

Article

Research on Sideslip Identification and Adaptive Path Tracking Control of Deep Belief Network Rice Transplanter Based on Optuna Optimization and SHAP Interpretation

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Abstract

Aiming at the path tracking oscillation problem caused by sideslip of navigation agricultural machinery in complex farmland environments, this paper takes the Yanmar YR-70D transplanter as the research object and proposes an adaptive control method based on deep belief network (DBN) sideslip identification. Based on the preview tracking model, this method dynamically adjusts the preview distance by real-time identifying the sideslip status via DBN. In this research, the Optuna framework is utilized to optimize the DBN model, and the SHAP framework is introduced to quantify the feature contribution. The results show that, considering both real-time performance and accuracy, when the combined variable of “lateral deviation + heading deviation” with a data length of 20 is adopted, the prediction accuracy of the model reaches 88.04%, among which heading deviation (HD) has the highest contribution with a SHAP value of 0.957. Comparative experiments indicate that the accuracy of DBN is comparable to that of mainstream models such as LSTM and Transformer, but its forward propagation speed (0.0487 ms) is better than other models’. Upland field experiments verify that under different test factors of vehicle speed and slope angle, the line-on time (1.83–5.60 s), line-on distance (1.46–5.07 m), and maximum overshoot (0.32–15.75 cm) of the adaptive control group are all superior to those of the fixed-parameter control group. Paddy field experiments further confirm that under the working condition of 1.0 m/s vehicle speed and 15° slope, the above three indicators of the experimental group are 0.85–3.1 s, 0.75–3.14 m and 0–7.44 cm, respectively, all of which are better than those of the control group. The proposed method demonstrated superior path tracking performance under the operating conditions of the tested rice transplanting machines, indicating its potential application in lateral slip perception adaptive navigation control. However, further verification is still needed with different types of transplanting machines, field environments, and operating conditions to assess its general applicability.



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Keywords: Deep Belief Network (DBN); Optuna parameter optimization; SHAP interpretation framework; rice transplanter; sideslip identification; adaptive control

1. Introduction

Agricultural machinery navigation constitutes the fundamental core of intelligent agricultural machinery [1]. With the rapid development of intelligent agricultural machinery, autonomous navigation and path tracking technologies have become key research topics for improving the operational accuracy and autonomy of agricultural vehicles [2]. Path tracking accuracy is a critical indicator for evaluating the performance of agricultural machinery navigation systems, and path tracking control technology directly determines the operational precision of automatically navigating agricultural machinery in complex farmland environments, serving as the key to ensuring that agricultural machinery can accurately travel along pre-planned routes [3,4]. Common path tracking control methods include PID control [5,6], fuzzy control [7,8], pure pursuit [9,10], preview control [11,12], sliding mode control [13,14], optimal control [15,16] and model predictive control [17–19], all of which have been widely applied in automatic navigation of agricultural machinery. However, complex ground conditions in farmland environments often induce sideslip displacement of automatically navigating agricultural machinery, making it difficult for the machinery to maintain the predetermined travel path accurately [20–22]. To improve the path tracking accuracy and system robustness of agricultural machinery during dynamic operation in complex farmland environments, adaptive control technology has become a current research hotspot in the field of agricultural machinery navigation. Existing research mainly focuses on three directions: active perception and compensation for sideslip states, dynamic parameter optimization based on modern control theory, and neural network-driven nonlinear mapping control.

In research on active perception and compensation under sideslip conditions, Jing Y et al. [20] proposed an adaptive navigation method based on sideslip estimation to address the sideslip problem during grader operation. In this method, a sideslip estimator is established via a kinematic model to predict the wheel sideslip angle in real time; meanwhile, an improved nonlinear function is adopted to realize online self-tuning of PID parameters, and an adaptive control system is constructed. Experimental results show that this method reduces the mean absolute lateral deviation and standard deviation of path tracking by 6.78 cm and 10.1 cm, respectively, improving the accuracy and robustness of the system in complex environments. Aiming at the kinematic model distortion caused by soft ground in orchards, Bayar et al. [21] proposed a model-driven control method integrating sideslip estimation and compensation. This method fuses high-precision positioning and encoder data to calculate the longitudinal and lateral sideslip velocities in real time and feeds the results back to the car-like model to realize dynamic compensation for front-wheel steering and rear-wheel speed. Experimental results demonstrate that this method reduces the lateral and heading deviations of the vehicle when traveling between rows and turning at headlands.

In the research on dynamic parameter optimization based on modern control theory, Huang et al. [23] proposed a fuzzy sliding mode adaptive path tracking method to address the problems of low tracking accuracy and chattering of the tractor–trailer system in complex environments. This method first establishes a nonlinear kinematic deviation model incorporating joint angles and designs the control law based on sliding mode control (SMC). To eliminate the “chattering” phenomenon of traditional SMC, a fuzzy controller is introduced to adjust the switching gain online, thus realizing the dynamic optimization of control intensity. Experimental results show that this method can achieve rapid deviation correction and stable tracking and improve the robustness and dynamic response of the multi-body agricultural machinery system. Ma et al. [24] proposed an LQR optimization method based on fuzzy control, aiming at the problem that fixed weight parameters limit the tracking accuracy of unmanned transplanters when following curved paths. In this

study, a kinematic deviation model was established, which takes the predicted lateral deviation and heading deviation as inputs and realizes online adjustment of the state weighting matrix Q of LQR through fuzzy inference. Simulation results demonstrate that, compared with the fixed-parameter LQR method, the proposed adaptive method reduces the mean lateral deviation by more than 50% on paths with different curvatures and improves the steady-state accuracy and adaptive capability under complex trajectories.

In the research on neural network-driven nonlinear mapping control, Zhao Yongchun et al. [25] proposed an adaptive control algorithm coupled with virtual radar perception and a two-stage deep neural network (DNN) to address the wheel slip and nonlinear interference caused by complex orchard pavement. In this study, virtual radar was used to process images, and the first-stage DNN was used to extract path status; then the second-stage DNN was introduced to integrate lateral deviation, heading angle, and track slip rate, realizing deep mapping and real-time compensation from perception to motor speed. Experimental results show that the algorithm has extremely strong robustness on frozen-pulpy pavement, and the maximum lateral deviation is only 0.072 m at a vehicle speed of 0.8 m/s. Aiming at the strong coupling and underactuated characteristics of multi-degree-of-freedom systems, Hazem et al. [26] used radial basis neural networks (RBNNs) to adjust the gain of the LQR controller in real time online and introduced the Bayesian regularization (BR) algorithm to optimize the network weights, realizing dynamic compensation for position and velocity deviations. Experimental results indicate that compared with traditional LQR and fuzzy control, this method has higher accuracy and robustness and can more effectively suppress system vibration and shorten recovery time.

The above research indicates that the current studies on adaptive control of agricultural machinery navigation have made significant progress but still face practical engineering challenges related to algorithm complexity, parameter dependence, environmental interference, and real-time implementation [19]. To address these issues, this study aims to select a compact and highly flexible control algorithm as the foundation and incorporate an identification model with hierarchical feature extraction and lightweight modeling advantages. By enabling fast and accurate identification of navigation states, we propose an adaptive control scheme that is easy to deploy and features rapid response. Our team has previously conducted a preliminary study on the feasibility of side-sliding identification and adaptive preview control for transplanting machines through simulation methods [27]. However, there is still a lack of measured data support and closed-loop verification on the actual machines. The related issues need to be further investigated.

2. Materials and Methods

2.1. Experiment Platform

2.1.1. Transplanter and Navigation Control System Platform

To meet the experimental requirements, this paper uses the YR-70D Yanmar transplanter (Yanmar Agricultural Machinery Co., Ltd., Wuxi, China) and the GNSS agricultural machinery navigation control system as the experimental platform, which is additionally equipped with a laptop for system debugging. The transplanter and navigation system platform are shown in Figure 1. The navigation system consists of a positioning antenna, a navigation controller (integrated with a pose sensor), an electric steering wheel, a wheel angle sensor, and a touch screen. In addition, the technical specifications of the transplanter and the navigation system are presented in Table 1.

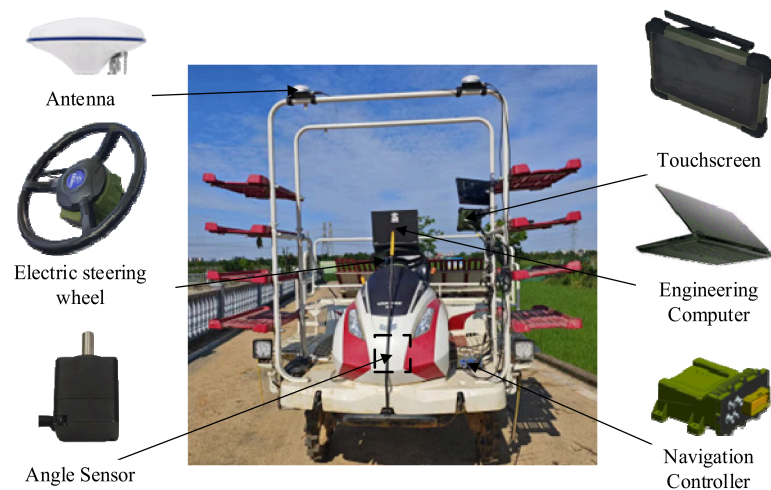


Figure 1. Test platform for navigation system of transplanting machine.

Table 1. Main technical specifications of rice transplanter and navigation system.

