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CROP YIELD PREDICTION METHOD BASED ON LSTM AND KAN

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ABSTRACT. The accurate prediction of crop yield is of great significance in agricultural production and food security. We combine Convolutional Neural Network (CNN) and Long Short Term Memory Network (LSTM) to design a new CLKA-NET model. CNN is used for feature extraction, and LSTM network is used to capture the temporal dependence of data sequence. Then, Kolmogorov-Arnold Network (KAN) layer is used to perform nonlinear transformation on LSTM output to extract deep level features. Finally, the Fully Connected Neural Network (FCNN) is used to output yield prediction results based on environmental factors and historical data. We used the Kaggle dataset for experimental validation and compared it with other models. The results indicate that our model performs well in crop yield prediction tasks and has a lower RMSE. The research method in this article has high accuracy and provides an effective crop yield prediction tool for agricultural producers and policymakers, which helps to improve crop yield and quality, promote food security and sustainable agricultural development.

1. Introduction

Accurate prediction of crop yield is crucial for agricultural production, food security, and economic stability. Globally, agriculture is the cornerstone of human survival and development, and fluctuations in crop yields directly affect global food supply and food prices [3,15–17]. Therefore, scientists and agricultural practitioners have been dedicated to developing accurate methods and models to reliably predict crop yields, and to formulate reasonable agricultural management and policies based on these predictions. In the agricultural production process, environmental factors such as climate conditions, soil quality, and water resource availability play a crucial role. These factors directly influence the growth and development of crops, thereby affecting the final yield and quality. With the continuous changes in climate and the ongoing increase in population, the demand for accurate crop yield predictions has become more urgent. Only through accurate predictions can agricultural producers take timely measures to cope with adverse climate conditions or other environmental stresses, maximizing crop yield and quality, thus ensuring the stability and security of the food supply. In this context, utilizing environmental factors to predict crop yield has become one of the focal points of current research. Traditional statistical models typically use historical crop yield data and related environmental factors,

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such as meteorological data and soil characteristics, to establish prediction models [1,2]. These models can provide a certain degree of predictive accuracy but are often limited by data constraints and model assumptions. In recent years, with the rapid development of machine learning and artificial intelligence technologies, more and more research has begun to explore the use of these advanced technologies to improve the accuracy and efficiency of crop yield predictions. Machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and neural networks are widely used in crop yield prediction. These algorithms can learn complex patterns and relationships from large amounts of data, thereby improving predictive accuracy. Khaki et al. [6] combined CNN and Recurrent Neural Networks (RNN) to design a network that predicted soybean and corn yields in 13 states of the United States. Romero et al. [12] applied decision trees and association rule mining to classify the factors constituting durum wheat yield. Zeng et al. [18] used Support Vector Regression to predict winter wheat yield in the Guanzhong Plain of Shanxi Province. Lin et al. [9] utilized the Random Forest algorithm to predict winter wheat yield in Henan Province using remote sensing, climate, and soil data. In recent years, with the development of deep learning theory and the enhancement of GPU performance, CNN [7] and LSTM [4,14] have achieved significant success in the field of time series prediction due to their powerful ability to capture spatial features. Kolmogorov-Arnold Network (KAN) [10] can efficiently approximate complex multivariate functions and have important applications in neural networks, especially for tasks requiring efficient approximation and handling of high-dimensional data, fully leveraging their advantages in processing multivariate inputs and complex nonlinear relationships. Russello [13] used CNN to predict grain yield based on satellite images. Nevavuori et al. [11] proposed a CNN model to predict crop yield using NDVI and RGB data obtained from drones. Since crop growth is a typical time series accumulation process, the LSTM model is more suitable for extracting time series features to solve the crop yield prediction problem. In summary, using environmental factors and other multi-source data to predict crop yield is an important direction in current agricultural research. This paper aims to address the shortcomings of different methods and models in existing research and proposes a CLKA-NET model based on LSTM networks and KAN to provide new ideas and methods for crop yield prediction. Specifically, we will explore the potential and application of this method in crop yield prediction. Through this research, we hope to provide agricultural producers and policymakers with more accurate and reliable crop yield prediction tools, thus contributing to food security and sustainable agricultural development.

