IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 8 February 2023, accepted 26 February 2023, date of publication 6 March 2023, date of current version 22 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3253386

RESEARCH ARTICLE

Agricultural Text Classification Method Based on Dynamic Fusion of Multiple Features

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This work was supported in part by the Ministry of Education Research of Social Sciences Youth Funded Projects under Grant 22YJCZH091, and in part by the Science and Technology Project of Henan Province under Grant 232102210079 and Grant 222102210020.

ABSTRACT The traditional text classification methods, which treats the values in agricultural text as characters, will lose the original semantic expression of numerical features. In order to fully mine the deep latent semantic features in agricultural text, a novel text classification method based on multivariate feature dynamic fusion is proposed. The Bi-directional Long Short Term Memory network (Bi-LSTM) model with attention mechanism was used to extract the global key semantic features of the text; the multiple windows Convolution Neural Network were used to extract the local semantic information of the text at different levels; Numerical value features containing essential semantic expression were extracted by artificial method to construct the numerical value feature vector. By introducing the attention mechanism to dynamically fuse the extracted multiple semantic features, which can further enrich the deep semantic expression of agricultural text and effectively improve the effect of agricultural text classification with phenotypic numerical type.

INDEX TERMS Attention mechanism, bi-directional long short term memory network, convolution neural network, dynamic fusion of multivariate features, numerical value features.

I. INTRODUCTION

In recent years, with the rapid development of agricultural information technology, many agricultural technology websites, resource databases and information platforms have emerged. Text as the most common form of data carrying, contains a huge amount of information. How to obtain implicit knowledge quickly and accurately from batch text resources is one of the main tasks of text classification in the field of agricultural information.

Agricultural text classification is a branch of text classification. It can obtain potentially useful information from massive complex and noisy agricultural text information, and guide practical activities such as agricultural production and research [1], [2]. The agricultural texts that record the phenotypic agronomic traits of wheat are classified according to the cold resistance of wheat, which belongs to the classification of agricultural texts. Traditional text classification methods mainly used machine learning methods such as K-nearest neighbor (KNN) [3], Naive Bayesian (NB) [4] and Support Vector Machine (SVM) [5]. The traditional method are used for agricultural text classification [6], [7], [8], [9] and effectively improves the performance of text classification, but it requires manual feature extraction to achieve text classification. With the problems of redundancy, sparsity and diversity of agricultural texts, the accuracy and comprehensiveness of text feature expression cannot be guaranteed if manually construct feature engineering.

Deep learning can automatically extract key features, does not need complex feature engineering, and has strong adaptability and mobility. It has been widely applicated in image processing [10], [11] and natural language processing [12], [13], [14]. Particularly, deep learning is widely used in text classification and the effect is better [15], [16], [17], [18], [19]. The neural network is also used for the agricultural text classification task. Liang et al. [20] calculated sentence

The associate editor coordinating the review of this manuscript and approving it for publication was Zhipeng Cai.

similarity by using word2vec and LSTM for 3007 common rice problems to achieve accurate matching between user problems and common rice problems. Xu et al. [21] constructed a Seq2Seq question-and-answer model based on word2vec and attention mechanism optimization, which significantly improved the accuracy of question-and-answer for rice diseases and insect pests. Zhao et al. [22] used BI-GRU neural network to achieve efficient classification of tomato pest questions. Jin et al. [23] used the method of Bi-GRU combined with Mul-CNN to classify the short text of the problems raised by farmers according to 12 categories of problems such as pests and weeds, market sales and animal diseases. Feng et al. [24] proposed a deep convolutional neural network with four-layer residual module structure, which realized the accurate and efficient classification of rice knowledge texts with different sample sizes and different complexity. Shi et al [25] used BERT and deep active learning to select more valuable and representative data from unlabeled data for manual labeling, and construct labeled data sets to improve the efficiency and effect of agricultural news text.

The above research on agricultural text classification shows that existing research mainly focuses on industry division and intelligent question answering. Standard agricultural corpus is relatively lacking, and different experiments need to build corresponding corpus. The traditional method of artificial feature engineering is not only complex, but also poor adaptability. Compared with traditional machine learning, deep learning technology has improved the effect of agricultural text classification. However, in the process of automatic extraction of text semantic features, the values in the phenotypic features of agricultural text [26], [27] will be treated as characters, and the numerical semantic information with practical significance cannot be fully considered or even ignored. The influence of these meaningful numerical features on the performance of text classification is rarely analyzed.

