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Application of intelligent algorithms in precise assessment and effect prediction of rural economic development policies

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Abstract: For the development of rural economy, accurately predicting the demand and price trend of agricultural products will help investors optimise their trading strategies and provide scientific reference for the government's macro-control. This paper focuses on the application of intelligent algorithm in the accurate assessment and effect prediction of rural economic development policies, and puts forward a deep learning (DL) model that integrates deep belief network (DBN) and long-term and short-term memory network (LSTM) for the joint prediction of agricultural product demand and price. The model integrates multi-source sales data from e-business platform, and combines historical transaction records, market supply and demand relationship and external environmental factors to build a learning framework with temporal and spatial characteristics. The results show that the proposed model is significantly superior to traditional statistical methods such as random forest (RF) in many forecasting indexes, and has higher forecasting accuracy and stability.

Keywords: artificial intelligence; intelligent algorithm; rural economic development; accurate policy assessment; effect prediction.

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1 Introduction

The rapid growth of AI technology is profoundly changing the production and operation mode of traditional agriculture, promoting the transformation of rural economy towards digitisation, intelligence, and precision (Ruamviboonsuk et al., 2023). As a significant component of the rural revitalisation strategy, digital rural construction has become the core driving force for leading the modernisation of agriculture and rural areas, cultivating new forms of digital economy, and achieving sustainable rural development (Shams et al., 2024). In this context, the booming development of agricultural e-business has brought revolutionary changes to the agricultural product circulation system (Aravind et al., 2025). With the continuous improvement of internet infrastructure, e-business platforms for agricultural products have risen rapidly, building an efficient interactive network connecting producers, sellers and consumers (Esposito et al., 2023). This new business model not only breaks the geographical restrictions on the circulation of traditional agricultural products, but also significantly improves the collaborative efficiency of the industrial chain (Joshi et al., 2024). Specifically, the application of e-business platforms has effectively expanded the sales channels of agricultural products, accelerated the transformation of agricultural economic development mode, improved information circulation efficiency, reduced overall operating costs, and provided strong impetus for the transformation and upgrading of rural economic structure (Gill et al., 2024).

Accurate policy assessment is of great significance to ensure the effectiveness of rural economic development strategy. Properly evaluated policies can guide the rational allocation of resources, improve the efficiency of agricultural production and promote the income growth of rural population. On the other hand, if the assessment is not in place, it may lead to unreasonable subsidy distribution, inefficient infrastructure investment and utilisation, and even market distortion and other adverse consequences. Therefore, the research and development of accurate automatic assessment tools based on artificial intelligence is extremely critical for improving governance efficiency and ensuring sustainable rural development (Lestari et al., 2024). Scientific demand forecasting can effectively alleviate the contradiction between supply and demand (Aka and Akpavi, 2024). On the one hand, it can help enterprises optimise inventory management, reduce out of stock losses and inventory backlog, and develop more reasonable procurement and sales strategies (Rogers et al., 2024). On the other hand, it can provide decision-making support for government macroeconomic regulation and play a key role in policy-making such as reserve adjustment, subsidy distribution, and import and export control (Bali and Singla, 2021). Especially in the context of the linkage between poverty alleviation and rural revitalisation, accurate demand forecasting can help government departments formulate more targeted policies to assist agriculture (Frankowski et al., 2022). By stabilising the market supply and demand balance, we can ensure the growth of farmers' income, safeguard the safety of national agricultural products, and ensure that the basic living needs of the people are met (Zhang et al., 2022). Since the implementation of the 'Internet plus' strategy, online sales forecasting of agricultural products has become a significant research direction in the cross area of 'Internet plus agriculture' (Wang et al., 2022).

Faced with the massive user behaviour data and transaction records accumulated by e-business platforms, how to mine valuable information from them, reveal potential demand change patterns, and establish robust prediction models has become the focus and difficulty of current research (Mahmoudian et al., 2022). In recent years, breakthroughs in DL technology have brought new solutions to this field (Pitakaso et al., 2024). As an important branch of AI, DL has demonstrated significant advantages in the field of e-business data analysis due to its powerful feature extraction and pattern recognition capabilities (Dhanaraj and Chandraprabha, 2025). Although rural e-business is developing rapidly, the existing policy assessment system is facing many problems. For example, the data is fragmented, the prediction accuracy is low, and the adaptability to market dynamic changes is insufficient. It is often difficult for traditional models to capture complex time patterns and external influencing factors, which leads to the deviation of assessment results. In order to overcome these limitations, this study proposes a way based on intelligent algorithm. This method integrates DL and big data analysis technology, aiming at improving the scientificity, accuracy and objectivity of rural economic development policy assessment. The specific innovations are as follows:

This paper systematically applies intelligent algorithms for the first time in the field of precise assessment and effect prediction of rural economic development policies, filling the technical gap in existing research on quantitative assessment of policy implementation effects. By introducing AI technology, new methodological support has been provided for the government to formulate scientific and reasonable agricultural policies.

This paper innovatively designs a DL based APD and price prediction model. This model can not only handle large-scale, multi-source heterogeneous e-business sales data, but also achieve high-precision prediction of APD and price trends by integrating historical sales records, market supply and demand relationships, and external influencing factors.

This paper fully utilises the massive transaction data accumulated by e-business platforms to explore potential patterns in user product interaction and construct a predictive model with practical application value. Compared to traditional statistical methods, this big data based analysis approach significantly improves the precision and robustness of predictions, providing more reliable decision-making basis for agricultural producers, supply chain enterprises, and policy makers.