2. Materials and methods

2.1. **Principles of LSTM Networks.** LSTM is a special type of Recurrent Neural Network (RNN) that has a stronger memory capacity compared to standard RNN, making it better suited for handling long-term dependencies. The key innovation in LSTM networks is the introduction of a triple gating mechanism, which includes the forget gate, input gate, and output gate. This gating mechanism effectively addresses the issues of gradient vanishing and gradient explosion that occur during the training of long sequences, thus enabling LSTM to perform better on tasks involving long sequences. The structure is illustrated in Figure 1. The operational principles of an LSTM network can be described by the following set of equations:

(1)Forget Gate Mechanism: As a regulatory component in the memory retention process, the forget gate modulates the retention degree of historical cellular state information across temporal sequences. This gate processes the concatenated vector composed of the preceding hidden state h_{t-1} and current input x_t, subsequently generating retention coefficients through nonlinear transformation. These coefficients, constrained within the interval [0,1], quantify the preservation proportion for each cellular state element. This process can be mathematically expressed as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2.1}$$

where W_f denotes the trainable weight matrix that projects the concatenated input-hidden vector into gate space, b_f represents the corresponding bias vector, and $\sigma(\cdot)$ signifies the logistic activation function that ensures output normalization.

(2)Input Gate Mechanism: Serving as the information integration controller, this gate regulates the integration intensity of novel information into the cellular memory system. Through processing the concatenated vector formed by historical hidden state h_{t-1} and current input x_t, this mechanism generates dual outputs: an update coefficient vector i_t quantifying cellular state modification weights within [0,1], and a candidate value vector V_t for updating the cell state within [-1,1]. The mathematical implementation involves two Equation in(2.2) and (2.3):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{2.2}$$

$$V_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{2.3}$$

where W_i and b_i denote learnable parameter matrices for generating the update gate control signal, while W_c and b_c parameterize the nonlinear feature transformation for candidate state generation. The $\sigma(\cdot)$ is the sigmoid function, and the hyperbolic tangent $\tanh(\cdot)$ ensures nonlinear feature normalization.

(3)Cell State Updating Mechanism: The cell state C_t is dynamically adjusted by integrating historical memory and novel features through gated operations. Specifically, the forget gate f_t modulates the retention degree of prior cell state C_{t-1}, while the input gate i_t controls the incorporation of candidate value V_t generated from current inputs. This hybrid update process is mathematically defined as:

$$C_t = f_t \odot C_{t-1} + i_t \odot V_t \tag{2.4}$$

where $\odot$ denotes element-wise multiplication (Hadamard product), enabling localized adjustments to memory retention and renewal.

(4)Output Gate Mechanism: The output gate regulates the exposure intensity of long-term memory stored in the cell state to subsequent network layers. By integrating the preceding hidden state h_{t-1} and current input vector x_t, this gate generates a modulation coefficient $o_t \in [0, 1]$ through sigmoid normalization, which quantifies the contribution of each cell state element to the final output. The operational principle is mathematically formulated as Equation (2.5):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{2.5}$$

where W_o and b_o denote the learnable weight matrix and bias term specific to the output gate.

(5) Hidden State Generation: The hidden state h_t acts as a gated output of the cell state C_t, selectively propagating information to downstream layers and subsequent time steps. This is achieved through element-wise modulation of the hyperbolic tangent-transformed cell state by the output gate o_t, as formalized in Equation (2.6):

$$h_t = o_t \odot \tanh(C_t) \tag{2.6}$$

where,$\odot$ denotes Hadamard product (element-wise multiplication), enabling localized feature amplification or suppression. $\tanh(C_t)$ compresses the cell state into the range $[-1, 1]$, stabilizing gradient flow while preserving directional information of memory features . $o_t \in [0, 1]$ quantifies the exposure intensity of each cell state element, determined by the output gate.