In view of the lack of agricultural corpus, this paper uses Python to crawl the national audit wheat feature text, constructs the wheat text corpus, and classifies the text according to whether the wheat has cold resistance. Aiming at the problem that some phenotypic values have substantial semantic information in wheat agricultural text corpus constructed in this paper will be ignored, combined with machine learning and deep learning based on other text classification studies, this paper proposes a multi-feature dynamic fusion method for agricultural text classification.

As one of the classic tasks of NLP, Bi-LSTM and CNN have achieved good results in the task of text classification in different fields. Bi-LSTM captures the global feature representation of text in the sequence, while CNN focuses on the local feature information of text in the convolution window. The combination of the two can obtain the comprehensive feature representation information of the text globally and locally, thus ensuring the effect of classification.

The main work of this paper is as follows:

(1) Bi-directional long-term and short-term memory network model combined with attention mechanism (Bi-LSTM-ATT) is used to obtain the global feature representation between all contexts. At the same time, the attention to keyword semantic information is increased to obtain the key semantic feature representation in the global range.

(2) Multi-scale convolution kernel convolutional neural network (Mul-CNN) is used to obtain the feature representation of agricultural text sequence in a local scope.

(3) According to the characteristics of agricultural text containing numerical values, we extract and code the values in the text separately. This paper extract phenotypic values with substantial semantic expression and construct numerical feature vectors.

(4) We adopt the attention mechanism to dynamically calculate the importance of the three features, the local features of different levels obtained by neural network, the key features in the global scope and the constructed feature vector are dynamically fused to improve the accuracy of agricultural text classification with phenotypic values.

II. RELATED WORK

In agricultural text classification, Ji et al. [6] used SVM method, according to land selection, seed selection, irrigation and fertilization six categories, to achieve the collection of crop cultivation knowledge text classification. Wei et al. [7] constructed the keywords database of agricultural industry classification, constructed the text classification model of support vector machine through feature word selection and weight calculation, and classified agricultural texts according to planting, forestry, animal husbandry and fishery. Zhou et al. [8] used the method of naive Bayes combined with the selection of CHI value feature words to classify the agricultural texts collected by the network according to agricultural information, agricultural technology, agricultural product market and agricultural product supply and demand information. Zhao et al. [9] used the collected agricultural texts to establish a corpus, and constructed an agricultural text classifier based on naive Bayes according to the four categories of agricultural news, agricultural technology, agricultural market and agricultural product prices.

Deep learning is widely used in text classification research. Kim [15] used convolution and pooling operations of convolutional neural network to extract the key feature information of text for text classification. Kalchbrenner et al. [16] used the strategy of dynamic convolution and pooling to model the semantics of data in convolutional neural networks, and achieved excellent performance in multiple tasks. Lai et al [17] used recursive convolution neural network to capture context information as much as possible when capturing local semantic features of text, and achieved good results in document-level text classification. Li et al. [18] combined the advantages of CNN and LSTM, establishes the hybrid model CNN-LSTM for Chinese news text classification. Liu et al. [19] used Bi-LSTM to encode the lexical information to get the information before and after the sentence, and then calculates the word level and feature level importance by scalar and vector attention respectively, obtains rich multi-channel CNN semantic representation of the text, which improves the performance of text classification.

The breakthrough of deep learning especially neural network in text classification task promotes the application of deep learning technology in agricultural text classification task. Liang et al. [20] used the word2vec model trained in the agricultural field corpus, the training dataset was mapped into vectors and used as input to train the sentence similarity computing model. The model was validated on the test dataset and compared with the other three sentence similarity methods: the method based on HowNet, the method based on cosine distance of word vectors, and the method based on word2vec and CNN. Sampling results of the sentence similarity calculation indicated that the result of this model was more reasonable for human. The rice FAQ question-answering system developed by this model can accurately match users' questions and the questions in rice FAQ, and better help farmers solve problems in rice production.