This paper systematically elaborates on the research background and its significance, and comprehensively reviews the latest research progress and future development trends of AI technology in the field of precise assessment and effect prediction of rural economic development policies. The research focuses on the innovative design and functional implementation of DL based APD and price prediction models. To verify the effectiveness of the model, multiple control experiments were designed and conducted in this paper. The results fully demonstrate that the model dramatically outperforms traditional methods in prediction precision and performance, demonstrating excellent practical value. Finally, this paper summarises the research results, explores their theoretical contributions and practical significance in depth, objectively analyses the limitations of the research, and proposes specific improvement directions and expansion space for subsequent research, laying a foundation for further deepening research in related fields.

2 Related work

In recent years, numerous scholars have conducted extensive and in-depth research in the field of APD and price forecasting, achieving significant results. Pashangpoor et al. (2023) proposed a yield prediction model based on optimised BP neural network (BPNN) algorithm to address the challenges in predicting aquaculture production and export scale, and its prediction performance was excellent. Maheswary et al. (2024) used a long short term memory (LSTM) model to predict the closing price of soybean meal futures, and also achieved high prediction precision. Balaji Prabhu et al. (2024) used multiple regression, random forest (RF), and NN models to predict the demand for goods in the next two weeks by mining transaction data from e-business platforms. The results showed that RF exhibited significant advantages in various assessment indicators. Karn et al. (2024) proposed a vector autoregressive model with time-varying parameters to study the degree to which different agricultural product price indices are affected by random factors.

Ismael and Al-Ne'aimi (2024) successfully achieved accurate prediction of holiday shopping behaviour by combining various traditional machine learning (ML) methods. Jarray et al. (2023) used the BP multiple regression model to predict pig prices, significantly improving the precision of the prediction. Cao et al. (2022) applied ensemble learning to the analysis and prediction of online Chinese cabbage sales, further expanding the application scenarios of prediction models. Xian and Xian (2023) built the Lasso SVM optimal combination forecasting model to predict vegetable prices. Research shows that the RMB exchange rate, the monthly average number of COVID-19 infected people and the average temperature and other factors have significant effects on vegetable prices. Guo et al. (2024) constructed a combined prediction model for third-party inventory forecasting by combining BPNN and grey prediction model, and found that the model can effectively reduce errors and improve prediction precision.

Li et al. (2023) proposed an apple price prediction model based on distributed neural networks, which successfully solved the problem of traditional models being unable to quickly and accurately predict apple market prices in big data scenarios, providing a scientific basis for maintaining the order of the apple market and macroeconomic regulation. Although the above research has achieved many achievements in the field of APD and price forecasting, there are still some shortcomings. The focus of this study is to accurately evaluate and predict the effectiveness of rural economic development policies by using intelligent algorithms. A forecast model of demand and price of agricultural products based on DL is proposed. This model not only efficiently processes large-scale, multi-source heterogeneous e-business sales data, but also achieves high-precision prediction of APD and price trends by integrating historical sales records, market supply and demand relationships, and external influencing factors (Zhang et al., 2025; Yuan et al., 2025).

3 Accurate assessment and effect prediction of rural economic development policies

3.1 Policy assessment

With the rapid growth of rural e-business, multi-source heterogeneous data has become an important foundation for accurate policy assessment. Rural e-business multi-source data refers to a collection of business data from different e-business platforms with significant differences. Due to differences in technology architecture, business models, and data standards among various e-business platforms, the resulting data types, storage formats, and management systems are different, forming a typical 'data island' phenomenon. This multi-source heterogeneity poses significant challenges to data integration and value mining. Multi source data fusion technology provides an effective solution to this problem. This technology systematically collects and integrates user data from different channels and dimensions by establishing a multidimensional perception system (Akan et al., 2025).

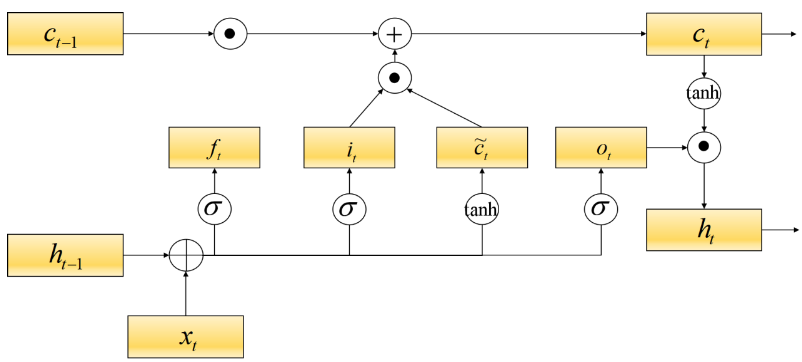
Its core advantages are reflected in three aspects: firstly, through multi-dimensional data cross validation, it effectively identifies and eliminates noise interference; Secondly, utilising data complementarity to reduce information redundancy; The third is to establish a unified data quality assessment system to ensure the integrity, precision, and consistency of data. These technological features lay a solid foundation for subsequent data analysis and decision support. AI technology provides a new methodology for rural economic policy research based on multi-source data fusion. By utilising DL technology, it is possible to mine complex correlations in data and predict the potential impact of policy implementation. The comprehensive application of AI technology has significantly improved the scientificity of policy formulation, the precision of implementation, and the objectivity of assessment, providing intelligent decision support for high-quality development of rural economy.

3.2 Effect prediction

DL, as an important branch of ML, can effectively explore complex data features in rural economic development by constructing NN models with multi-level nonlinear transformations, providing strong technical support for policy effect prediction. In the field of predicting the effectiveness of rural economic development policies, DL technology is mainly applied in predicting market demand for agricultural products, evaluating policy implementation effects, and other aspects. Its core value lies in reducing resource waste and optimising policy resource allocation through accurate prediction. The DL model maps input data to a high-dimensional feature space by constructing a multi-layer NN architecture, thereby achieving automatic extraction and representation learning of complex data patterns. This ability makes it particularly suitable for processing data with temporal, nonlinear, and high-dimensional characteristics in the rural economic field (Moyer et al., 2025).