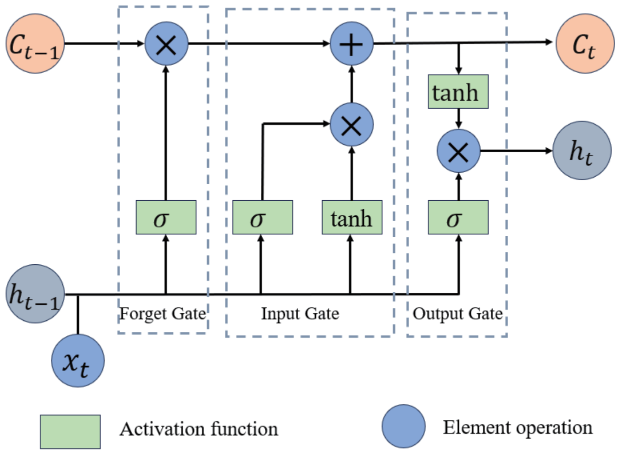

FIGURE 1. LSTM network structure diagram

The workflow of a LSTM network can be divided into the following steps: input processing, calculating the forget gate, calculating the input gate and candidate memory cell, updating the memory cell, calculating the output gate, and computing the final output. The specific steps are as follows: LSTM receives the input x_t at the current time step, the hidden state h_{t-1} from the previous time step, and the memory cell state C_{t-1} from the previous time step. First, the forget gate outputs f_t, which determines how much information from the previous cell state C_{t-1} should be retained. Then, the input gate i_t determines how much new information will be added to the memory cell. The candidate memory cell V_t represents the new candidate information. The forget gate f_t controls the extent to which the previous memory cell C_{t-1} is forgotten. The input gate i_t and the candidate memory cell V_t control the update of the memory cell C_t at the current time step. The LSTM finally outputs the hidden state h_t at the current time step through the output gate. This hidden state not only contains the processing result of the current input x_t but also retains the information passed down from the previous time steps.

LSTM layer is primarily used to capture the key features that change over time within the dataset. These features include climate variations during different stages of crop growth, seasonal effects, and long-term trends. By processing these time-dependent features, the LSTM effectively extracts hidden temporal patterns from the data, providing more representative input data for the subsequent KAN layer. This process ultimately enhances the accuracy of the final predictions.

2.2. **KAN Theorem.** KAN is a type of network model capable of approximating any multivariate continuous function, possessing powerful nonlinear mapping capabilities. Similar to MLP structures, KAN also features a fully connected structure. While MLP sets fixed activation functions on neurons, KAN sets learnable activation functions on weights. Compared to traditional multi-layer neural networks, KAN require fewer parameters when handling high-dimensional data, reducing both computational complexity and the risk of overfitting. KAN achieves approximation of high-dimensional inputs by constructing combinations of one-dimensional functions. The basic principles of KANs networks are as follows: Kolmogorov-Arnold Representation Theorem: Any continuous multivariate function $f(x_1, x_2, \ldots, x_n)$ can be represented as a sum of several one-dimensional functions shown in (2.7).

$$f(x_1, x_2, \ldots, x_n) = \sum_{q=1}^{2n+1} \Phi_q\big(\sum_{p=1}^{n} \phi_{q,p}(x_p)\big) \tag{2.7}$$

where Φ_q and $\phi_{q,p}$ are single-variable one-dimensional continuous functions. Grain yield prediction involves various factors, including climate data, soil information, etc. KAN can effectively handle these multivariable inputs by leveraging the Kolmogorov-Arnold Representation Theorem to decompose high-dimensional inputs into combinations of one-dimensional functions, thereby achieving efficient approximation of complex functions. There often exists nonlinear relationships between grain yield and each input variable. KAN are capable of accurately capturing and modeling these complex nonlinear relationships through the nonlinear combination of one-dimensional functions.