Xu et al. [21] constructed a Seq2Seq question and answer model based on word2vec and Attention optimization for rice pest and disease question and answer. This study has obtained over 20,000 articles of network Q & A data with the crawler technology. The test results showed that the test results of Seq2Seq QA model with word2vec and Attention mechanism are more accurate compared with the other two models. The established Q & A model enhanced the Q & A accuracy obviously and could solve the problems during rice cultivation and production. Zhao et al. [22] constructed the classification model of tomato pests and diseases based on word2vec and bi-directional gated recurrent unit (BIGRU) to classify the user's questions. The word vector was used as the initial corpus. Two neural network methods and a machine learning method were adopted to train the classification model. Totally 2000 tomato pests and diseases related questions were selected, which were divided into two categories: tomato diseases and tomato pests. The results showed that the classification accuracy, recall rate and F1 value by using the BIGRU model were 2-5 percentage points higher than those by using convolutional neural network (CNN) and K-nearest neighbor (KNN) classification algorithm. Jin et al. [23] proposed a short text classification method based on BiGRU_MulCNN model to improve the performance of data classification. In the model, Jieba word segmentation tools and agricultural dictionary were selected to text segmentation, then TF_IDF algorithm was adopted to expand the text characteristic and weighted word vector according to the text of key vector, and bi-directional gated recurrent unit was applied to catch the context feature information, multi-convolutional neural networks was finally established to gain local multidimensional characteristics of text. Batch normalization, Dropout, Global Average Pooling and Global Max Pooling were involved to solve overfitting problem. The results showed that the model could classify questions accurately with an accuracy of 95. 9%. Compared with other models such as CNN model, RNN model and CNN/RNN combinatorial model, BiGRU_MulCNN had obvious advantages in classification performance in intelligent agro-technical information service.Feng et al. [24] proposed a deep convolutional neural network with four-layer residual module structure, which realized the accurate and efficient classification of rice knowledge texts with different sample sizes and different complexity. Through comparative analysis of six text classification models including FastText, BiLSTM, Atten-BiGRU, RCNN, DPCNN and TextCNN, it was concluded that the text classification model designed was able to precisely classify rice knowledge texts with different sample sizes and different levels of complexity. The model can realize accurate and efficient classification of rice knowledge text, meeting practical application requirements. Shi et al. [25] on the news corpus of 19 847 samples crawled and cleaned by crawler technology from Sina and other news websites, aiming at screening agricultural related news from diversified news samples of various topics. The experiment result shows that the BERT model, combined with discriminative active learning sampling function, has the best news text classification effect and the lowest annotation data requirements.

III. A WHEAT TEXT CLASSIFICATION MODEL BASED ON DYNAMIC FUSION OF MULTIPLE FEATURES

Bi-LSTM captures the global feature representation of text in the sequence, while CNN focuses on the local feature information of text in the convolution window. The combination can capture globally and locally text information, thus ensuring the effect of classification. The agricultural text classification model fusion agricultural text classification model constructed in this paper is shown in Figure1.

Model is divided into agricultural text data processing, Word2vec vector representation of text, Bi-LSTM-ATT and Mul-CNN model, Dynamic fusion of multiple features and output of sigmoid classification result. Bi-LSTM-ATT model is used to extract global key semantic features, and Mul-CNN model is used to extract local semantic features at different levels of phrase level. The input of the model is the wheat text after cleaning, labeling and word segmentation, and the text length is n. The input text consists of a series of segmented words $(w_1, w_2, \ldots, w_{n-1}, w_n)$. To convert text characters into numerical text vectors that can be processed by computer, this paper uses Word2Vec to train word vectors and initializes them in the embedding layer of neural network. For each word w_i in the text, it is mapped to the word vector x_i by finding the words table. Currently, $x_i = E(w_i)$, where $E \in R^{V*d}$, V is the size of the vocabulary, and d is the dimension size of the training word vector.

A. Bi-LSTM_ATT MODEL

The long-term and short-term memory network is an improvement of the recurrent neural network. It can not