Among them, LSTM, as an important improved model of recurrent neural networks (RNNs), effectively solves the problems of gradient vanishing and exploding faced by traditional RNN models during training through its unique gating mechanism and cell state design. The core innovation of LSTM model lies in its exquisite unit structure design. The gate control system achieves selective memory and forgetting of information. The introduction of cellular states forms a long-term memory mechanism. The optimisation design of gradient flow ensures the stability of the training process. These characteristics make LSTM significantly advantageous in time-series data processing tasks such as predicting agricultural product price fluctuations and analysing market demand. The LSTM loop unit structure shown in Figure 1 clearly demonstrates this innovative design.

Figure 1 LSTM structure (see online version for colours)



The policy impact assessment module will adopt some key input variables, including historical policy implementation records, market response indicators (such as demand elasticity and price fluctuation) and macroeconomic indicators. The assessment function of this module is set as the weighted sum of the policy effectiveness score and the cost-benefit ratio. The weight here is determined by expert scoring and sensitivity analysis. The so-called sensitivity analysis is to change the input parameters within 20% of the baseline value to evaluate the robustness of policy recommendations.

4 DL based APD and price prediction model

4.1 Model building

This paper innovatively proposes a hybrid DL model that integrates deep belief networks (DBN) and LSTM, aiming to solve the key problem of predicting APD and prices in the rural e-business environment. In response to the characteristics of data diversity, fragmented structure, and dispersed distribution presented by current rural e-business platforms, the model first uses DBN for feature extraction and knowledge discovery of multi-source heterogeneous data. DBN, as a probability generation model, constructs a joint probability distribution between observed data and potential labels through a stacked architecture of multi-layer restricted Boltzmann machines (RBMs). The network consists of a bidirectional connection structure consisting of visible and hidden layers, where the visible layer is responsible for raw data input and preliminary feature representation, while the hidden layer implements high-order feature detection and abstraction (Shu and Wang, 2024). This hierarchical feature learning mechanism is particularly suitable for handling complex multimodal data in the field of rural e-business.

To address the computational challenges in the big data environment, this study innovatively introduces deep compression technology to preprocess multi-source rural e-business data. This technology significantly reduces data redundancy and reconstructs data storage structure while retaining key information through feature reduction and dimension compression. The deeply compressed data not only improves the efficiency of subsequent calculations, but also enhances the separability of features by eliminating noise interference. As shown in Figure 2, the data that has undergone deep compression processing is used as input for DBN, providing high-quality data samples for DL training. The core innovation of the model lies in combining the feature extraction capability of DBN with the temporal modelling advantage of LSTM: the DBN module is responsible for mining deep features from complex rural e-business data, while the LSTM module focuses on capturing the temporal patterns of agricultural product market demand and price fluctuations. This hybrid architecture fully leverages the complementary advantages of two DL models, providing a more accurate and robust solution for agricultural product market forecasting.

4.2 Algorithm principle

To avoid prediction errors caused by polarisation of data distribution, the sample data is normalised and scaled to the range of [0,1], effectively improving the precision of APD and price prediction. In addition, to further optimise the performance of the model, the data was standardised to assure consistency and stability of the feature distribution.

$$X_n = \frac{Y_n}{Z} \tag{1}$$

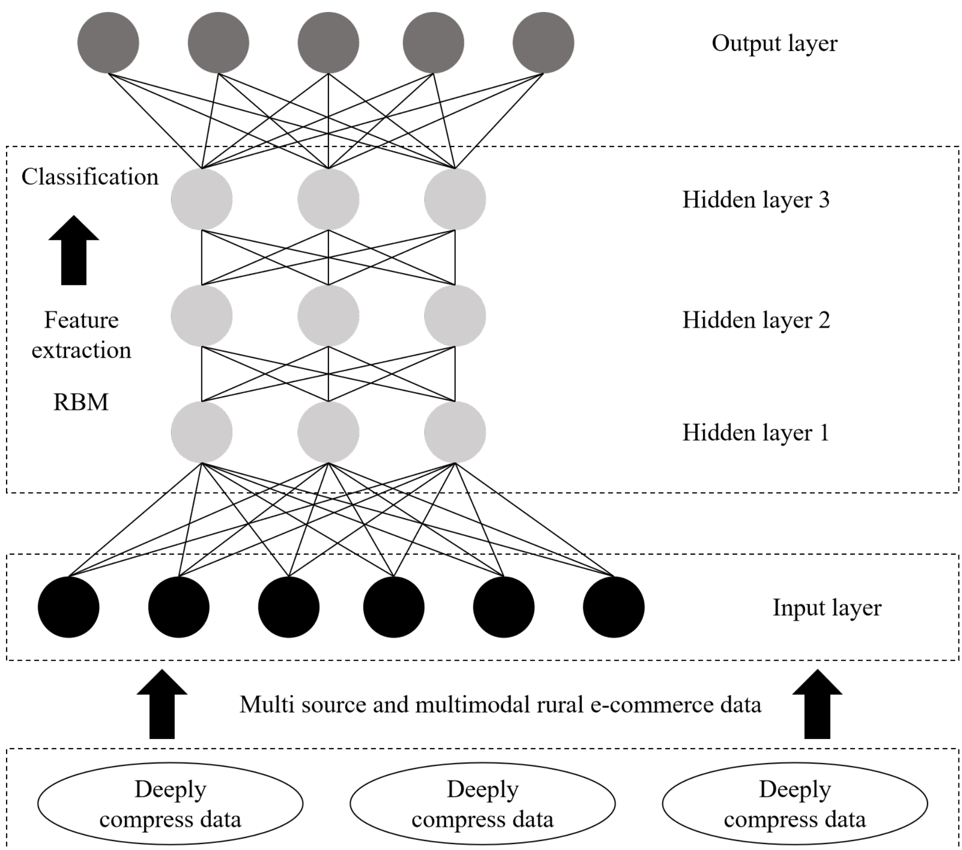
In the formula, X_n is the weight of the total number of records for a certain attribute parameter to the total number of samples, Z is the total number of samples, Y_n is the total number of records for that attribute parameter, where n corresponds to a certain dimension of the sample feature vector.