Technical Indicators	Parameters
Vehicle Model	YR-70D
Overall Dimensions (Length × Width × Height mm)	3470 × 2200 × 2330
Wheelbase, Front Track Width, Rear Track Width (mm)	1050, 1220, 1210
Operating Speed Range (km/h)	0~5.75
Navigation Equipment Model Name	ST901BD-2.5GD
Trajectory Straightness Accuracy (Medium Speed)	0.99 cm
Interline Spacing Precision (Medium Speed)	0.80 cm

Note: Navigation equipment model (Beidou Tuojiang Technology Co., Ltd., Nanjing, China).

2.1.2. Adaptive Control Algorithm and Control Parameter Pre-Processing

(1) Basic control algorithm

This study utilized the Ackermann steering geometric principle to construct the kinematic model of the transplanting machine’s two-wheeled vehicle and also referred to the pre-sight control model established by the small-angle linearization method proposed in Reference [11], which are shown in Figure 2a,b, respectively.

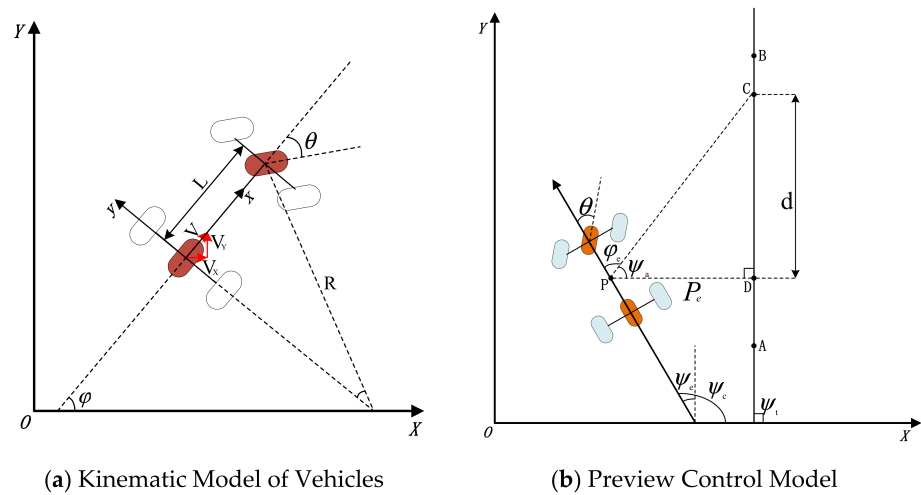


Figure 2. Kinematic model and preview control model for two-wheel rice transplanters.

Based on the linear velocity formula and the geometric relationships of the model in Figure 2a, the following equation can be derived:

$$\dot{\varphi} = \frac{V}{R} \quad (1)$$

$$R = \frac{L}{\tan \delta_f} \quad (2)$$

$$\dot{\varphi} = \frac{V \tan \delta_f}{L} \quad (3)$$

$$\dot{X} = V \cos \varphi \quad (4)$$

$$\dot{Y} = V \sin \varphi \quad (5)$$

Note: V represents the control point velocity, in m/s; V_X and V_Y denote the velocities along the X-axis and Y-axis directions, respectively, in m/s; φ is the current heading angle, in rad; $\dot{\varphi}$ is the yaw rate, in rad/s; δ_f is the virtual wheel steering angle, in rad; L is the wheelbase, in m; R is the turning radius, in m.

Based on the analytical process presented in Reference [11], it can be derived that when $k = 2L/V$, the optimal steering decision angle satisfies the following Formula (6):

$$\theta = \frac{2L}{V} \left(\varphi_e + \arctan \left(\frac{P_e}{d} \right) \right) \quad (6)$$

where φ_e is the heading deviation, P_e is the position deviation, L is the vehicle wheelbase, V is the vehicle speed, and d is the preview distance.

(2) Control Parameter Configuration

Duan et al. [27] constructed a simulation system to clarify the mechanism of path tracking oscillation induced by state variables of the transplanter navigation system and suppress the navigation path tracking oscillation caused by sideslip. A multi-factor simulation experiment was carried out with forward speed, positioning error and wheel angle tracking lag time as experimental factors, and the first constraint condition of path tracking oscillation was obtained as shown in the Formula (7):

$$d = 0.180826 - 0.096112V + 4.42955p_e - 1.67884T_d - 1.17851Vp_e + 1.64992VT_d - 2.20971p_eT_d - 0.001885V^2 - 0.165695p_e^2 + 3.11837T_d^2 \quad (7)$$

where d denotes the dynamic preview distance, m; V denotes vehicle speed, m/s; p_e indicates positioning error, m; T_d it represents the wheel angle lag time, s. In the practical system, the identification result of steering angle tracking lag based on the DBN model obtained from previous research [28] is adopted as a substitute.

(3) An Adaptive Suppression Method Based on Sideslip Detection for Rice Transplanters

Under complex working environments, the automatic navigation of rice transplanters is affected by multiple factors, including the mismatch of the vehicle kinematic model, fluctuations in surface adhesion, and measurement errors of state variables. When sideslip occurs, a fixed look-ahead distance easily causes oscillations in path tracking. To address this issue, this paper constructs a sideslip severity recognition model based on a Deep Belief Network (DBN) and designs an adaptive dynamic look-ahead distance regulator on this basis (as shown in Figure 3). Taking sideslip severity as the core regulation target, this regulator realizes real-time recognition of navigation status via DBN and dynamically corrects the look-ahead distance parameter, thereby suppressing system oscillations and improving navigation stability.

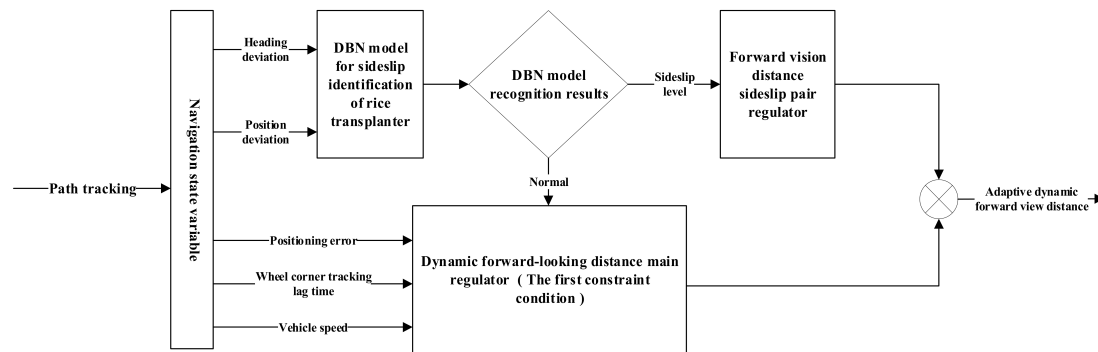


Figure 3. Adaptive dynamic look-ahead distance adjuster.

Based on the aforementioned adjustment mechanism, the formula of the adaptive dynamic preview distance regulator can be expressed as follows:

$$d_{out-end} = d_{out-main} + d_{out-slip} = d_{out-main} + k \bullet O \quad (8)$$

Among them, $d_{out-end}$ denotes the total dynamic preview distance output by the regulator; $d_{out-main}$ is the preview distance output under the first constraint, which is given by Formula (7); $d_{out-slip}$ represents the preview distance output by the sideslip auxiliary regulator for preview distance; k is the preview distance adjustment coefficient; O is the sideslip degree in path tracking. According to the previous simulation study [27], the optimal value of k is 0.992.

To ensure the effectiveness of the sideslip constraint, after the adaptive preview distance adjustment module is activated, the intervention time is extended proportionally according to different degrees of sideslip. The intervention time T is calculated by Formula (9), with the unit being second.

$$T = O, O \in \{1, 2, 3\} \quad (9)$$

2.2. Data Acquisition and Dataset Construction for Paddy Transplanter Lateral Sliding Navigation

2.2.1. Data Analysis and Collection for Sideslip Navigation of Rice Transplanters

To conveniently obtain navigation data on the sideslip state of transplanters, slopes at different angles were laid along the field navigation path to induce sideslip of the transplanter. The field experiment was conducted in June 2025 at the farmland in Shibui Town, Xinjian District, Nanchang City, as shown in Figure 4.



Figure 4. On-site data acquisition test.

When sideslip occurs, the geometric relationship of the transplanter's kinematic model and the linear velocity constraints, i.e., Equations (1)–(5), will be invalidated. In this case, the yaw rate, heading angle and position deviation will no longer satisfy the conventional kinematic constraints. Owing to the sudden change in the actual track angle, as can be

inferred from Equation (5), position deviation is essentially the time-series integral of the product of the vehicle's linear velocity and the sine of the track angle. Therefore, sideslip directly induces a non-linear sudden change in position deviation, which further interferes with the calculation of the desired wheel angle and the steering control of the wheels. Based on this mechanism, the occurrence of sideslip can be directly reflected in the variation trends of state variables, including position deviation, heading deviation, yaw rate and wheel angle.

Based on the above analysis of the correlation mechanism between navigation kinematics process and sideslip, the following key parameters were recorded in real time during the experiment: lateral deviation and heading deviation, heading angle, track angle at control points and sideslip angle (the difference between track angle and heading angle), Gaussian coordinates (X, Y), yaw rate, commanded wheel deflection angle and actual wheel deflection angle, as well as body pitch angle and roll angle. A total of 24 valid sets of navigation data were collected in the experiment.

2.2.2. Definition and Classification of Sideslip Levels

Based on the sideslip classification criteria proposed in Reference [27], the degree of sideslip is divided into four categories according to the maximum sideslip angle during navigation. The classification standards and descriptions for sideslip levels are shown in Table 2.

Table 2. Classification criteria for sideslip level.