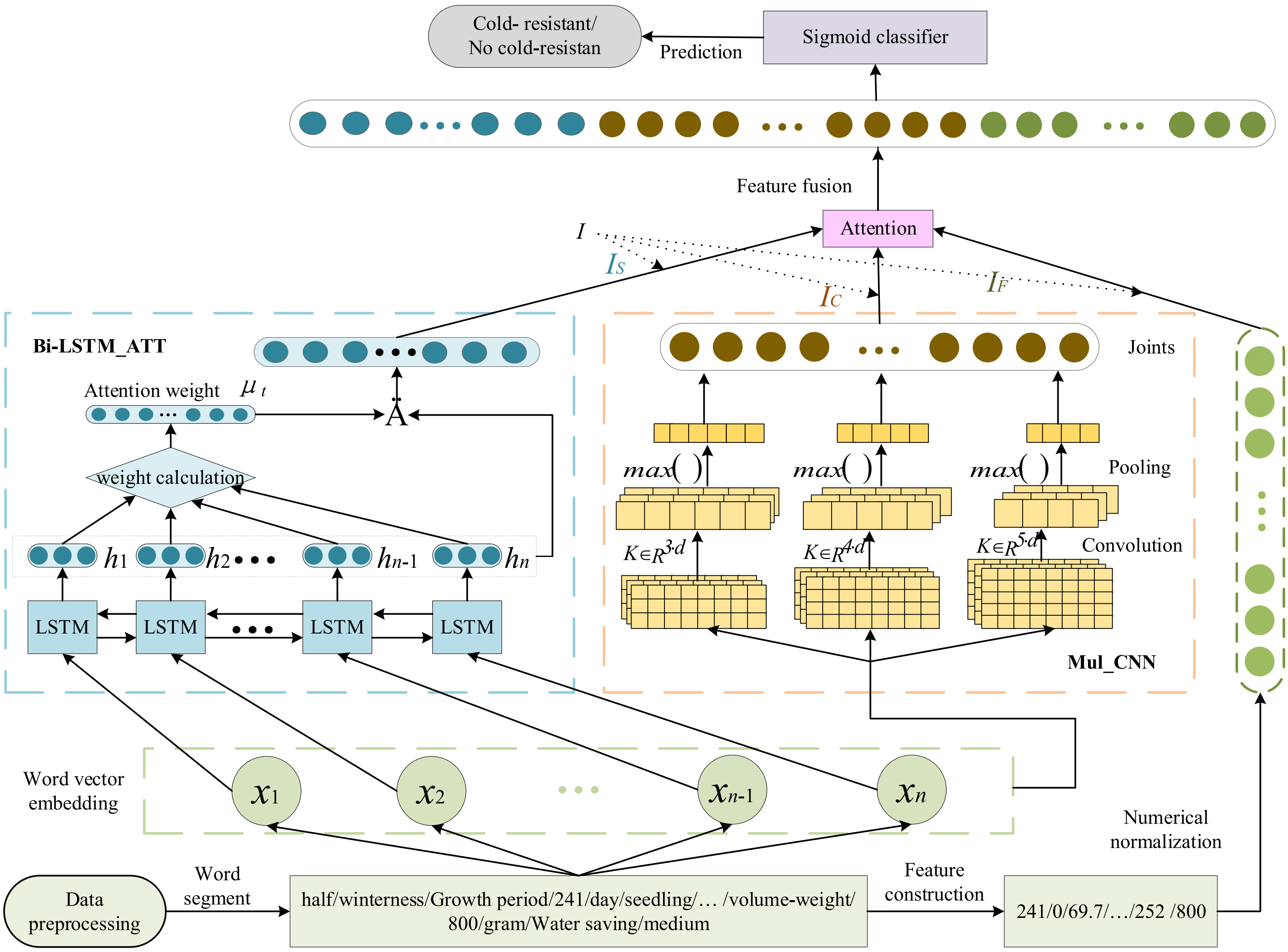


FIGURE 1. Agricultural text classification model based on multiple feature fusion.

only capture the long order dependence in the input wheat text features, but also better grasp the global relationship of the input features. Bi-LSTM is composed of two LSTMs with opposite directions, which can not only obtain forward semantic feature information, but also backward semantic feature information, and can fully capture the context information of feature word text.

Attention mechanism can make full use of limited attention to quickly screen out key information from numerous information and suppress invalid information, thereby improving the efficiency and accuracy of information processing. The network structure of the bidirectional long-term and short-term memory network with attention mechanism is shown in Figure 2.

The attention mechanism realizes the resource redistribution of Bi-LSTM output feature information. This layer assigns the weight of input information, and the calculation is shown in Equation (1) (2) (3):

$$\mu_t = tanh\left(\boldsymbol{W}_w \cdot h_t + b_w\right) \tag{1}$$

$$\alpha_t = exp\left(\mu_t^T \cdot \mu_w\right) \Big/ \sum\nolimits_t exp\left(\mu_t^T \cdot \mu_w\right) \tag{2}$$