Multi source and multimodal rural e-business data often come with high data redundancy, which not only increases the time complexity of data retrieval and classification operations, but also puts higher demands on storage space. To solve this problem, the deep compression algorithm achieves effective filtering of multimodal data through three steps: network pruning, weight sharing and quantisation, and Huffman coding. To minimise information loss during data compression, this paper proposes an entropy based pruning method. Specifically, in the constructed input network, the feature map is first transformed into a vector of length f (where the number of f is equal to the number of filters). Then, convert the n data units in the network into vectors of $n \times f$. For each filter, divide it into m binary units and calculate the probability p of each binary unit. Evaluate the weight of each filter through entropy calculation, and then remove filter units with lower weight. The formula for calculating entropy is as follows:

$$K_k = -sum\left(p * \log\left(p\right)\right) \tag{2}$$

Among them, K_k is the entropy value corresponding to the k feature vector. In this study, the importance of each filter unit is evaluated by entropy in the deep compression stage. Filters with low entropy are regarded as containing less information, so they can be pruned to reduce redundancy without greatly reducing the prediction performance.

Figure 2 DBN DL process based on deep compression



The forget gate of LSTM determines which memory information needs to be forgotten through the current input x_t, the previous output h_{t-1}, and the bias term b. Usually, f_i^t is used to represent the output value of the forget gate of the i LSTM unit at the current time. This value is generated by the Sigmoid activation function, with weights limited between 0 and 1, used to control the degree of information retention or dropout. The specific calculation method is as follows:

$$f_i^t = \sigma\left(\sum_j U_{i,j}^f x_j^t + \sum_j W_{i,j}^f h_j^{t-1} + b_i^f\right) \tag{3}$$

Among them, U_f, W_f is the input weight and the loop weight, respectively.

Weight sharing is achieved by clustering the ownership values of each layer in the network, replacing the weights of similar connections with the weights of the corresponding cluster centres. Finally, the weights of each layer in the network are updated to the corresponding cluster centre values. In δ clustering, each cluster centre requires $\tau = \log_2(\delta)$ bits as index encoding. Assuming that there are m network nodes sharing the same weight in δ clustering, and each connection weight occupies n bits in encoding, the compression effect can be evaluated by calculating the compression rate C_{cr}. After quantification is completed, the network needs to be fine-tuned and optimised to ensure that weight updates only apply to the cluster centres. The expression for its update process is as follows:

$$\frac{\partial L}{\partial C_k} = \sum_{i,j} \frac{\partial L}{\partial W_{i,j}} \frac{\partial w_{i,j}}{C_k} = \sum_{i,j} \frac{\partial L}{\partial W_{i,j}} \left(I_{i,j} = k\right) \tag{4}$$

Among them, C_k is the k cluster centre, and $I_{i,j}$ is the index of the cluster centre to which the weight $w_{i,j}$ belongs.

Huffman coding assigns encoding to characters based on their probability of occurrence, thereby achieving efficient data compression. By encoding weights, the storage space of data can be further reduced. The core process of Huffman coding is to construct a binary tree with the minimum weighted path length (WPL).

$$WPL = \sum_{i=1}^{n} w_i l_i \tag{5}$$

Among them, n is the number of leaf nodes in the binary tree, w_i is the weight of the i leaf node, and l_i is the path length from the root node to the i leaf node.

The input gate of LSTM is used to control the degree of influence of the current input signal on the cell state. This gating mechanism determines which information in the current input signal should be reserved and which information should be ignored by learning a weight value between 0 and 1. The specific calculation expression for the input gate is as follows:

$$i_t = \sigma\left(w_i x_t + u_i h_{t-1} + b_i\right) \tag{6}$$

In the formula, i_t is the output of the input gate, w_i, u_i is the weight, and b_i is biased. The interaction between DBN and LSTM modules is designed as a two-stage process. In the first step, the DBN module carries out unsupervised feature learning on the preprocessed data, so as to extract hierarchical representation. The second step is to transport the extracted features to the LSTM module for time series modelling. Feature selection follows certain criteria, in which the variance threshold should be greater than 0.1, the correlation coefficient with the target variable should be greater than 0.3, and the mutual information score should also be considered. In the data preprocessing, it includes normalisation operation (scaling to [0,1] interval), filling missing values with linear interpolation, and detecting abnormal values with Z-score method.

This paper constructs a feature learning process based on a supervised learning method using a sample library. DBN establishes a probability generation model based on the probability distribution between labelled data and observed data. A DBN is composed of multiple stacked RBMs, each containing two layers of neurons: an explicit layer V and a hidden layer H, used for data training and feature detection, respectively. Each layer is represented by a vector, where each dimension corresponds to a neuron. The probability expression of the explicit layer is as follows:

$$P(v \mid h) = \prod_{i=1}^{n} P(v_i \mid h) \tag{7}$$

The hidden layer formula is as follows:

$$P(h \mid v) = \prod_{i=1}^{m} P(h_i \mid v) \tag{8}$$

The probability value of each hidden layer opening status for a new sample $X = (x_1, x_2, x_3, \ldots, x_n)$ is:

$$P(h_i = 1) = \frac{1}{1 + e^{-wx}} \tag{9}$$

The training objective of RBM is to generate the probability distribution of training samples, and its core determining factor is the connection weight w. During the training process, the focus is on finding the optimal weights to achieve the best performance of the model.