2.3. **Proposed CLKA-NET Network.** The paper proposes a CLKA-NET network. CNN have powerful feature extraction capabilities in raw data, so we incorporate CNN into the model to capture temporal and spatial dependencies, automatically learn, and extract complex features from the data. Specifically, the CNN layers can identify local patterns and spatial relationships in the data, extracting high-dimensional feature representations. Next, we feed the features extracted by the CNN into the LSTM layer. The LSTM layer excels at handling sequential data, capturing long and short-term dependencies over time, thus outputting a hidden state sequence containing temporal dependencies. The introduction of LSTM allows the model to effectively deal with the gradient vanishing and exploding problems in time series data, ensuring good performance even on data with long temporal spans. To further enhance the model's non-linear expression capabilities, we introduce KAN. KAN, through a series of nonlinear transformation functions, can better capture complex patterns and features. By inputting the hidden state sequence output from the LSTM layer into KAN, the model can extract and integrate deep-level features of the data more deeply. The nonlinear transformation functions of KAN have powerful expression capabilities, capable of handling complex relationships in high-dimensional data, compensating for the shortcomings of the LSTM layer in certain complex pattern recognition tasks. Finally, the model structure, combining CNN, LSTM, and KAN layers, as shown in Figure 2, can more accurately extract and process multi-level features in the data, improving the accuracy of crop yield prediction.

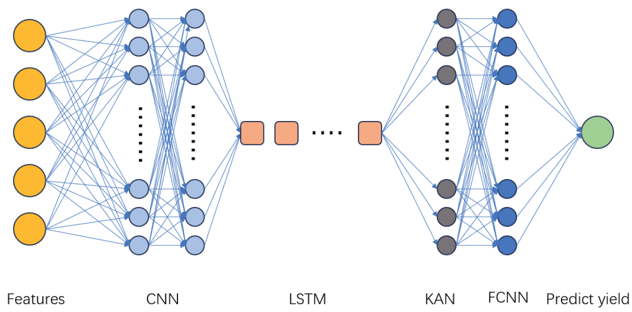

FIGURE 2. CLKA-NET network architecture

2.4. **Implementation Steps of the Improved Method.** Step 1: Data Preprocessing. Standardize the input data to ensure that all features are on the same scale, facilitating better learning by the model.

Step 2: CNN Feature Extraction. Utilize convolutional layers and pooling layers to extract spatial features from the input data. Convolutional layers extract local features using filters.

Step 3: LSTM Time Series Modeling. Take the features extracted by CNN as input and employ LSTM layers to capture the temporal dependencies of the data. LSTM layers are effective in handling long time series data, retaining important temporal information.

Step 4: KAN Nonlinear Mapping. Pass the output of LSTM to the KAN layer. Through the combination of multiple one-dimensional functions, achieve approximation and nonlinear mapping of high-dimensional data.

Step 5: FCNN Output Prediction. Pass the output of KAN to the fully connected layer for nonlinear transformation, ultimately outputting the prediction results. The fully connected layer adjusts weights to enhance the model's expression capability and improve prediction accuracy.

The algorithm is described in pseudocode as Algorithm 1.

3. RESULTS

3.1. **Data Source.** The dataset used in this study is sourced from Kaggle, named Agricultural Crop Yield in Indian States Dataset [5]. This dataset contains agricultural data of various crops planted in Indian states from 1997 to 2019. It provides important features related to crop yield prediction, including crop type, crop year, planting season, state, planting area, yield, annual rainfall, fertilizer usage, pesticide

Algorithm 1 Training Process of CLKA-NET Model

Require: A training set $X = (x_1, x_2, \ldots, x_n)$ and learning rate η
Ensure: A well-trained CLKA-NET model
Standardize the input data: $X_{\text{norm}} = \text{MinMaxScaler}(X)$
Define model layers:
  $\text{cnn\_layer} = \text{Conv1d}(\text{in\_channels} = 9, \text{out\_channels} = 512, \text{kernel\_size} = 3, \text{padding} = 1)$
  $\text{lstm\_layer} = \text{LSTM}(\text{input\_size} = 512, \text{hidden\_size} = 512, \text{num\_layers} = 1, \text{dropout} = 0.1)$
  $\text{kan\_layer} = \text{MultKAN}(\text{width} = [\text{seq\_dim}, \text{hidden\_size}, \text{pred\_dim}], \text{grid} = 3, k = 3, \text{seed} = 1)$
  $\text{fcnn\_layer} = \text{Linear}(\text{in\_features} = \text{seq\_dim}, \text{out\_features} = \text{pred\_dim})$
for epoch $= 1$ to N **do**
  for each X_i in X_{norm} **do**
    Apply CNN layer: $\text{cnn\_out} = \text{cnn\_layer}(X_i)$
    Apply LSTM layer: $(\text{lstm\_out}, \text{hidden\_state}) = \text{lstm\_layer}(\text{cnn\_out})$
    Apply KAN layer: $\text{kan\_out} = \text{kan\_layer}(\text{lstm\_out})$
    Apply FCNN layer: $\text{output} = \text{fcnn\_layer}(\text{kan\_out})$
    Compute loss: $\text{loss} = \text{LossFunction}(\text{output}, y_i)$
    Backpropagate loss: loss.backward()
    Update parameters: optimizer.step()
  end for
end for