Maximum Sideslip Angle $\beta/^\circ$	Sideslip Severity
$\beta < 4$	Normal State
$4 < \beta \leq 6$	Level 1
$6 < \beta \leq 8$	Level 2
$8 < \beta$	Level 3

2.2.3. Construction of the Dataset

To obtain the dataset required for model training, a data processing program is compiled on the MATLAB platform based on the sideslip level classification criteria shown in Table 2 to process the raw data acquired in Section 2.2.1, thus yielding a dataset with clearly defined classification labels. The workflow for dataset construction is illustrated in Figure 5, and a brief description of the construction process is provided as follows:

- (1) MATLAB 2021a is employed to read the raw data contained in 24 CSV files. Subsequently, the built-in findpeaks and find functions of MATLAB are utilized to identify each peak and trough of the sideslip angle, as well as the one zero point preceding and following each peak/trough (this interval is defined as a peak cycle).
- (2) The sideslip data is sliced and intercepted using a cyclic rolling time window (the window size varies with different data lengths). The sliced data is classified by sideslip severity based on the peak (or trough) value within the current wave cycle. If more than half of the data in the window falls within the next wave cycle, the classification is determined in accordance with the next wave cycle. Other navigation state variable data within the corresponding time period are processed through slicing, recombination, labeling and classification. Finally, 24 groups of datasets with different data lengths are obtained and saved in the format of an .xlsx spreadsheet;
- (3) To prevent data leakage in K-fold cross-validation, for each data length, 10 files were randomly selected from the 24 original data files according to the label category; 200 samples were extracted from each selected file to construct a new dataset. Samples from the same original file were assigned a unified number, and the K-fold cross-

validation was conducted based on this number. The distribution of dataset labels is shown in Table 3, with a total of 2000 groups of samples for each category. All samples participated in 10-fold cross-validation, with approximately 1800 groups of samples in each fold for training and 200 groups as the in-fold validation set. This study did not reserve an additional independent external test set. The reported prediction accuracy in the paper is the average result of the 10 in-fold validation subsets. After determining the optimal hyperparameters through cross-validation, all samples were retrained to obtain the final DBN model.

Table 3. Description of model training data distribution.

Type of Sideslip Degree	Number of Training Samples (Pieces)	Number of Test Samples (Pieces)	Classification Label
Normal state	1800	200	0
First-level sideslip	1800	200	1
Secondary sideslip	1800	200	2
Three-stage sideslip	1800	200	3

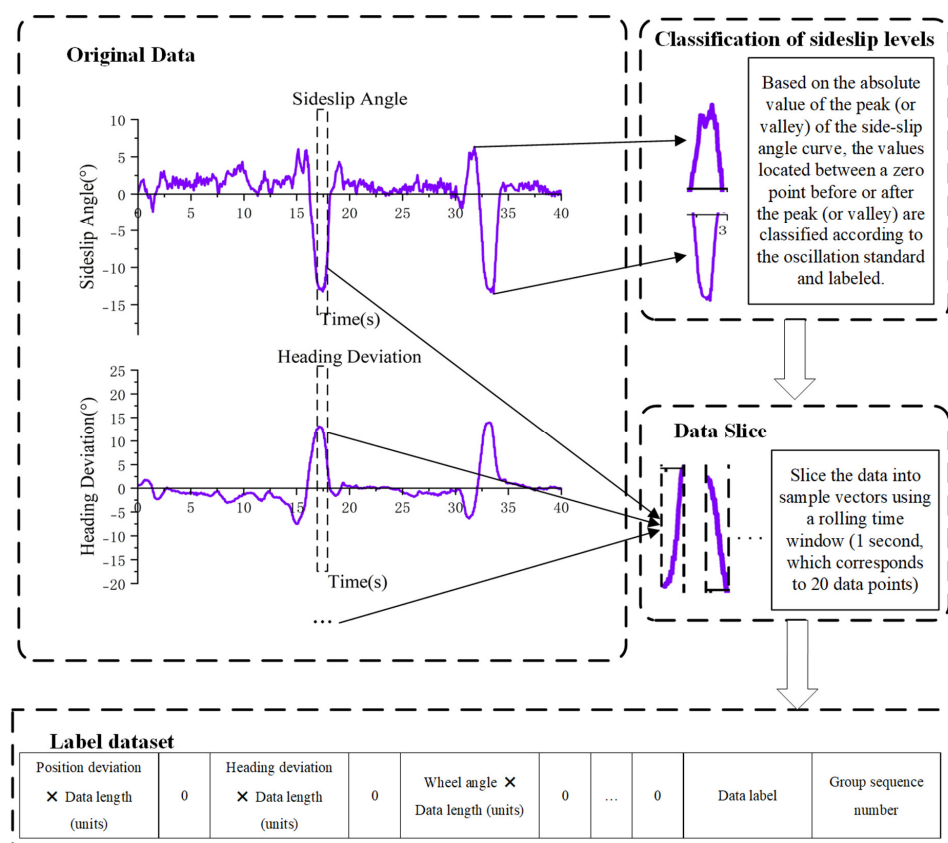


Figure 5. Data set production process.

2.3. A DBN Model Training Framework Based on Optuna Optimization and SHAP Feature Analysis

Aiming at the problems that manual adjustment of hyperparameters of deep learning models based on experience is inefficient, and the internal decision-making logic of deep networks has the nonlinear “black box” characteristic, which makes it impossible to quantitatively analyze the mapping mechanism of input features to sideslip states, this study proposes a DBN-based agricultural machinery guidance state recognition and classification framework that integrates automatic hyperparameter optimization and model

interpretability analysis. This framework is intended to clarify the specific contribution of each feature variable to sideslip state prediction, select the optimal variables, and improve the prediction accuracy and robustness of the model. The specific workflow is shown in Figure 6, which mainly includes automatic hyperparameter optimization based on the Optuna framework, DBN model training, K-fold cross-validation evaluation, optimization of model input variables, and model interpretability analysis based on SHAP values.

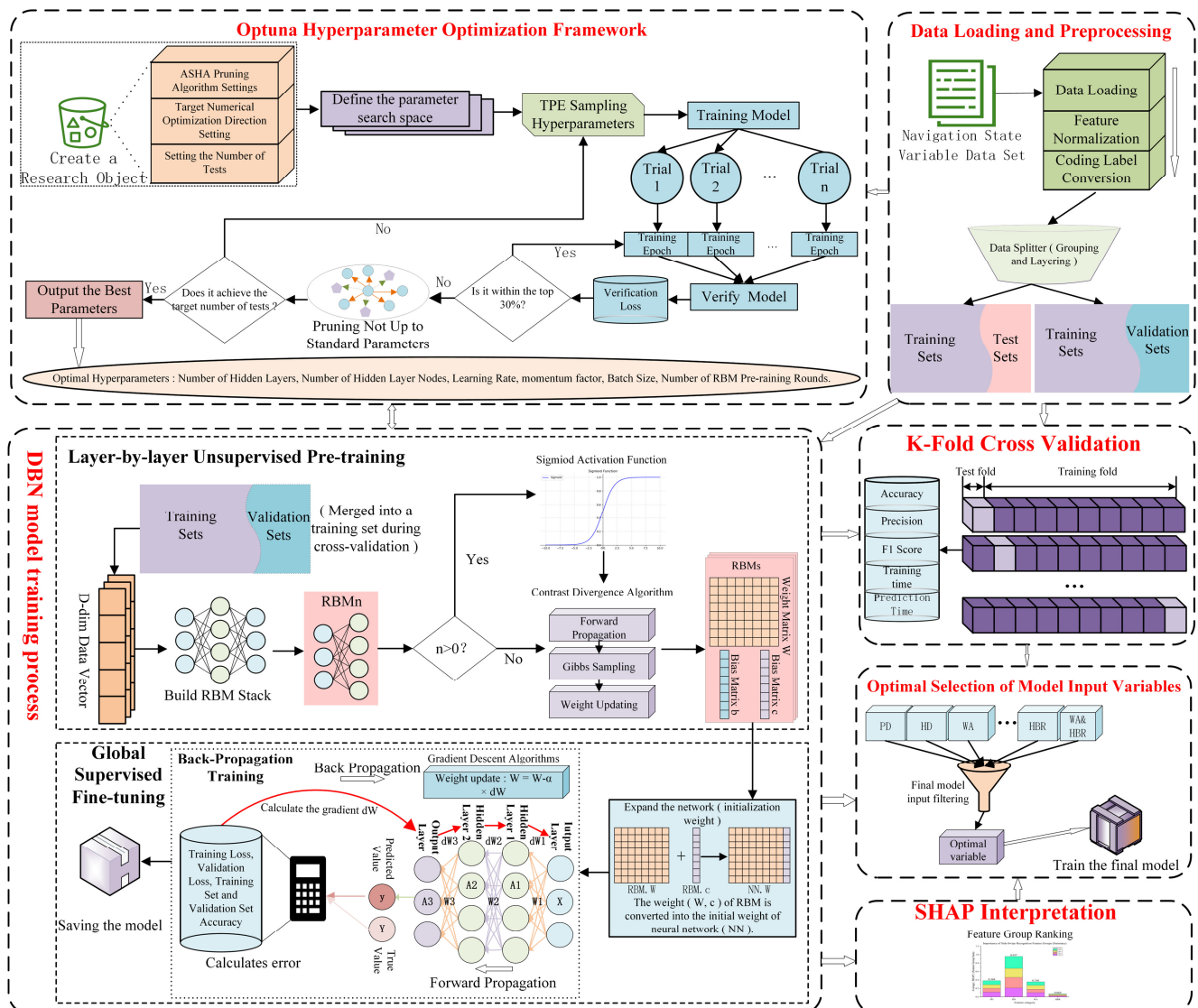


Figure 6. A DBN model training framework based on Optuna optimization and SHAP feature analysis.