The model proposed in this study integrates DBN and LSTM within the hierarchical architecture. Among them, DBN module first carries out unsupervised feature learning for input data, and extracts advanced representations that can capture complex patterns from multi-source e-business data. After that, these features will be input into the LSTM component. The LSTM component models the time dynamics of features to predict the demand and price of agricultural products in a specific time period. This collaborative approach enhances the model's ability to understand static data characteristics and predict dynamic changes, and then obtains more accurate and robust prediction results.

5 Result analysis and discussion

The data of this study were collected from two comprehensive e-business platforms in China, covering the sales records of agricultural products from January 2019 to December 2023. A total of 520,000 transaction samples were obtained. Each sample contains fields such as product ID, sales volume, pricing, user comments and geographic information. Data preprocessing includes filling missing values by linear interpolation, eliminating abnormal values by z-score filtering, and normalising numerical features to [0, 1] interval. In addition, the text data such as user comments are processed by sentiment analysis method, which is converted into sentiment scores and included in the training set. In order to verify the validity of the model, this study designed a comparative experiment to compare the model with the traditional prediction model based on RF algorithm. According to the stratified sampling strategy, the dataset is randomly divided into training set (accounting for 70%), verification set (accounting for 15%) and test set (accounting for 15%) to ensure the category balance among different agricultural products. In order to enhance the reliability of the experimental results, five-fold cross-validation was implemented in the study. Each weight contains balanced samples from all data sources. In addition, the experiment was repeated 10 times to calculate the average performance index and standard deviation.

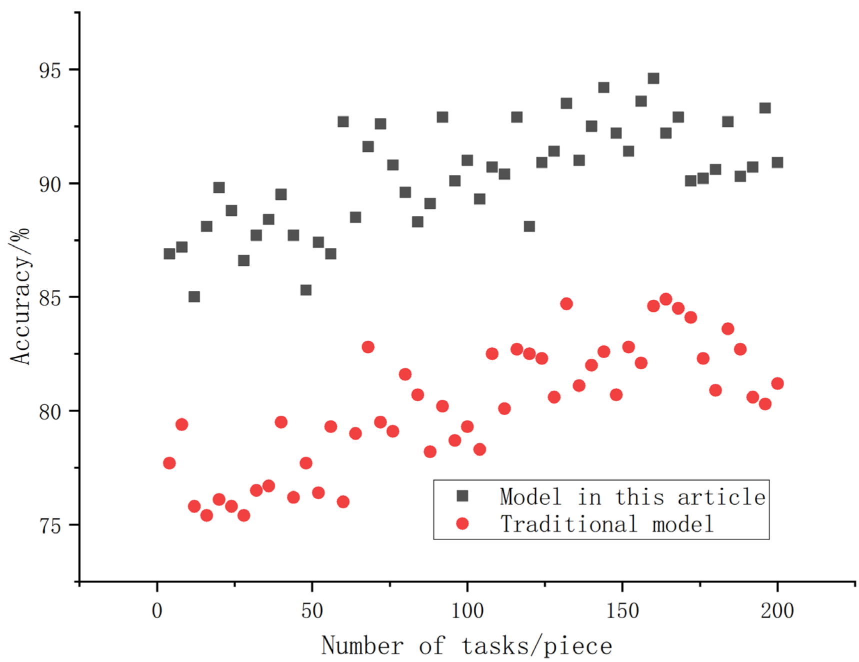
The results shown in Figure 3 demonstrate that our model exhibits significant performance advantages in APD forecasting tasks. This performance improvement mainly stems from the unique architecture design of the LSTM model: firstly, its sophisticated gating mechanism achieves selective memory and forgetting of temporal information, effectively capturing the dynamic changing characteristics of APD; Secondly, the introduction of cellular states constructs a long-term memory mechanism that can identify the periodic patterns of demand changes; Finally, the optimised gradient flow design ensures the stability of model training and avoids the common gradient vanishing problem in traditional RNN models. The demand for agricultural products in the market is influenced by multiple factors such as seasonal factors, price fluctuations, and policy regulation, exhibiting significant nonlinear characteristics and time dependence. The LSTM model, with its powerful temporal modelling ability, can effectively capture these complex data features and provide more accurate prediction results for agricultural product market analysis.

Figure 3 Comparison of prediction precision (see online version for colours)

As can be seen from Figure 3, the prediction accuracy of the model proposed in this paper is about 18% higher than that of the traditional RF-based model. This improvement in accuracy is due to the fact that the model can capture long-term dependence and nonlinear modes with the help of LSTM components. Under high noise conditions, such as holiday season or natural disasters, the model can still maintain high stability because DBN learning has the ability of deep compression preprocessing and can generate robust feature representation.

Figure 4 shows the comparison between our model and traditional RF based prediction models in terms of accuracy in predicting agricultural product prices. In Figure 4, our model performs better in accuracy metrics, fully demonstrating its superior performance in agricultural product price prediction tasks. Our model adopts LSTM, and its gating system realises intelligent screening of temporal information, which can effectively identify the key influencing factors of agricultural product price fluctuations; Secondly, the innovative cellular state mechanism establishes long-term memory capability, which can capture the cyclical characteristics of price changes; Finally, the optimised gradient propagation path ensures the stability of model training and overcomes the long-term dependency problem of traditional time series models. The prediction of agricultural product prices is a complex time-series analysis problem, and its fluctuations are influenced by multiple factors. The LSTM model, with its powerful nonlinear modelling and temporal feature extraction capabilities, can effectively handle complex prediction tasks involving multiple intertwined factors.