usage, and yield. The focus of this dataset is to predict crop yield based on agronomic factors such as weather conditions, fertilizer and pesticide usage, and other relevant variables. The dataset is presented in tabular form, with each row representing data for a specific crop and its corresponding features. It consists of 19652 rows and 10 columns (9 features and 1 label). Figure 3 shows the distribution of data volume across different years in the dataset. Figure 4 displays the distribution of data volume for annual rainfall in the dataset, the unit of rainfall is milliliters. Figure 5 illustrates the data distribution of production in the dataset, the unit of production is metric tons.

3.2. **Evaluation Metrics.** The effectiveness of yield prediction model is evaluated using Mean Squared Error (MSE), Root Mean Square Error ($RMSE$), Mean Absolute Error (MAE) and the coefficient of determination (R^2). Their calculations are shown in (3.1) - (3.4) respectively:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3.1}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^p)^2} \tag{3.2}$$

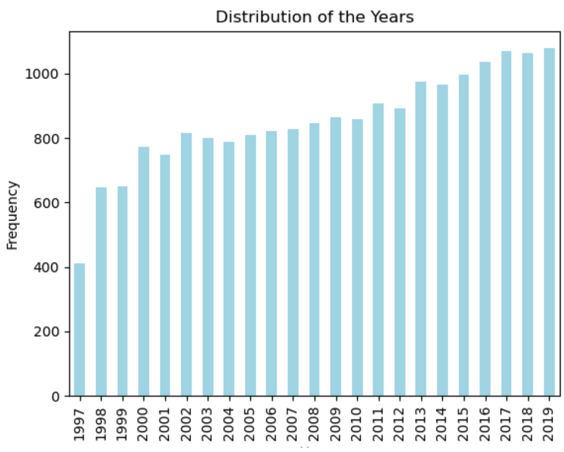

FIGURE 3. Distribution of data volume across different years

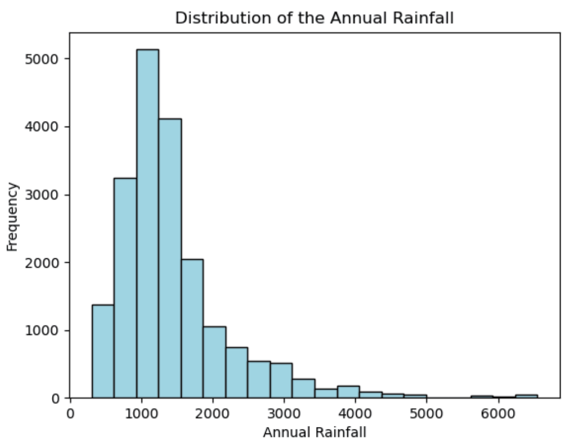

FIGURE 4. Distribution of data volume for annual rainfall

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{3.3}$$

$$R^2 = 1 - \sum_{i=1}^{n}(y_i^p - y_i)^2 / \sum_{i=1}^{n}(y_i - \overline{y})^2. \tag{3.4}$$

In the above equations, y represents the average statistical yield, with units of $10^3 kg/hm^2$. y_i and y_i^p respectively denote the actual yield and predicted yield for the $i-th$ unit. The higher the value of indicator R^2, the better the model performance is, and the lower the value of indicators MSE, $RMSE$, and MAE, the better the model performance is.