2.3.1. Structure of the DBN Model

Deep Belief Networks (DBN) were first proposed by Hinton et al. in 2006 [29]. Long-term applied research on DBN has been carried out in fields including medical detection, industrial fault diagnosis and environmental monitoring. As a stable and reliable method, it is one of the critical approaches for engineering applications. Its core network structure is stacked with multiple layers of Restricted Boltzmann Machines (RBMs) [29], as shown in Figure 7.

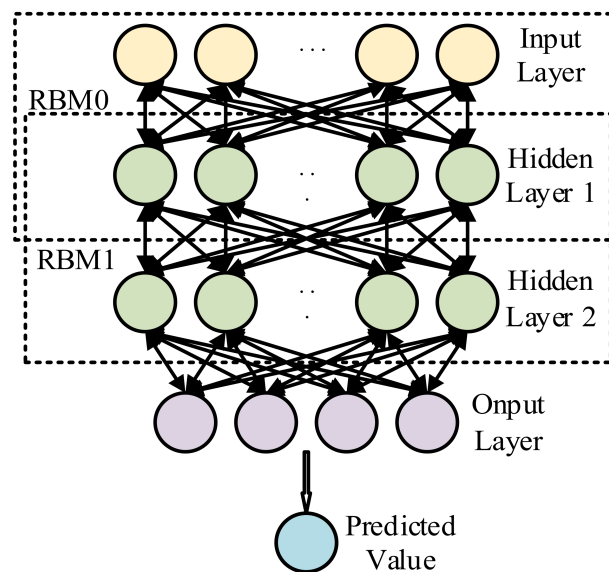


Figure 7. DBN model structure.

2.3.2. Hyperparameter Optimization

To improve the efficiency of hyperparameter exploration for machine learning models, this study employs the Optuna framework to implement automatic hyperparameter optimization. This framework supports dynamic construction of the search space and integrates Tree-structured Parzen Estimator (TPE) sampling and median pruning strategies to balance search efficiency and computational cost. Specifically, TPE sampling constructs a probabilistic surrogate model based on the Bayesian optimization principle and leverages historical observation data to guide the search to converge toward high-performance regions; meanwhile, median pruning terminates underperforming trials in real time by monitoring validation set metrics, thereby reducing overall computational overhead.

2.3.3. Model Evaluation Indicators

To comprehensively and objectively evaluate the performance of the DBN model in the multi-class classification task of transplanter sideslip, this study adopts the K-fold cross-validation method to assess the model performance and quantifies the model performance by calculating Accuracy, Precision and F1-score. The specific formulas are shown as Formulas (10)–(13):

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \times 100\% \quad (10)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (11)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (12)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100\% \quad (13)$$

Among them, *TP* is the number of samples correctly predicted by the model as a positive class, *FP* is the number of samples incorrectly predicted by the model as a positive class, *FN* is the number of samples incorrectly predicted by the model as a negative class, and *TN* is the number of samples correctly predicted by the model as a negative class.

2.3.4. Interpretability Analysis Method of SHAP Model

Given the “black box” nature of deep learning models, this study introduces the SHAP framework based on cooperative game theory to conduct interpretability analysis. By

quantifying the contribution of each feature to the prediction output, this method clarifies the logical association between variables and the target, thereby verifying whether the decision-making process of the model conforms to actual physical laws [30].

The core of the SHAP method lies in quantifying the average marginal contribution of each feature to the prediction result across all combinations of feature subsets by calculating the Shapley value ϕ_i of each feature. The Shapley value of an individual feature represents the average marginal contribution of the i -th feature to the model's prediction result. It is obtained by calculating the weighted average of the marginal contributions generated by the feature across all possible feature subset combinations, and the calculation formula is as follows:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} [f(S \cup \{i\}) - f(S)] \quad (14)$$

Among them, ϕ_i : The contribution of the i -th feature to the predicted value of the model (Shapley value). N : The set of all input features in the model. n : The total number of features (that is, the size of the set N). S : A feature subset ($S \subseteq N \setminus \{i\}$) that does not contain feature i . $|S|$: the number of features contained in subset S . $f(S)$: The predicted value of the model when only the special i in subset S is used. $f(S \cup \{i\})$: The predicted value of the model after adding feature i to the feature subset S . $[f(S \cup \{i\}) - f(S)]$: The marginal contribution of feature i in the context of subset S . $\frac{|S|!(n-|S|-1)!}{n!}$: The weight coefficient represents the probability of the occurrence of the specific feature combination.

3. Experiments and Result Analysis

To verify the accuracy and effectiveness of the research methodology proposed in this study in sideslip detection and oscillation suppression, this study sequentially carried out training and performance comparison of the DBN-based sideslip detection model, multi-factor experiments on navigation control suppression parameters for sideslip-oscillation on dryland slopes, and validation experiments in paddy fields.

3.1. Characteristic Analysis of Sideslip Identification and Comparative Evaluation of Models

3.1.1. Experiment on Optimal Selection of Model Input Variables and Interpretability Analysis Based on Cross-Validation

(1) Experiment Procedure

To improve the accuracy and robustness of the model for identifying the sideslip morphology of transplanter, this study designs an experiment of input variable optimization and interpretability analysis based on the Deep Belief Network (DBN) model. As shown in Table 4, an experimental factor configuration consisting of 10 groups of navigation state variable combinations and three data lengths (10, 20 and 30 sampling points) is constructed. By adopting a 10-fold cross-validation strategy and taking the mean and standard deviation of the model's prediction accuracy on the validation set as evaluation criteria, the optimal feature variables with high accuracy and strong robustness are screened out. Subsequently, the model is trained with the full data of the optimal data length; the SHAP (Shapley Additive Explanations) framework is introduced to calculate Shapley values, and the influence weight of each variable on the recognition result is determined through ranking analysis of feature importance and dependence, which clarifies the logical relationship between navigation status and sideslip morphology at the theoretical level.

Table 4. Optimization of experimental factor configuration for model input variables.

Peer Group	Type	Peer Group	Type	Data Length
1	Position deviation	6	Position deviation + front wheel steering angle	10, 20, 30 (all groups)
2	Heading deviation	7	Position deviation + yaw rate	
3	Front wheel steering angle	8	Heading deviation + front wheel steering angle	
4	Yaw angular velocity	9	Heading deviation + yaw rate	
5	Position deviation + heading deviation	10	Front wheel steering angle + yaw rate	

(2) Experiment results and analysis

(a) Analysis of Optimal Selection Experimental Results for Model Input Variables Based on Cross-Validation

From the dataset created in Section 2.2.3, training sets with different variable combinations and data lengths were selected for model training. First, the Optuna algorithm was used to identify the optimal hyperparameters, which were then applied to perform 10-fold cross-validation. The mean $\pm$ standard deviation of prediction accuracy, precision, and F1 score across ten cross-validation runs on the validation set were calculated for each group of variables trained by the DBN model. The experimental results are shown in Table 5 and Figure 8.

Table 5. A 10-fold cross-validation prediction accuracy of the model for sideslip detection with data variables of different lengths.

Peer Group	Variable Type	The Prediction Accuracy Under Different Sample Lengths (%)		
		10	20	30
1	Position deviation	58.13% $\pm$ 3.77%	57.35% $\pm$ 1.80%	26.20% $\pm$ 1.68%
2	Heading deviation	70.97% $\pm$ 5.16%	70.79% $\pm$ 1.46%	76.96% $\pm$ 1.79%
3	Front wheel steering angle	52.42% $\pm$ 2.45%	57.64% $\pm$ 1.68%	61.66% $\pm$ 1.79%
4	Yaw angular velocity	29.86% $\pm$ 2.44%	25.04% $\pm$ 0.28%	34.10% $\pm$ 0.66%
5	Position deviation + heading deviation	79.31% $\pm$ 3.19%	88.04% $\pm$ 0.89%	89.39% $\pm$ 1.39%
6	Position deviation + front wheel steering angle	63.20% $\pm$ 2.85%	81.84% $\pm$ 1.07%	85.40% $\pm$ 1.30%
7	Position deviation + yaw rate	56.39% $\pm$ 3.74%	58.45% $\pm$ 1.74%	58.14% $\pm$ 1.60%
8	Heading deviation + front wheel steering angle	78.59% $\pm$ 3.55%	84.86% $\pm$ 1.15%	86.80% $\pm$ 1.06%
9	Heading deviation + yaw rate	73.38% $\pm$ 4.55%	73.05% $\pm$ 1.54%	75.58% $\pm$ 1.93%
10	Front wheel steering angle + yaw rate	53.74% $\pm$ 2.59%	61.16% $\pm$ 1.73%	65.11% $\pm$ 1.26%

As illustrated in Table 5 and Figure 8, the time series length exhibits a positive effect on the model performance of most experimental groups (WA, PD&HD, PD&WA, HD&WA, WA&HBR). When the data length increases from 10 to 20, the recognition performance of the model improves significantly; when the data length further increases from 20 to 30, the growth rate of the model's recognition performance slows down markedly. Increasing the data length from 10 to 20 enables the model to obtain richer dynamic evolution characteristics of the transplanter, effectively covering the nonlinear time-varying process from sideslip excitation to response of the transplanter. When the data length is further increased to 30, the introduction of excessive historical redundant information leads to the slowdown of performance growth.

A small number of experimental groups show high sensitivity and instability to data length. Specifically, when the data length is 30, the accuracy of position deviation (PD) drops sharply from 57.35% to 26.20%, and the dispersion of precision and F1-score increases drastically. In addition, yaw rate (HBR) yields the lowest values across all evaluation indicators, indicating that under the current working condition of low speed and high slip rate in the field, this variable has weak direct mapping correlation with the macroscopic sideslip level and can hardly characterize the sideslip pattern independently.