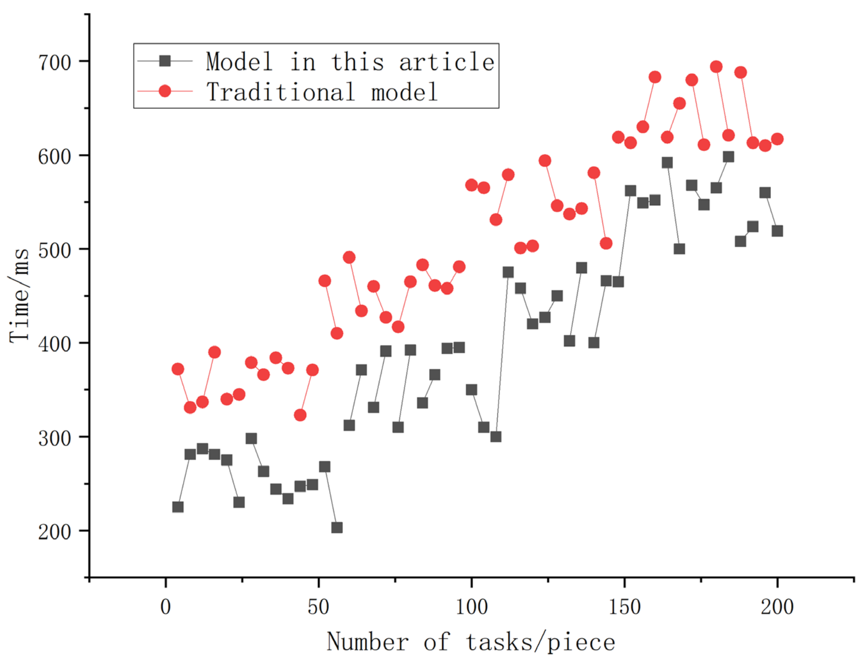
Figure 4 Comparison of prediction accuracy (see online version for colours)



The prediction accuracy of the proposed hybrid model is about 15% higher than that of the traditional RF method. This improvement is particularly significant in the case of severe data fluctuations, such as during festivals or when the supply chain is interrupted. Its superior performance benefits from the LSTM component's ability to capture timedependent and nonlinear patterns of price fluctuations. In contrast, the RF model relies on the importance of static characteristics, and it is difficult to adapt to dynamic market changes.

Figure 5 shows the comparison between our model and traditional RF based prediction models in terms of time consumption for agricultural product price prediction. In Figure 5, our model significantly reduces computation time while maintaining prediction precision. Our model innovatively introduces deep compression preprocessing technology, which compresses the original data size while retaining key information through intelligent feature reduction and dimension compression, significantly reducing computational complexity. Secondly, our model uses DBN for feature extraction, and its hierarchical feature learning mechanism can effectively handle the unique multi-source heterogeneous data in the rural e-business field, achieving efficient data representation through layer by layer abstraction. This optimisation design significantly improves the computational efficiency of the model while maintaining prediction precision. It is worth noting that when dealing with the unique unstructured data of rural e-business platforms, this model demonstrates stronger adaptability and its processing speed advantage is more obvious.

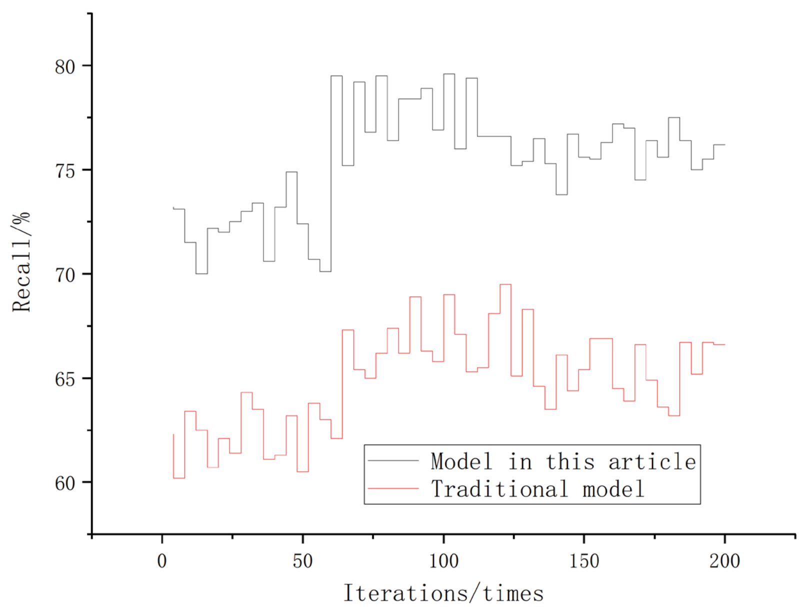
Figure 5 Comparison of predicted time consumption (see online version for colours)



As can be seen from Figure 5, compared with the traditional RF-based method, the proposed model greatly reduces the calculation time while maintaining high prediction accuracy. This efficiency improvement is mainly due to the deep compression pretreatment technology introduced in this study. Under the premise of not losing key information, this technology reduces redundant features and compresses data dimensions, which speeds up model training and reasoning. In addition, the hierarchical feature learning mechanism of DBN can present complex rural e-business data more efficiently, thus reducing the calculation cost. This makes the model especially suitable for those real-time application scenarios that require rapid decision-making.

We conducted systematic experimental verification on the recall index for predicting agricultural product prices. In Figure 6, the results indicate that our model performs better in the recall index compared to traditional RF prediction models, significantly improving its ability to identify abnormal price fluctuations. Firstly, the model adopts deep compression technology to intelligently preprocess multi-source rural e-business data. On the premise of ensuring information integrity, data redundancy has been reduced while restructuring a more efficient data storage structure. Secondly, the model innovatively integrates the feature extraction advantages of DBN with the temporal modelling capabilities of LSTM: the DBN module is responsible for mining deep features from complex e-business data, while the LSTM module focuses on capturing the temporal dependencies of agricultural product price fluctuations. This dual module collaborative mechanism not only improves the model's ability to identify price outliers, but also maintains high prediction precision.