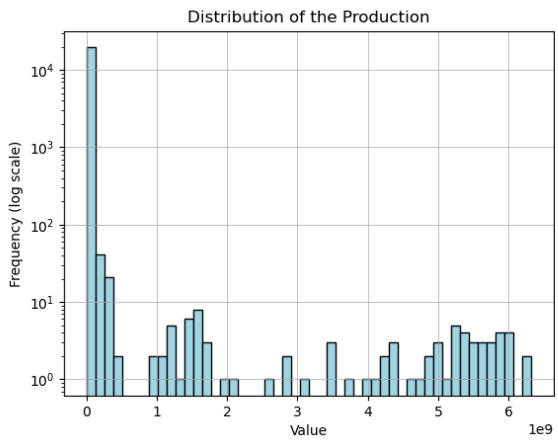

FIGURE 5. Distribution of yield data

3.3. **Experiment Configuration.** The experimental environment utilizes the Windows 10 operating system, with an Intel 13th generation i5-13500HX processor and an NVIDIA RTX 4070 graphics card with 8GB of memory. The development language is Python, and PyCharm is used as the editor. During the model training phase, the initial learning rate is set to 0.001, and the optimizer used is AdamW. The error curve during model training is depicted in Figure 6. It can be observed that the curve tends to stabilize when the number of iterations reaches 2000, indicating model convergence.

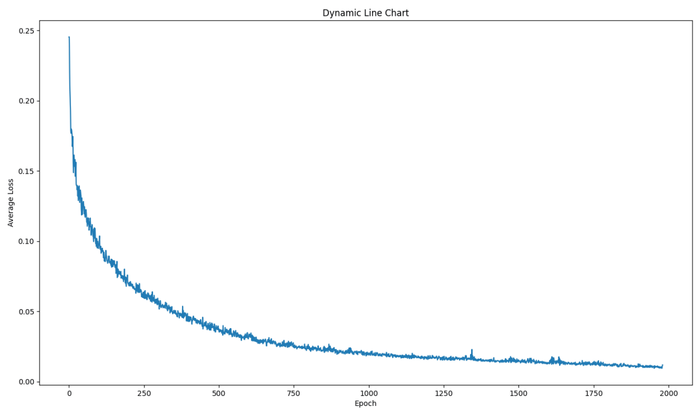

FIGURE 6. Loss-Epoch curve

3.4. **Comparative Experiments.** To evaluate the accuracy of the CLKA-NET crop yield prediction model proposed in this paper, the following seven benchmark models were used for comparison on the dataset:

1. RNN

Recurrent Neural Network are neural networks for sequence data, where each output depends on previous computations. They are good for handling sequences but struggle with long-term dependencies due to vanishing gradients.

2. LSTM

Long Short-Term Memory is an advanced RNN designed to handle long-term dependencies using gating mechanisms, solving the vanishing gradient problem.

3. GRU

Gated Recurrent Unit simplifies LSTM by combining gates and reducing complexity, offering similar performance with less computational cost.

4. Seq2Seq

Sequence to Sequence model converts one sequence to another, commonly used in translation and text generation, often enhanced by attention mechanisms.

The results are shown in Table 1. Compared with RNN, LSTM, GRU and Seq2Seq models, the CLKA-NET model proposed in this paper has the lowest MSE, $RMSE$, MAE value, and the R^2 value is slightly higher. Based on the evaluation results of different time series prediction models, the following conclusions can be drawn: The CLKA-NET model performs well in all evaluation indicators. Specifically, The CLKA-NET model performs slightly better than Seq2Seq. In contrast, the performance of the RNN and GRU models is at a moderate level. Although their R^2 are 0.9953 and 0.9936 respectively, showing a good fit, they are slightly inferior in MSE, $RMSE$, and MAE. The LSTM model performs the weakest in all evaluation indicators, indicating that its prediction accuracy is relatively low. In summary, the CLKA-NET model is more suitable for high-precision time series prediction tasks due to its superior performance in prediction accuracy. According to the experimental data in Table 1, we can obtain the improvement percentage of the CLKA-NET model in the four evaluation indicators compared with models RNN, LSTM, GRU and Seq2Seq, as shown in Table 2.