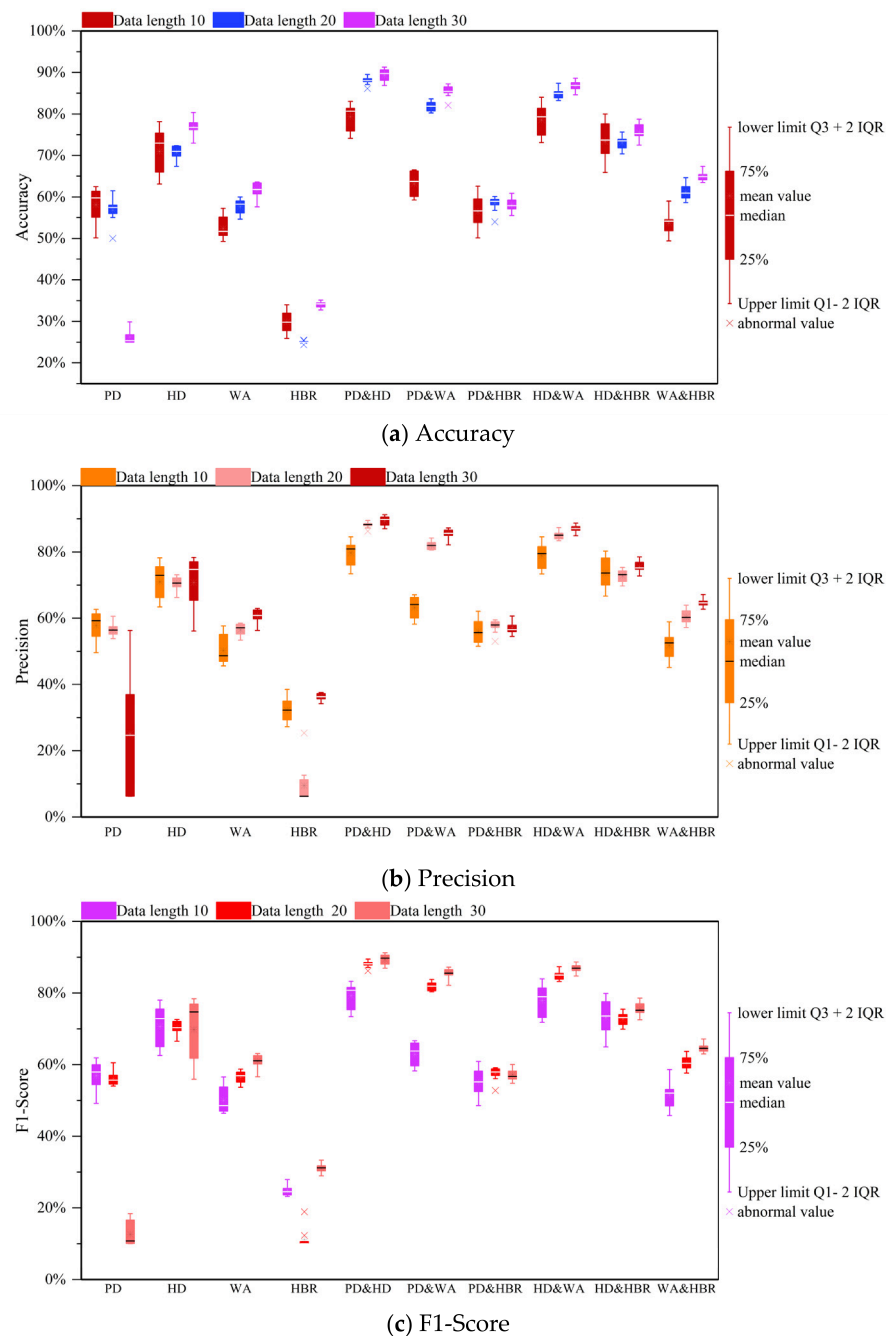


Figure 8. Plots of 10-fold cross-validation evaluation metrics for each data variable in sideslip detection models.

Comparing the performance of different input variable combinations, from the perspective of univariate performance comparison, heading deviation (HD) has the strongest feature discriminative power, outperforming other single variables in all indicators, and is a key variable for sideslip recognition. In terms of the performance of combined variables, the combination of “position deviation + heading deviation (PD&HD)” achieves the optimal performance. When the data length is 20 and 30, the accuracy reaches 88.04% and 89.39%, respectively; meanwhile, its F1-score and precision outperform other combinations, and the dispersion of all indicators is small, demonstrating excellent model robustness and stability.

The above analysis shows that although the “PD&HD” feature combination with a time series length of 30 has higher recognition accuracy from a statistical perspective,

it has a higher computational load and longer detection delay. In engineering applications, it is necessary to comprehensively trade off statistical performance and the real-time constraint of the navigation system. Experimental results show that the “PD&HD” combination with a time series length of 20 performs stably in terms of accuracy and dispersion ($88.04\% \pm 0.89\%$) and takes into account both system real-time performance and technical generalizability. Therefore, this study finally selects the “position deviation + heading deviation (PD&HD)” combination with a length of 20 as the data input of the sideslip recognition model.

(b) Validation of model decision-making mechanism based on SHAP full-volume features

To verify the rationality of feature screening and analyze the decision-making logic of the model, this study uses full data with a data length of 20 to train the model and introduces the SHAP interpretation framework. This research aims to verify the in-depth mechanism of the aforementioned results of the input variable optimization experiment and quantitatively decouple the marginal contribution of each driving feature to the identification of the sideslip level of the rice transplanter. The results are shown in Figure 9.

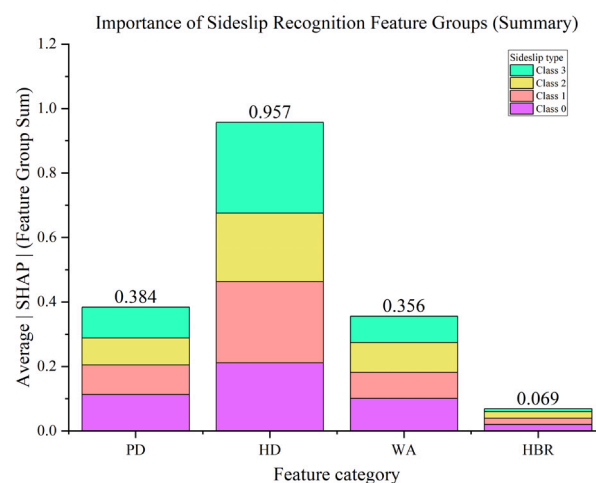


Figure 9. Quantitative comparison of the contribution of different navigation state variables to the recognition of sideslip grade based on SHAP values.

As can be observed from the data presented in Figure 9, the SHAP contribution values of the four characteristic variable groups, namely position deviation, heading deviation, wheel angle and yaw rate, in model prediction are 0.384, 0.957, 0.356 and 0.069, respectively. Among them, the SHAP value of heading deviation (HD) is 0.957, the highest among all variables, indicating that it is the core judgment basis for the model to predict sideslip states; the next are position deviation (PD) (0.384) and wheel angle (WA) (0.356), which can provide supplementary information for the model to judge sideslip levels and improve the accuracy of model prediction. The SHAP value of yaw rate (0.069) is the lowest, indicating that this variable contains less characteristic information of sideslip levels and has a limited supporting effect on model decision-making.

From the perspective of vehicle dynamics mechanisms, when an agricultural machine encounters sideslip in complex paddy fields or on slopes, the vehicle body often experiences yaw (HD) first, and the heading angular velocity and heading deviation will undergo instantaneous violent jitter. In contrast, lateral deviation (PD), as a cumulative quantity of spatial geometric position, has a certain lag in its response. The quantitative results of SHAP analysis are completely consistent with the above physical laws, which not only verifies the scientificity of variable optimization at the mechanism level but also provides a

solid physical prior basis for the subsequent adaptive controller to dynamically adjust the forward-looking distance.

3.1.2. Comparative Experiment on Identification Performance Between DBN Model and Mainstream Benchmark Models

(1) Experiment procedure

To objectively evaluate the performance of the Deep Belief Network (DBN) in the sideslip recognition task, this section selects Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), Temporal Convolutional Network (TCN) and Transformer as benchmark models for comparative experiments based on the variable optimization results presented in Section 2.1.1. In all experiments, the combination of position deviation (PD) with a data length of 20 and heading deviation (HD) is uniformly adopted as the model input, and 10-fold cross-validation is employed to reduce random errors caused by dataset partitioning.

To ensure the fairness of the benchmark comparison and avoid improper manual parameter tuning based on experience leading to the comparison model being in suboptimal performance, this study uniformly introduces the Optuna automatic hyperparameter optimization framework based on Bayesian optimization, the specific hyperparameter search spaces for each comparison model are shown in Table 6. Under the same computational resource constraints (the hardware platform is an Intel Core i5-9300H CPU @ 2.40GHz, 16GB RAM, this study does not use GPU computing. The side slip state recognition only processes navigation numerical information and does not involve high-dimensional data such as images. The CPU can meet the computing requirements; for different architectural characteristics, a comprehensive search is conducted on key parameters such as network depth, hidden layer dimension, learning rate, etc. The system sets the maximum number of experiments to 20 as the explicit termination and convergence criterion. During the 100 rounds of supervised fine-tuning in each experiment, the median pruning strategy is introduced as a local elimination mechanism: compare the current validation set loss every 10 rounds. If the intermediate loss of the current hyperparameter combination is worse than the median of the completed experiments in the past, then determine that this branch does not converge and immediately perform pruning to significantly save computing costs. The statistics of the inference delay of all comparison models only count the time used in the forward propagation process, and all adopt the single-sample online inference method (batch size = 1). It simulates the actual working mode of the rice transplanting machine navigation system and conducts mean $\pm$ standard deviation statistics of 100 inference-delay measurements. The objective function of automatic optimization is defined as the average multi-class cross-entropy loss E_{loss} of the model on the validation set, as shown in Equation (15):

$$E_{loss} = -\frac{1}{N} \cdot \sum_{i=1}^N [y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)] \quad (15)$$

(2) Experiment results and analysis

Based on the aforementioned 10-fold cross-validation experimental setup, Table 7 presents detailed statistical results of performance metrics for the DBN model compared with four baseline models—MLP, LSTM, TCN, and Transformer—on the validation set. The data in the table represent the average values $\pm$ standard deviation across 10 independent trials, covering accuracy, precision, recall, F1-score, and prediction time as evaluation metrics, while also comparing the average forward propagation inference time required by each model to process a single time-series sample.