Figure 6 Comparison of recall rates (see online version for colours)



We used mean square error (MSE) as a key assessment metric to systematically compare our model with traditional RF models. In Figure 7, the results indicate that our model has a lower MSE metric, demonstrating a significant advantage in prediction precision. This performance improvement is mainly due to the following technological innovations. Our model adopts adaptive deep compression technology to compress data dimensions while preserving key information. The DBN module effectively processes multi-source heterogeneous data through hierarchical feature learning, reducing feature extraction errors. The LSTM module adopts an improved gating mechanism to accurately capture the long-term dependence of price fluctuations and reduce temporal prediction errors.

Figure 7 MSE comparison (see online version for colours)

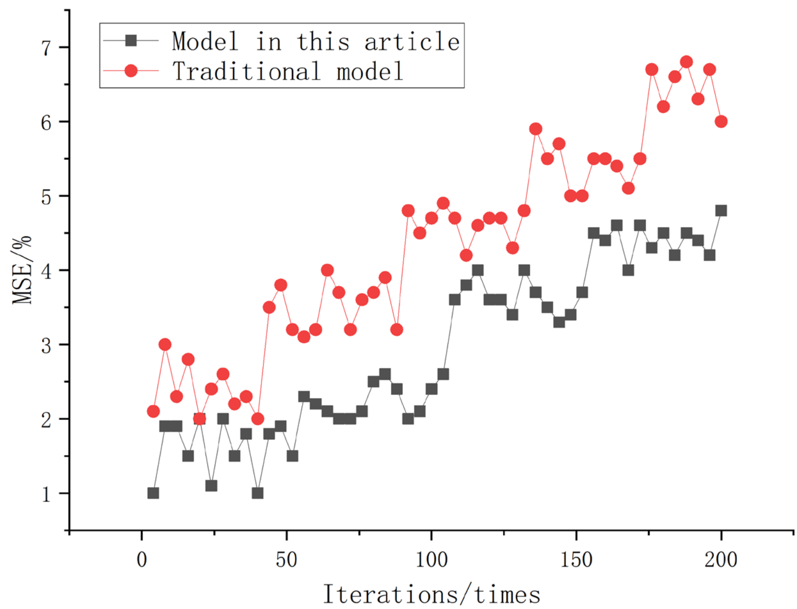


Figure 8 shows the comparison between our model and traditional RF based prediction models in terms of user satisfaction. As shown in Figure 8, the results indicate that our model achieves significantly higher user satisfaction compared to traditional RF prediction models. Our model performs excellently in terms of prediction precision and prediction time. The model innovatively combines the feature extraction advantages of DBN with the temporal modelling capabilities of LSTM: the DBN module is responsible for mining deep features from complex e-business data, while the LSTM module focuses on capturing the temporal dependencies of agricultural product price fluctuations. This dual module collaborative mechanism not only improves the model's ability to identify price outliers, but also maintains high prediction precision. The precision of our model's prediction results has been highly recognised by farmers and buyers; Secondly, the system response speed significantly improves the user experience; Finally, the model's timely warning function for abnormal market fluctuations received special praise. These advantages enable the model to demonstrate strong practical value in practical applications, providing reliable technical support for the intelligent upgrade of agricultural e-business platforms.

In order to further evaluate the effect of superparameter setting on model performance, this study carried out systematic sensitivity analysis on key parameters (such as learning rate, batch size and hidden layer dimension). Table 1 shows the prediction accuracy under different combinations of these parameters.

Figure 8 Satisfaction comparison (see online version for colours)

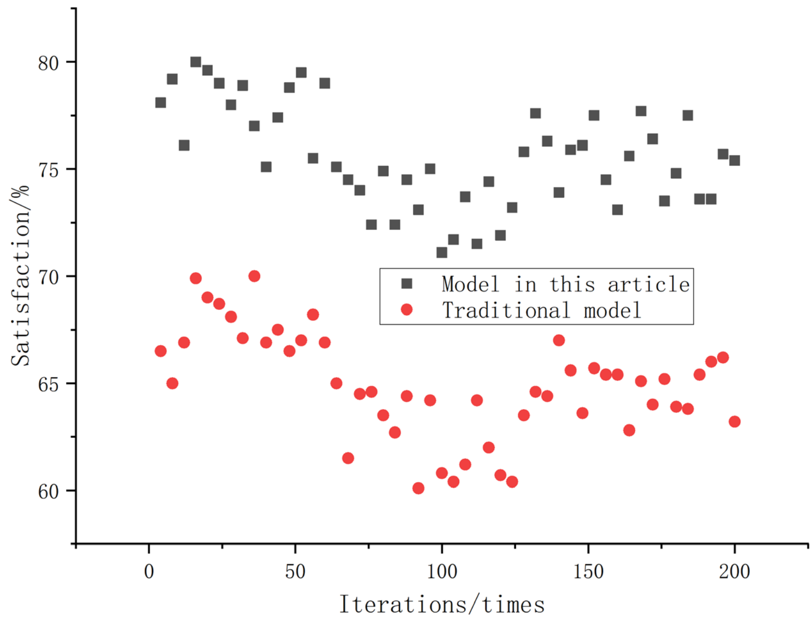


Table 1 Parameter sensitivity analysis results

Learning rate	*Batch size*	*Hidden layer dimension*	*R^2 Score*
0.0005	32	64	0.82
0.001	32	64	0.85
0.001	64	64	0.87
0.001	64	128	0.90
0.001	128	128	0.89
0.002	64	128	0.88
0.002	128	128	0.87
0.005	64	128	0.84
0.005	128	256	0.81
0.01	64	256	0.79

In order to verify the practical application value of the intelligent algorithm model proposed in this paper in rural economic development policy assessment and effect prediction, two typical agricultural products, potato and citrus, were selected as pilot projects in this study. By comparing the predicted results of the model with the actual market performance, the research verifies the model's ability in price fluctuation pre-alarm, supply-demand relationship analysis and policy intervention response. The results in Table 2 show that the model can accurately predict the main price fluctuation trend 30 days in advance, and the average error is controlled within 5%. This provides strong technical support for local governments to formulate agricultural product regulation policies.