$$S = \sum\nolimits_t \alpha_t \cdot \mu_t \tag{3}$$

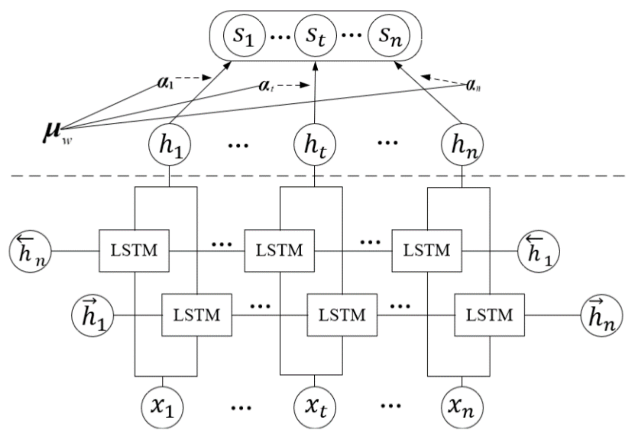


FIGURE 2. Bi-LSTM-Att model structure.

In Equation (1), h_t is the input information obtained from the previous layer, $\boldsymbol{W}_w$ is the weight matrix of the attention layer, and b_w is the bias term. In Equation (2), μ_w is randomly initialized ad constantly changed during training and learning, α_t is the contribution of input h_t corresponding information to classification decision. In Equation (3), S is the semantic feature captured after the weight assignment calculation.

B. Mul_CNN MODEL

Convolution neural network can automatically learn the deep characteristics of input data from complex network structure. Convolution kernels of different sizes can get different levels of semantic feature representation. The input agricultural feature text word vector is used as the input of convolutional neural network. The input text vector is convolution calculated by using multiple convolution kernels of different sizes, and the local features of different levels are extracted according to different window ranges.

The text vector of the convolution layer input wheat is $\boldsymbol{X} \in \boldsymbol{R}^{L\cdot d}$, and each row of the vector represents a feature vector with the feature dimension of d. The convolution kernel vector used in convolution operation is $\boldsymbol{K} \in \boldsymbol{R}^{m\cdot d}$, m represents the window size of convolution kernel. The experimental data in this paper are the feature text of wheat. After word segmentation in the feature text of wheat, the number of word segmentation with different features is concentrated in the range of 3∼5, and the previous experience value set by CNN convolution kernel is mostly 3,4,5. Considering the number of agricultural phrases after each feature word segmentation and previous experience, the size of convolution kernel window size m is 3,4,5, sliding step size is 1. The convolution input text window is $\{x_{1:m}, x_{2:m+1}, \cdots, x_{L-m+1:L}\}$, where the convolution eigenvalues of each window at the n_{th} position are calculated as follows:

$$C_n^m = f\left(\sum\nolimits_{n\in L} W_m \otimes x_{n:n+m-1} + b_m\right) \tag{4}$$

In Equation (4), W_m is the weight value of convolution kernel $W_m \in \boldsymbol{R}^{m\cdot d}$, (m = 3, 4, 5), $b_m \in \boldsymbol{R}$ is offset, $\otimes$ is convolution, $f(x)$ is activation function. The calculation of the characteristic information of the sliding window after a convolution kernel convolution operation is shown in Equation (5):

$$C_n^m = \left[C_1^m, C_2^m, \cdots, C_{L-m+1}^m\right] \tag{5}$$

For the local wheat semantic features obtained by convolution calculation, the pooling layer is used to filter out redundant semantic information and reduce the number of parameters. Pooling can speed up the operation of the network and effectively prevent overfitting of the model. In this paper, the maximum pooling calculation is used to extract features, and the semantic feature that can most represent the input information represents $C_{1,max}^m$, and the maximum pooling value is set to 2. For convolution windows with different sizes, 100 convolution filters are included. When convolution kernels with sizes of $\boldsymbol{K} \in \boldsymbol{R}^{3\cdot}$, $\boldsymbol{K} \in \boldsymbol{R}^{4\cdot}$ and $\boldsymbol{K} \in \boldsymbol{R}^{5\cdot}$ are used respectively, the semantic features of convolution pooling are shown in Equation (6) (7) (8):

$$C^3 = \left[C_{1,max}^3, C_{2,max}^3, \cdots, C_{100,max}^3\right] \tag{6}$$

$$C^4 = \left[C_{1,max}^4, C_{2,max}^4, \cdots, C_{100,max}^4\right] \tag{7}$$

$$C^5 = \left[C_{1,max}^5, C_{2,max}^5, \cdots, C_{100,max}^5\right] \tag{8}$$

The splicing layer splices the semantic features extracted by convolution kernels of different sizes after convolution pooling to obtain the local semantic feature information at different levels of the text, and a total of 300 features are obtained. As the input of the next network layer, the multi-size convolution semantic feature information C is calculated as shown in Equation (9):