Table 6. Configuration table of hyperparameter search spaces for all comparative models.

Parameter Type	Parameter Name	DBN	MLP	LSTM	TCN	Transformer
Structural parameter	Hidden layers	1–3	1–3	1–3	1–3	1–3
	Hidden layer dimension	{32, 64, 128}	{32, 64, 128}	{32, 64, 128}	{32, 64, 128}	{32, 64, 128}
	Certain parameters	-	-	-	convolution kernel: [3,7]	Number of attention heads: {2, 4, 8}
Regularization	Dropout	[0.1, 0.5]	[0.1, 0.5]	[0.1, 0.5]	[0.1, 0.5]	[0.1, 0.5]
Optimization parameters	Learning rate	$[1 \times 10^{-4}, 0.1]$	$[1 \times 10^{-4}, 0.1]$	$[1 \times 10^{-4}, 0.1]$	$[1 \times 10^{-4}, 0.1]$	$[1 \times 10^{-4}, 0.1]$
	Batch size	{16, 32, 64}	{16, 32, 64}	{16, 32, 64}	{16, 32, 64}	{16, 32, 64}
	Optimizer/Momentum	Adam	Adam	Adam	Adam	Adam
Iterative control	Number of search rounds	20	20	20	20	20
	Number of training iterations	3000	200	200	200	200

Table 7. Results of comparative experiments on identification performance between dbn model and other models.

Model	Accuracy	Precision	F1-Score	Prediction Time (ms)
DBN	88.04% $\pm$ 0.89%	88.16% $\pm$ 0.87%	88.06% $\pm$ 0.87%	0.0487 $\pm$ 0.0233
MLP	79.99% $\pm$ 2.06%	79.85% $\pm$ 2.25%	79.72% $\pm$ 2.20%	0.88 $\pm$ 1.3934
LSTM	88.79% $\pm$ 1.57%	88.90% $\pm$ 1.51%	88.78% $\pm$ 1.55%	1.1711 $\pm$ 0.2220
TCN	86.86% $\pm$ 0.98%	86.02% $\pm$ 1.00%	86.87% $\pm$ 1.00%	0.7333 $\pm$ 0.3011
Transformer	88.61% $\pm$ 1.20%	88.63% $\pm$ 1.21%	88.54% $\pm$ 1.20%	1.1025 $\pm$ 0.35

Analysis of experimental data shows that the LSTM model achieves the highest values in terms of accuracy (88.79%), precision (88.90%) and F1-score (88.78%), followed by the Transformer. The DBN model also delivers competitive performance in accuracy (88.04%), precision (88.16%) and F1-score (88.06%), and the TCN model also performs well. By contrast, the MLP baseline model shows a significant gap in accuracy, precision and F1-score compared to the other models. In terms of model prediction speed, the DBN model exhibits excellent performance: its average single prediction time is only 0.0487 ms, which is one order of magnitude faster than Transformer (1.1025 ms), TCN (0.7333 ms), LSTM (1.1711 ms) and MLP (0.88 ms). Although MLP has a simple structure, its inference latency is higher than that of DBN, which further demonstrates the efficiency of the DBN architecture in the forward feature propagation path. DBN has a superior real-time performance advantage during forward propagation, and its low-overhead characteristic in forward propagation reserves a larger computational margin for real-time systems, making it more suitable for engineering scenarios with stringent real-time requirements.

Comparative experiments show that the DBN model is comparable to Transformer, TCN and LSTM models in identification accuracy and can effectively extract navigation data features when transplanter sideslip occurs; in terms of real-time inference speed, DBN has obvious advantages and meets the real-time requirements of the sideslip identification task. Therefore, considering both identification accuracy and computational efficiency, selecting DBN as the core model for sideslip pattern identification has greater practical engineering value.

3.2. Rice Transplanter Lateral Slip Identification and Adaptive Control: Upland Field Validation Experiment and Result Analysis

To empirically validate the adaptive control method designed in this study, a dry-field experiment focusing on the identification and adaptive control of sideslip phenomena of transplanters during navigation was conducted at the experimental base in Shibu Town,

Xinjian District, Nanchang City, Jiangxi Province, in December 2024. The experimental site is shown in Figure 10.



Figure 10. On-site experiment for slip identification on dry farmland.

(1) Experiment method

Navigation path tracking experiments were conducted, respectively, under vehicle speeds of 0.8 m/s, 1.0 m/s, and 1.2 m/s, with the initial position deviation within 1 cm and the initial heading deviation within 1° , as shown in Figure 11. Ramps with the same base dimension (100 cm $\times$ 30 cm) but different inclination angles (10° , 15° , 20°) were arranged on different navigation paths to induce sideslip of varying degrees. The Deep Belief Network (DBN) model was adopted to identify the navigation status; the forward-looking distance parameter was adjusted and controlled in real time based on the identification results, and the state variable information, including lateral position deviation, heading deviation, and vehicle speed, was stored in real time simultaneously.



Figure 11. Sideslip experiment simulation device for dry farmland.

(2) Evaluation indicators

A comparative experiment was conducted by setting up two groups: one with adjustable forward viewing distance (experimental group) and one without regulation (control group). Four indicators were selected as evaluation metrics: the navigation recovery time of the transplanter after sideslip occurrence (i.e., the time required for the path deviation to re-stabilize within ± 5 cm after exceeding the ± 5 cm threshold post sideslip), the navigation recovery distance (corresponding spatial distance), the maximum absolute value of position deviation (the maximum lateral offset during the whole process), and the maximum overshoot (the peak deviation exceeding the target path during the sideslip recovery process). Three repeated tests were conducted under each speed condition, and the average values of the evaluation indicators were calculated.

(3) Experiment results and analysis

The mean values of relevant evaluation indicators for three replicate tests of each group in the dryland experiment were statistically analyzed, including launch time, launch distance, maximum absolute position deviation, and maximum overshoot. The statistical

results are shown in Table 8. Due to space limitations, this subsection only presents the data curves of representative experimental groups and control groups on a 15° slope at different speeds, as shown in Figure 12.

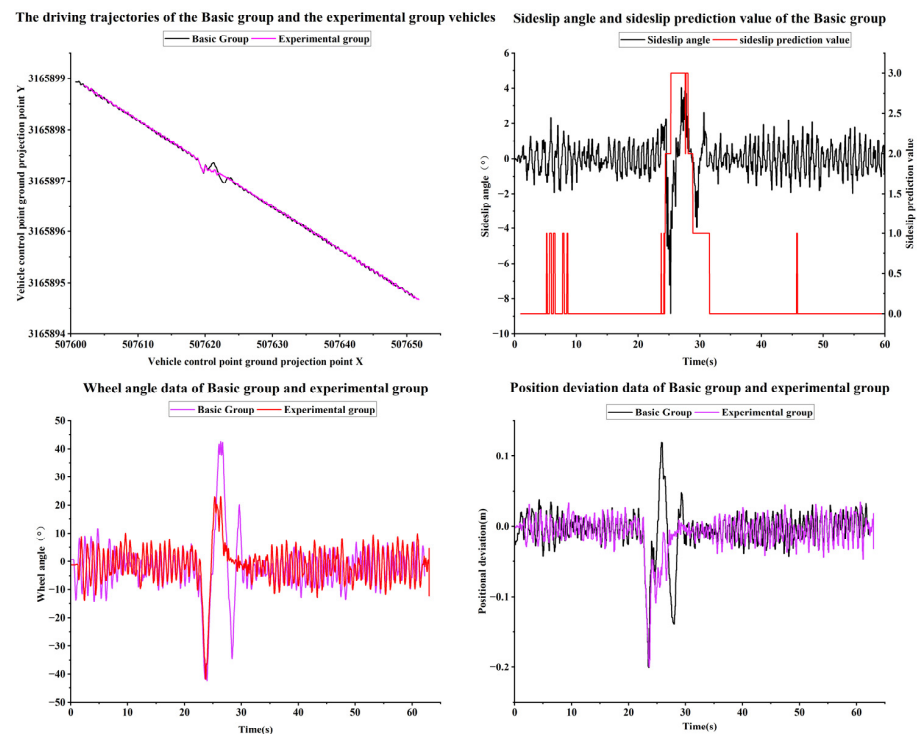
Table 8. Statistical table of experimental evaluation indicators for dry-field sideslip recognition and adaptive control.