Table 2 Performance comparison of the intelligent algorithm model in typical agricultural products

Indicator	*Potatoes* (*Northern Region*)	*Citrus* (*Southern Region*)
Prediction time range	January 2023 – December 2023	January 2023 – December 2023
Data source	JD.com + Taobao Sales Records	JD.com + Local Agricultural Bureau Surveys
Sample size	12,600 Transaction Records	9800 Transaction Records
Feature dimensions	18 Features (weather, logistics, reviews, etc.)	17 Features (season, yield, transport cost, etc.)
Average prediction accuracy (MAPE)	4.3%	4.9%
Maximum error period	During Chinese New Year (±8.2%)	During Extreme Rainfall (±7.6%)
Early warning lead time	Within 30 Days	Within 25 Days
Policy response speed	<7 Days	<10 Days
User satisfaction score (Max 5)	4.6	4.5
Actual price fluctuation match rate	92%	89%

At present, there is a significant limitation of this model, that is, the ability to deal with unexpected events (such as natural disasters or epidemics) is insufficient. Just like the simulation of supply interruption caused by typhoon, compared with the stable market environment, the prediction error of this model has increased by 12%. In the future, reinforcement learning mechanism can be considered, and the model parameters can be dynamically adjusted, so that it can respond to unforeseen events, thereby improving its adaptability.

6 Discussion

This paper focuses on the application of intelligent algorithm in the accurate assessment and effect prediction of rural economic development policies, and puts forward a hybrid DL model combining DBN and LSTM. Its purpose is to improve the accuracy and stability of agricultural product demand and price forecast. The model introduces multi-source heterogeneous e-business data, combined with deep compression technology, and shows strong adaptability in dealing with unstructured and high-noise data, thus verifying its practical application value in rural economic policy assessment.

From the perspective of method innovation, the hybrid model constructed in this study has distinctive characteristics. On the one hand, DBN module can efficiently extract the deep features of e-business sales data and solve the shortcomings of traditional statistical methods in complex pattern recognition. On the other hand, the LSTM module captures the long-term dependence in time series data with the help of gating mechanism, which improves the model's ability to predict the fluctuation trend of agricultural product prices. The organic combination of the two enhances the overall expressive ability of the model and also enhances its robustness in the dynamic market environment. Experiments show that compared with traditional RF methods, the model proposed in this paper has obvious advantages in prediction accuracy, recall rate and user satisfaction.

From the perspective of practical application, the results of this study provide strong support for the government to formulate scientific and reasonable rural economic policies. By mining and modelling the massive transaction data accumulated by e-business platform, the model can detect the potential risk of imbalance between supply and demand in advance, and help decision makers optimise resource allocation, adjust subsidy policies or intervene in market price fluctuations. In addition, this paper also designed a policy impact assessment module, trying to associate the model output results with specific policy measures, further enhancing the explanatory power and practicality of the model.

However, the current model also has some limitations. First, the training data mainly comes from the online e-business platform, and a large amount of offline transaction information is not covered, which may lead to poor regional representation. Secondly, the response ability of the model to unexpected events (such as natural disasters, epidemic outbreaks, etc.) needs to be improved, and the prediction error will increase in the face of extreme market fluctuations. Thirdly, the model is weak in interpretability, and it is difficult to meet the requirements of policy makers for transparency in decision-making process.

In view of these problems, future research can be improved from the following three aspects. The first is to build a more comprehensive data collection system and integrate online and offline multi-channel information. The second is to introduce reinforcement learning mechanism to enhance the dynamic adaptability of the model to unexpected situations. The third is to develop visual interpretation tools to improve the interpretability of the model and the user's trust. Through these improvement measures, it is expected to promote the in-depth application of intelligent algorithms in the field of rural economic policy assessment and help the high-quality development of rural revitalisation strategy.

7 Conclusion

This paper focuses on the innovative application of intelligent algorithms in the field of rural economic development policy assessment, and proposes a hybrid DL model that integrates DBN and LSTM for accurate prediction of APD and prices. The study integrated sales data from multiple e-business platforms, combined with DL methods to comprehensively analyse historical transaction records, market supply and demand dynamics, and external environmental factors, and constructed an intelligent analysis model with high prediction precision and robustness. The results show that compared to traditional models, our model exhibits significant advantages in prediction precision, providing more reliable decision-making basis for agricultural producers, supply chain enterprises, and policy-making departments.

However, there are still several limitations that need to be improved in this study. Firstly, the data used for model training mainly comes from e-business platforms and does not fully incorporate offline transaction information, which may lead to certain biases in the prediction results; Secondly, the current model's ability to respond to sudden events such as natural disasters, epidemics, etc. needs to be improved; Finally, the interpretability of the model still needs to be strengthened to better meet the requirements of policy makers for transparency in the decision-making process. Future research will focus on improving from the following three aspects. Build a more comprehensive multi-source data collection system; Introducing reinforcement learning mechanisms to enhance the dynamic adaptability of models; Develop visual interpretation tools to enhance the interpretability of models.

Competing interest

The authors declare no competing financial or non-financial interests.

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