M), short-video live broadcast (N), short-video sales (X), short-video live broadcast with goods (Y), and advertising propaganda (Z). Through the comparison of these five types of sales, we can clearly see that short-video live broadcasts are more important for sales.

From Figure 5, we can clearly see that with the change of sales time, when the total amount of sales is fixed, the change in the proportion of sales in different time periods also is very different. The main situation of this change is that, in summer, everyone has more space and energy for activities while, in winter, the weather is cold, and Volkswagen Smart conducts fitness activities indoors.

Figure 6 shows the optimization of the U-Net based neural network model proposed in this paper. From the figure, we can see the changes in time and live-broadcast mode, the key factors of the ground coordinates, and that the predicted value of the network model in this paper on the vertical axis also changes greatly.

From Figure 7, we can see that, with the change of the ground coordinates, the change trend of the predicted value of the ordinate also has obvious changes. It shows that, through the model proposed in this paper, the change of the prediction results is relatively stable on the whole and, at the same time, local changes occur due to influencing factors.

Figure 8 is a diagram showing the classification result of the short-video live-broadcast mode. We used the large public data set ImageNet to pre-train the model and then classified it on the data set we collected. The classification results are shown in the figure. From the classification results, we can see that the classification effect can basically meet the needs, and there is also a certain room for improvement.

Figure 9 shows the proportions of the data set categories established in this paper, where A, B, C, and D, respectively, represent the content of long videos, short videos, short-video live broadcasts, and short-video delivery. The data set we built by ourselves mainly solves the problem of the impact of short-video live broadcast on the sales of sports machinery and fitness equipment.

Figure 10 shows a forecast effect graph for each sales volume. In the figure, we mainly compare the actual sales volume (colored circle), the sales volume predicted by the model in red, and the sales volume of the network platform. From the figure, we can clearly see that the actual sales change area