Vehicle Speed (m/s)	Gradient (°)	Groups	Alignment Time (s)	Alignment Distance (m)	The Maximum Absolute Value of Position Deviation (cm)	Maximum Overshoot (cm)
0.8	10	Basic group	4.33 ± 0.70	3.34 ± 0.56	17.99 ± 0.72	9.72 ± 5.60
		Test group	2.32 ± 0.14	1.68 ± 0.15	16.93 ± 0.24	0.32 ± 0.26
	15	Basic group	5.67 ± 0.06	3.93 ± 0.08	19.30 ± 1.40	14.34 ± 0.49
		Test group	2.83 ± 0.79	1.90 ± 0.58	19.92 ± 1.53	2.84 ± 1.49
	20	Basic group	4.50 ± 0.74	3.50 ± 0.62	22.23 ± 0.36	6.78 ± 1.35
		Test group	2.97 ± 0.73	2.04 ± 0.55	21.1 ± 0.37	2.10 ± 1.52
1.0	10	Basic group	4.08 ± 0.58	3.46 ± 0.46	18.16 ± 0.73	11.04 ± 1.89
		Test group	2.23 ± 0.47	1.89 ± 0.39	17.57 ± 0.93	4.39 ± 0.99
	15	Basic group	5.12 ± 0.08	3.78 ± 0.11	19.61 ± 0.75	13.71 ± 0.60
		Test group	1.83 ± 0.08	1.91 ± 0.17	19.26 ± 0.94	2.97 ± 0.59
	20	Basic group	5.43 ± 0.29	4.72 ± 0.88	23.27 ± 0.15	12.54 ± 5.31
		Test group	2.23 ± 1.25	1.46 ± 0.59	19.87 ± 1.91	3.48 ± 2.73
1.2	10	Basic group	4.20 ± 0.15	3.99 ± 0.14	19.98 ± 0.39	11.18 ± 1.54
		Test group	3.18 ± 0.68	2.94 ± 0.72	17.45 ± 0.78	7.51 ± 5.17
	15	Basic group	6.63 ± 0.33	6.09 ± 0.05	29.86 ± 0.81	29.86 ± 0.81
		Test group	2.87 ± 0.25	2.53 ± 0.21	17.38 ± 1.04	10.36 ± 2.20
	20	Basic group	6.98 ± 0.70	6.07 ± 0.68	40.25 ± 2.39	40.25 ± 2.39
		Test group	5.60 ± 1.46	5.07 ± 1.48	22.48 ± 0.37	15.75 ± 0.55

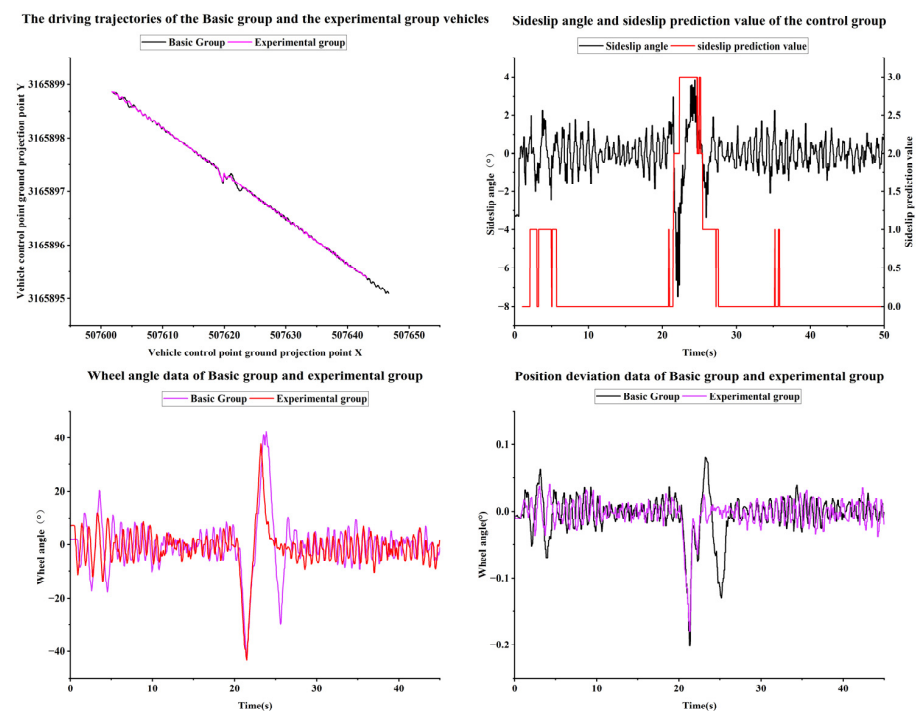
As shown in Table 8, under all combinations of test speeds and slope gradients, all navigation indicators of the adaptive control experimental group are better than those of the fixed-parameter control group. The line-acquisition time and line-acquisition distance of the experimental group range from 1.83 s to 5.60 s and 1.46 m to 5.07 m, respectively, which are lower than those of the control group (4.08 s to 6.98 s and 3.34 m to 6.09 m). Moreover, the indicators of both groups increase with the rise in driving speed. Under the extreme working condition with the maximum speed (1.2 m/s) and the maximum slope (20°), the maximum position deviation of the control group during the deviation correction and return process reaches 40.25 cm due to the untimely adjustment of the wheels, while that of the experimental group is only 22.48 cm. In addition, the maximum overshoot of the experimental group (0.32 cm to 15.75 cm) is also lower than that of the control group (6.78 cm to 40.25 cm). Taking the working condition with a speed of 1.0 m/s and a slope of 15° as an example, the line-acquisition time, line-acquisition distance and overshoot of the experimental group are 1.83 s, 1.91 m and 2.97 cm, respectively, which are 64.3%, 49.5% and 78.34% lower than those of the control group, respectively.

Analysis of the data curves in Figure 12 shows that after sideslip occurs, it can be observed from the position deviation data curves of the control group and the experimental group under different experimental factors that the experimental group performs more stably than the control group, with shorter line-acquisition time and distance. From the data curves of sideslip angle and the model-predicted value of the control group, it can be seen that the DBN model identifies vehicle sideslip in a timely and effective manner after sideslip occurs, and the recognition lag time is also controlled within a favorable range. However, it can also be observed from the data in the figure that inaccurate recognition or misrecognition exists in some cases, so the recognition accuracy still needs to be improved. From the wheel angle data of the experimental group and the control group, it can be seen that in the experimental group, after the navigation system receives the vehicle sideslip recognition result from the DBN, it reduces the output of wheel angle by increasing the

forward-looking distance parameter. Reducing the output of wheel angle can shorten the wheel angle tracking lag time and help the vehicle stabilize quickly. In contrast, the control group maintains the original forward-looking distance after sideslip occurs, which leads to an excessive expected wheel angle calculated by the navigation system. Excessive wheel angle will cause large lag in wheel angle tracking and thus affect the deviation correction process of the vehicle.

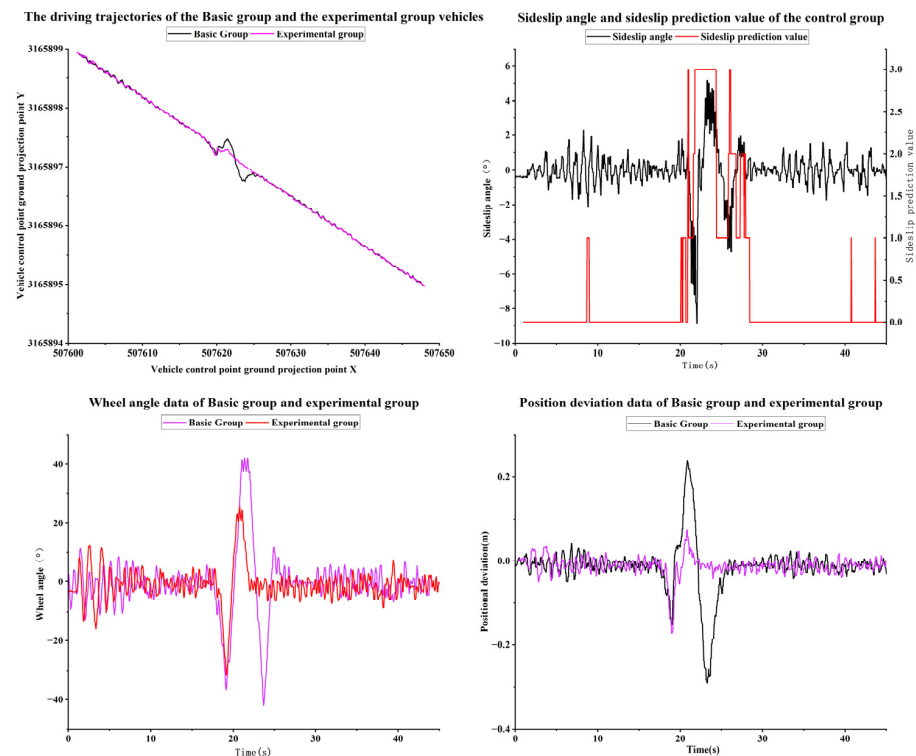


(a) Curve of Experimental Data from Dry Farm at 0.8 m/s—15°



(b) Curve of Experimental Data from Dry Farm at 1.0 m/s—15°

Figure 12. Cont.



(c) Curve of Experimental Data from Dry Farm at 1.2 m/s—15°

Figure 12. Field sideslip identification and adaptive control test data curve.

The above analysis shows that compared with the control method with relatively fixed parameters, the adaptive control strategy based on DBN sideslip recognition proposed in this study has advantages in the real-time performance and effectiveness of recognition, as well as in improving the stability of the control system under harsh working conditions. It can quickly adjust the front wheel angle through the adaptive algorithm for active adjustment, avoid long-term navigation oscillation caused by deviation correction delay, and accelerate the stabilization speed of transplanter navigation.

3.3. Paddy Field Validation Experiment for Sideslip Identification and Adaptive Control of Rice Transplanters

To further verify the adaptive control method based on sideslip identification for rice transplanters proposed in this study under actual paddy field operation conditions, a verification experiment under real-world paddy field working scenarios was carried out at the experimental base in Shibui Town, Xinjian District, Nanchang City, Jiangxi Province. The test site is shown in Figure 13.

(1) Experiment Method

As shown in Figure 14, to simulate a typical working scenario, a 15° inclined slope is filled along the navigation path. A navigation path tracking test is conducted with the vehicle moving at a speed of 1.0 m/s, under the conditions that the initial position deviation is controlled within 1 cm and the initial heading deviation is controlled within 1°. The DBN model is adopted to identify the navigation status, and a comparative test is carried out between two groups: the experimental group with forward-looking distance adjustment via setting and the control group without adjustment. Meanwhile, the navigation data is stored in real time.