Table 1. Comparative experiment of different models in yield prediction

Model	**MSE**	**RMSE**	**MAE**	$\mathbf{R^2}$
RNN	9.753×10^{-6}	3.123×10^{-3}	6.916×10^{-4}	0.9953
LSTM	19.78×10^{-6}	4.448×10^{-3}	9.592×10^{-4}	0.9905
GRU	13.20×10^{-6}	3.634×10^{-3}	7.619×10^{-4}	0.9936
Seq2Seq	7.878×10^{-6}	2.807×10^{-3}	5.403×10^{-4}	0.9962
CLKA-NET	7.566×10^{-6}	2.751×10^{-3}	4.990×10^{-4}	0.9964

The comparison between the proposed model the CLKA-NET and models RNN, LSTM, GRU and Seq2Seq is shown in the histogram in Figure 7 and the line chart in Figure 8. The CLKA-NET model has a lot of improvements over models RNN, LSTM and GRU, and a slight improvement over model Seq2Seq. The visualization results comparing predicted yield and actual yield are shown in Figure 9. From Figure 9, it can be observed that the majority of data points lie along the equality line. The overall fitting effect of the model to the actual data is good, indicating that the model performs well for grain yield prediction tasks.

TABLE 2. The improvement percentage of the CLKA-NET model

Model	MSE (%)	RMSE (%)	MAE (%)	R^2 (%)
RNN	22.42	11.91	27.84	1.08
LSTM	61.74	38.15	48.00	0.60
GRU	42.70	24.27	34.52	0.28
Seq2Seq	3.96	2.00	7.64	0.02

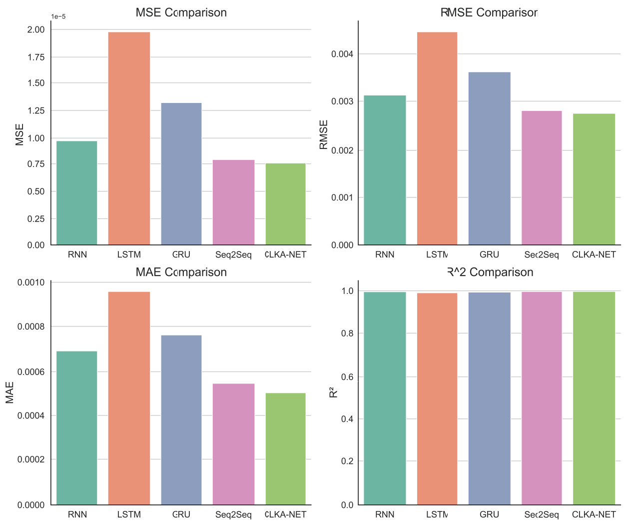

FIGURE 7. Histogram comparing with other models

3.5. **Ablation Experiment.** In order to illustrate the effectiveness of the CLKA-NET method proposed in this paper, an ablation experiment was conducted. The experimental results are shown in Table 3. The descriptions of different methods (A1–A4) are as follows:

1. A1: Model with only linear layers.
2. A2: Model without LSTM layer, only KAN layer and linear layer.
3. A3: Model without KAN layer, only LSTM layer and linear layer.
4. A4: The model proposed in this paper.

TABLE 3. Ablation Experiment of Different Methods

Method	MSE	RMSE	MAE	R^2
A1	10.31×10^{-6}	3.211×10^{-3}	6.553×10^{-4}	0.9951
A2	58.76×10^{-6}	7.665×10^{-3}	14.15×10^{-4}	0.9719
A3	19.78×10^{-6}	4.448×10^{-3}	9.592×10^{-4}	0.9905
A4	7.566×10^{-6}	2.751×10^{-3}	4.990×10^{-4}	0.9964

In Table 3, by comparing the data of the LSTM(A3) model and the CLKA-NET(A4) model proposed in this paper, we can conclude that combining the KAN