Figure 5. Changes in the Proportion of Sales in Different Periods

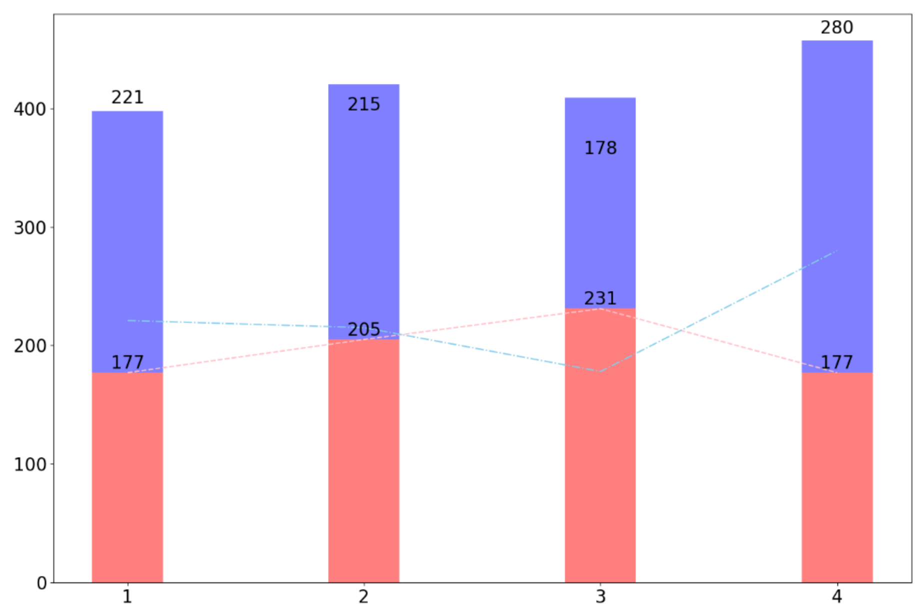


Figure 6. Network Model Optimization

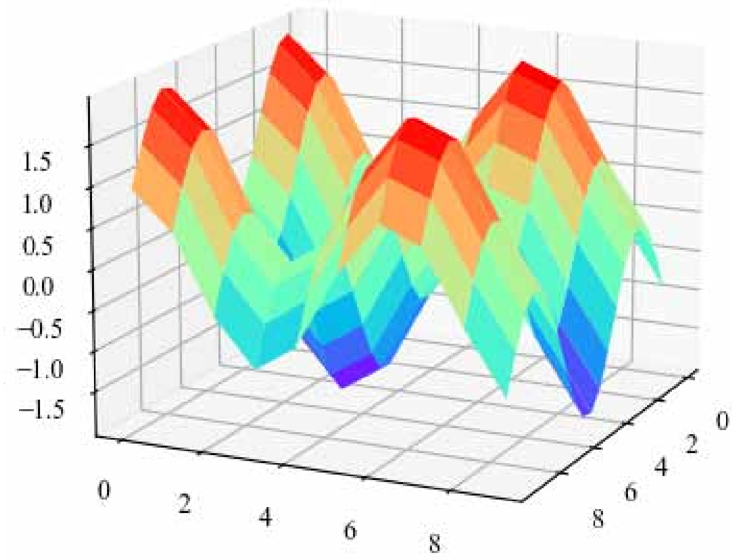
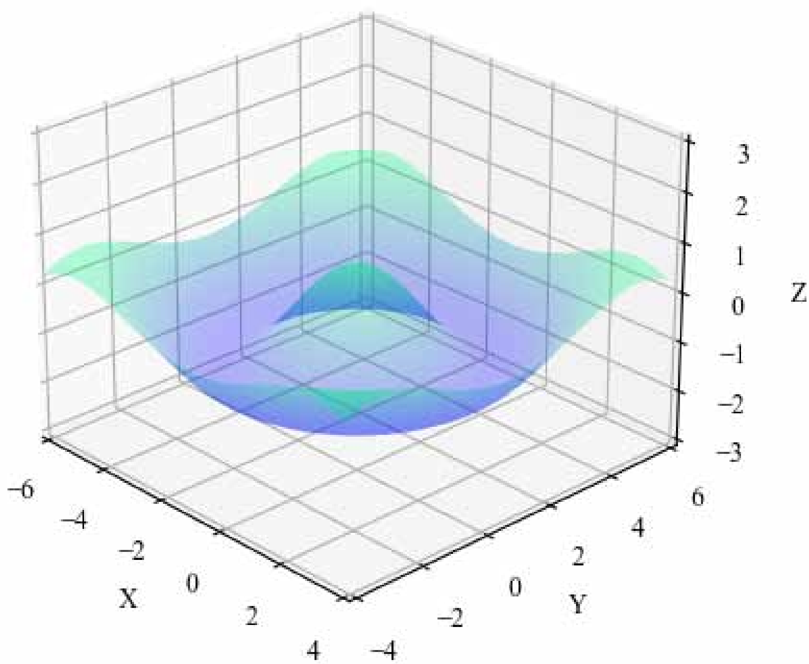


Figure 7. Change Trend of Predicted Value



predicted by the network model and the actual value are basically consistent with the actual. At the same time, we also found that the sales volume of the e-commerce network platform is much lower than the short-video live-broadcast method, indicating that the short-video live-broadcast method is more realistic.

Figure 8. Classification Results of Short-Video Live-Broadcast Methods

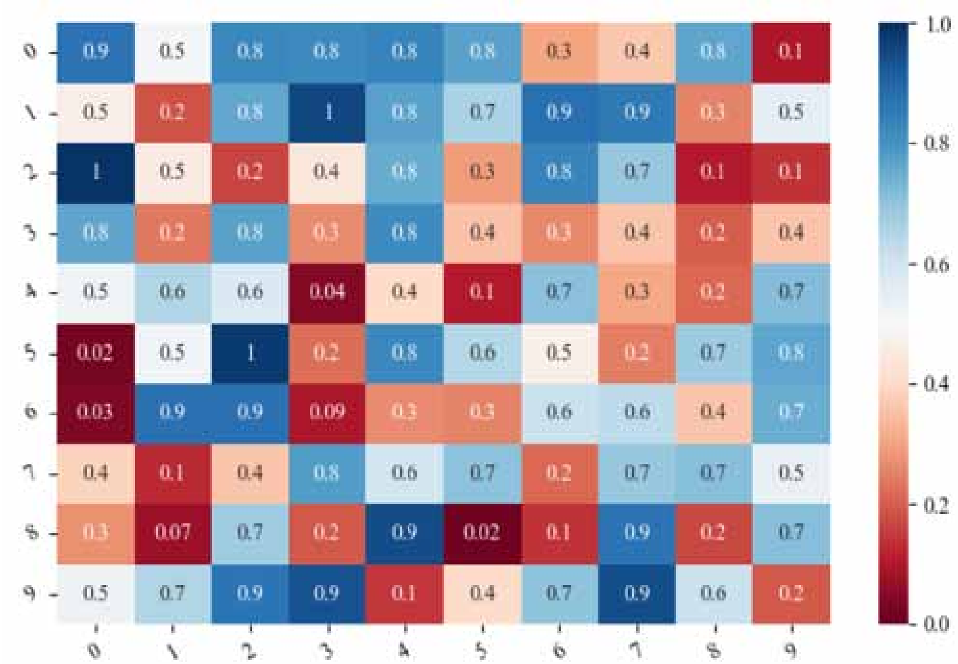
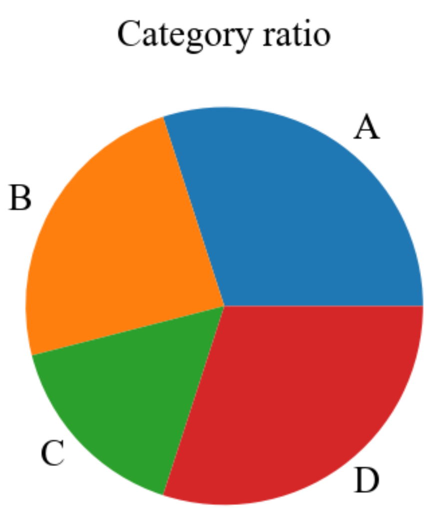
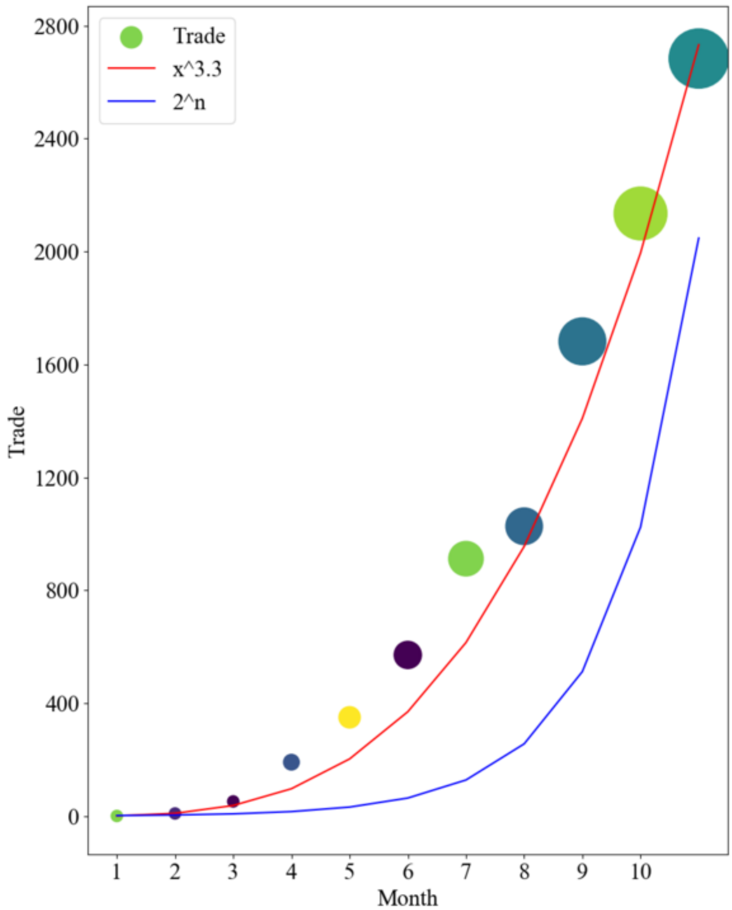