Figure 13. On-site experiment for paddy field sideslip identification.



Figure 14. On-site layout of the sideslipping device.

(2) Evaluation Indicators

In this paddy field experiment, the same evaluation indicators as those adopted in the dry field experiment are employed, namely navigation on-line time, on-line distance, maximum absolute value of position deviation, and maximum overshoot. Four repeated navigation experiments are conducted for both the experimental group and the control group.

(3) Experiment result

As shown in Figure 15, there are four sets of curve diagrams representing the navigation position deviation of the transplanting machine during repeated tests. The maximum position deviation, online time, online distance, and maximum overshoot after the sideslip occurred are presented in Table 9.

Table 9. Statistical table of evaluation indicators for paddy field verification tests.

Test Number	Groups	Recovery Time (s)	Recovery Distance (m)	The Maximum Absolute Value of Position Deviation (cm)	Maximum Overshoot (cm)
1	Basic group	5.75	4.22	23.12	12.10
	Test group	1.85	1.45	19.96	0.30
2	Basic group	3.5	3.42	20.41	15.06
	Test group	3.10	3.14	20.97	7.44
3	Basic group	3.6	3.56	18.07	13.32
	Test group	2.95	2.83	18.15	2.60
4	Basic group	5.35	4.30	23.47	18.16
	Test group	0.85	0.75	22.17	0
Mean value	Basic group	21.27 ± 2.19	4.55 ± 1.01	3.88 ± 0.39	14.66 ± 2.28
	Test group	20.31 ± 1.47	2.19 ± 0.91	2.04 ± 0.98	2.59 ± 2.98

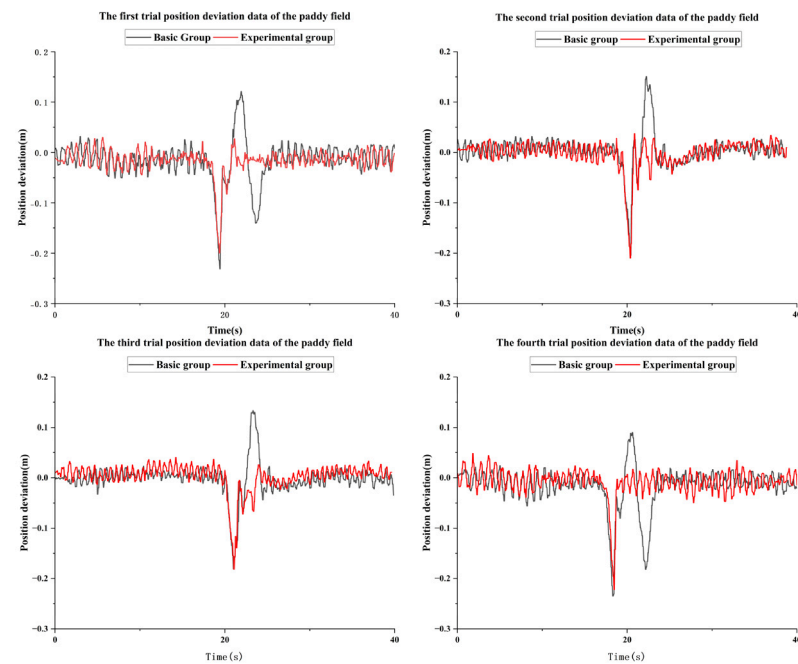


Figure 15. Data curve of water field experiment position deviation.

As can be observed from the data curves in Figure 15, the sideslip of the transplanter caused by the sideslip device leads to severe position deviation, and the maximum position deviation of the experimental group is close to that of the control group at this stage. However, in the subsequent control process, the position deviation curve of the experimental group is smoother than that of the control group, and no obvious overshoot occurs. Data in Table 9 shows that after the occurrence of sideslip, the experimental group outperforms the control group in three indicators, namely recovery time, recovery distance and maximum overshoot: the values of the experimental group are 0.85–3.1 s, 0.75–3.14 m and 0–7.44 cm respectively, while those of the control group are 3.5–5.75 s, 3.42–4.30 m and 12.1–18.16 cm respectively. All the above analyses indicate that the adaptive control method based on sideslip identification for transplanters proposed in this study achieves sound performance in actual paddy field operation environments and can effectively improve the stability of the control system under harsh working conditions.

4. Discussion

4.1. Analysis of the Performance and Input Features of the Side Slip Identification Model

Through experiments with different combinations of navigation state variables and data lengths, this paper selects the input for the side-slipping identification model of the transplanting machine. The results show that the combination of position deviation (PD) and heading deviation (HD) can be used for side-slipping state identification. For the PD + HD combination, the recognition accuracy is higher when the data length is 30 compared to 20, but increasing the data length will make the data window required for a single state judgment longer. Considering factors such as the real-time identification and saving computing resources, this paper selects the PD + HD combination with a data length of 20 as the model input.

The model comparison results show that the side-slipping state identification accuracy of DBN is 88.04%, which is lower than LSTM and Transformer, but its forward propagation time (0.0487 ms) is lower than the two comparison models'. Therefore, the main characteristic of DBN in this paper is that the calculation time is shorter, rather than the highest classification accuracy. For navigation systems that need to obtain the side-slipping

state in real time and adjust control parameters, the model inference time is a factor to be considered when choosing the model.

The SHAP analysis results show that the contributions of different navigation state variables to the side-slipping state identification results vary. Both PD and HD have an impact on the model output, and the feature contribution of heading deviation is larger. This result indicates that the navigation position and heading state can provide information for side-slipping state identification and also provides a basis for the PD and HD combination as the model input.

4.2. Side-Slip Identification and Adaptive Preview Control

The results of the dry field and water field experiments show that when the identification results of the side slip state are used for the adjustment of the preview distance, the path recovery process of the transplanting machine after side slip is improved. Compared with the fixed parameter control, the adaptive control method can adjust the preview distance according to the side slip state, and the online time, online distance, maximum position deviation and maximum overshoot in the experiment have all decreased.

The fixed parameter control adopts the same preview distance in different side slip states. When the side slip degree changes, the fixed parameters cannot be adjusted according to the current state, which may lead to an increase in the path recovery time or large fluctuations during the recovery process. This paper adjusts the preview distance based on the side slip identification results of DBN so that the preview parameters change with the side slip state, thereby changing the path tracking response of the vehicle.

Therefore, the method in this paper mainly achieves the adjustment of control parameters through the combination of side slip state identification and preview distance adjustment, rather than increasing the complexity of the preview controller itself. The shorter inference time of DBN also provides conditions for the application of this method in real-time navigation control.

4.3. Comparison with Previous Studies

The previous research of our team [27] mainly studied the feasibility of side-sliding identification and adaptive preview control for transplanting machines through simulation methods. Based on this, this paper collected navigation data in actual farmland environments, established a side-sliding state dataset, and conducted closed-loop experiments on the actual machines.

Compared with the previous research, this paper added side-sliding state identification based on measured data, used Optuna4.9.0 for model hyperparameter optimization, and utilized SHAP to analyze the contribution of input features to the model output. At the same time, DBN was compared with LSTM and Transformer, and the model inference time was tested. In terms of control experiments, this paper conducted real-machine verification under dry and wet field conditions and tested the side-sliding state identification and adaptive preview control methods.

4.4. Research Limitations and Future Prospects

This paper still has the following limitations. Firstly, the real machine test object was a rice transplanting machine, and it has not been verified on other types of agricultural machinery. Therefore, the applicability of the methods in this paper to other agricultural machinery still requires further experimentation.

Secondly, DBN can identify the side-slip state in real time, but there are still classification errors between different side-slip levels, and the accuracy of side-slip level identification still has room for improvement. Further research can be conducted from two aspects: data feature construction and model structure.

Finally, subsequent research will add tests on other types of agricultural machinery and different operating environments and adjust the model according to the motion characteristics of different agricultural machinery. On this basis, vehicle speed control can be added to the existing control method so that the transplanting machine can adjust the preview distance and driving speed simultaneously when it encounters navigation abnormalities.

5. Conclusions

This study addresses the problem of abnormal path tracking caused by lateral slip disturbances during the operation of transplanting machines in complex fields. A self-adaptive control algorithm based on the combination of lateral slip identification and preview tracking using a deep belief network (DBN) was designed, and its effectiveness was verified through simulations and field vehicle tests. The main conclusions are as follows:

- (1) In the model comparison test for identification, through variable optimization and SHAP interpretability analysis, the “heading deviation (HD) + position deviation (PD) combination with a time sequence length of 20” was determined as the optimal feature variable input. The test results show that the DBN model has an accuracy rate of 88.04% in classifying lateral slip states, and the single-step forward reasoning delay is 0.0487 ms. Its computational delay and classification accuracy meet the requirements for real-time operation of the navigation control system.
- (2) In the field closed-loop navigation comparison test, under the operation speed conditions set in this paper, the proposed adaptive preview control strategy has better path tracking performance than the fixed parameter control group. When the transplanting machine experiences lateral slip disturbances, the navigation start time, start distance, maximum position deviation, and maximum overshoot of the adaptive control group are all lower than those of the control group, effectively reducing the trajectory oscillation after lateral slip occurs and shortening the transition process and improving system stability.
- (3) The field test results confirm that by dynamically identifying the lateral slip state using DBN and adjusting the preview distance in real time, the problem of insufficient adaptability of the fixed-parameter control algorithm in specific disturbance conditions can be improved. This provides a feasible solution for improving the path tracking stability of transplanting machines in complex disturbance environments.

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