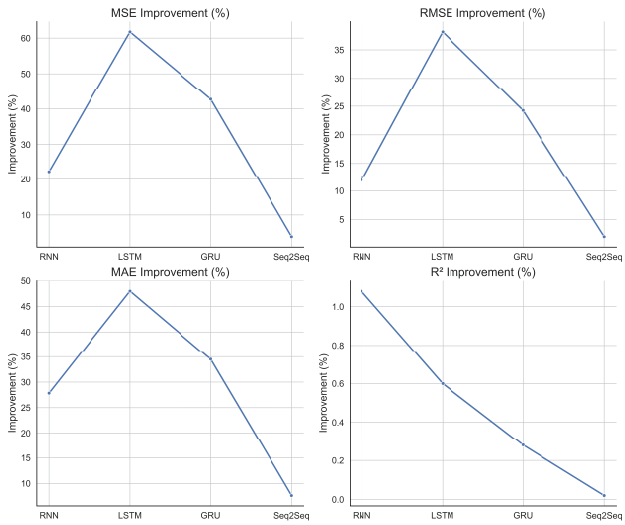

FIGURE 8. Line chart of percentages compared to other models

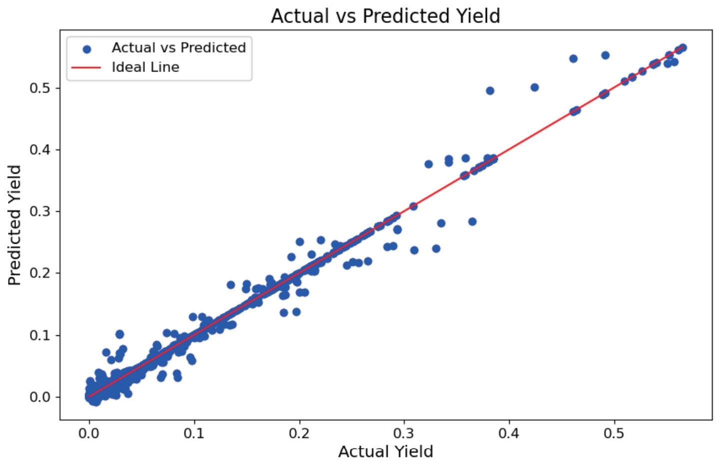

FIGURE 9. Scatter plot comparing predicted yield and actual yield

layer and the LSTM layer can effectively enhance the model's ability to capture implicit features in the time series and improve the model's ability and accuracy in yield forecasting.

4. Discussion

Our model incorporates LSTM and KAN, enabling better capture of long-term dependencies and crucial information in time series data. By combining climate and soil data, our model can more accurately predict crop yields, providing better decision support for agricultural producers to enhance crop yield and quality, thereby promoting agricultural sustainability.

However, our method also has some limitations. Firstly, due to the complexity of the model structure, there is a high demand for computing resources. The model relies heavily on high-quality data, which can be challenging to obtain, especially in the agricultural domain. Secondly, the model's performance under extreme weather events may not be robust enough and requires further improvement. Additionally, the model only considers climate and soil data, overlooking other potential factors affecting crop yield. Remote sensing data [8] is a valuable resource with significant potential to provide comprehensive and accurate information for crop yield prediction. Integrating remote sensing data with climate and soil data can further enhance the model's predictive capabilities and improve the overall understanding of factors influencing crop yield. Therefore, one future research direction is to incorporate remote sensing data into crop yield prediction models to achieve more precise and reliable predictions. Through continuous innovation and improvement, we can leverage modern technologies to address various challenges in agricultural production and make greater contributions to food security and agricultural sustainability.

5. Conclusions

This study proposes a comprehensive model, CLKA-NET, which integrates CNN, LSTM, KAN, and FCNN. The model utilizes CNN to extract features from input data, followed by feeding these features into the LSTM layer to capture sequential dependencies in the time dimension and output a sequence of hidden states. Then, the KAN layer is employed to perform nonlinear transformations on the LSTM outputs, extracting deep-level features, and finally, the FCNN layer integrates these features to output the prediction results. The model is primarily used for crop yield prediction based on climate and soil data.

Through experimental comparisons, we find that the model exhibits significant advantages in crop yield prediction, demonstrating lower $RMSE$. This indicates that the CLKA-NET model accurately captures the complex relationship between environmental factors and crop yield, thus providing reliable prediction results. Our research results indicate that utilizing deep learning models to handle time series data and multidimensional environmental factors can significantly improve the accuracy and stability of crop yield prediction. This is of great importance for agricultural producers and decision-makers, as it can help them better formulate agricultural management and policies, enhance crop yield and quality, and promote sustainable agricultural development and food security. Future research can further optimize the model structure, improve computational efficiency, and explore more environmental factors and data sources to further enhance predictive performance and applicability.

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