Figure 9. The Proportion of Self-Built Data Sets



With the widespread application of deep learning technology in various fields, sales prediction based on neural network models gradually has become one of the research hotspots. However, existing research has shown the potential of deep learning in improving the accuracy of predicting sales of sports machinery equipment, but it also faces challenges such as data limitations, model generalization ability, and practical application challenges. Therefore, in order to further improve

Figure 10. Monthly Sales Forecast



the sales forecasting model and promote its practical application, future research can explore and improve it from multiple aspects.

1. Expanding the coverage of data samples: Future research can attempt to obtain a wider and more diverse range of sales data samples, covering different regions, time periods, and sales channels to enhance the model's generalization ability and applicability.
2. In-depth research on model generalization ability: Further study can investigate the generalization ability of deep learning models in different market environments, and explore how to improve the stability and robustness of models through transfer learning, adversarial training, and other methods.
3. Integrating external factors: Ongoing work can consider incorporating external factors (such as weather, holidays, and promotional activities) into the model to better explain the fluctuations and changes in sales data and improve the predictive accuracy of the model.
4. Explainability improvement: Areas open to scrutiny include exploring interpretability improvement methods for deep learning models, making the predicted results of the model easier to understand and accept, and thereby improving its practical operability.

CONCLUSION

The short-video live-broadcast method in this paper is very challenging for the task of sports machinery and equipment sales. Mainly because there are many ways of short-video live broadcast, it is difficult to classify and analyze. In addition, there are many sales channels for sports equipment, and it is difficult to analyze from short videos. In order to achieve efficient and reliable data analysis, this paper proposes a CNN based on deep learning, which can better analyze the impact of short-video live broadcast on sports machinery and equipment. First, this paper proposes a U-Net-based CNN as the backbone network of this paper, which mainly realizes the impact of short-video live broadcast on sales. Second, this paper proposes a dense residual module based on the transformer lightweight module, which can effectively improve the global modeling ability of the network model and improve the prediction accuracy of the network model. Finally, through a large number of experimental data, it is proved that the method proposed in this paper has good practicability for the short-video live-broadcast method for sports equipment sales tasks and has better prediction accuracy and reasoning speed. In future work, we should focus on project tasks, establish data sets and CNN structures with stronger feature representation capabilities, and continuously improve the short-video live-broadcast method's ability to fit sports machinery and equipment sales tasks.

DATA AVAILABILITY

The figures used to support the findings of this study are included in the article. The data analyzed during the current research period can be obtained from the communication author, according to reasonable requirements.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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