$$C = \left[C^3, C^4, C^5\right] = [F_1, F_2, \cdots, F_{300}] \tag{9}$$

C. STRUCTURAL CHARACTERISTICS

Since the phenotypic values contained in agricultural texts have actual semantic expression, a new feature information is constructed by manually extracting features. The feature description of phenotypic values mainly includes 14 wheat traits such as growth period, plant height, panicle number per mu and bulk density. The corresponding 14 numerical features were manually extracted and complemented (padding 0 for the lack of description of corresponding traits), and then the numerical vectors after complement were normalized. The normalization calculation process of constructing feature F is shown in Equation (10).

$$F = \frac{x - min}{max - min} \tag{10}$$

In Equation (10), max and min are the maximum and minimum values of input data, respectively; x is the vector of experimental training; and F is the normalized result vector.

1) DYNAMIC MULTI-FEATURE FUSION METHOD

For obtaining the key semantic feature S, the multi-level convolution semantic feature C and the artificially constructed numerical feature F in the global scope of wheat, the attention mechanism is used to calculate the weight values of different wheat semantic feature information, and the weights of the three feature information $I = (I_S, I_C, I_F)$ are obtained. I_1, I_2, I_3 are used to represent I_S, I_C, I_F, respectively. The fused multivariate feature I_T is dynamically calculated by the weight matrix I and the obtained three semantic features, and the calculation is shown in Equation (11) (12).

$$\delta_i = exp\left(Q^T \cdot I_i\right) \Big/ \sum\nolimits_t exp\left(Q^T \cdot I_i\right) \tag{11}$$

$$I_T = \sum\nolimits_{i=1}^3 \delta_i \cdot \sum\nolimits_t \alpha_t \cdot I_i \tag{12}$$

D. OUTPUT

I_T can be regarded as a high-level expression of input text features. The abstract text vector I_T is passed by sigmoid classifier, and the probability p of the input text belonging to the cold and non-cold categories is calculated by formula (13).

$$p = sigmoid\left(W_c \cdot I_T + b_c\right) \tag{13}$$

In Equation (13), W_c and b_c represent the weight value and bias term of classifier sigmoid respectively.

IV. EXPERIMENTAL SETUP

A. EXPERIMENTAL DATA

The experimental data comes from the Chinese seed industry big data platform of the seed industry management department of the Ministry of Agriculture and Rural Affairs. Using Python to write crawlers to crawl wheat variety information from the national audit from 1978 to 2018, a total of 3 513 wheat varieties were characterized by 23 pure texts such as 'wheat varieties/maturity/seedling characteristics/.../ leaf division ability/ plant type/ water saving', and 14 numerical texts such as ' growth period/plant height/ bulk density/.../ear number per mu/number of ear kernels/1000-grain weight '. In view of the phenomenon of multi-word synonyms, wrong words and inconsistent constant units in the crawled text, this paper refers to the work of Wang et al. [28] and Entz et al. [29], combined with the suggestions of wheat breeders, adopts the method of automatic and manual combination to clean data, and retains 3 049 wheat texts with relatively complete characteristics. The agricultural corpus is complex and diverse, and there are many agricultural terms. When using Jieba word segmentation tool to default segmentation, some feature words will be over-segmented, which destroys the original meaning information. The experiment uses the self-defined vocabulary to do word segmentation. After the introduction of the self-defined glossary, the agricultural specialized characteristic nouns such as 'sedimentation index', 'crude gluten content' and 'falling number' are not segmented, which effectively solves the problem of the destruction of the semantic information of specialized nouns and ensures the integrity of the semantic information of characteristic words.

After the text data are cleaned and segmented, the agricultural professional name is retained. The character information recorded by a single wheat text is different, and the number of characteristic words after the segmentation of the sample text is also different. The word frequency distribution of wheat corpus after Chinese word segmentation appeared more times were plant height (3 061 times), seedling (2 803 times), bulk density (2 690 times), awn (2 639 times), grain number per spike (2 615 times) and so on. The number of characteristic words of all samples was mainly distributed between (135-155). The experiment set the length of the sample sentence to 150, used 0 to fill the sample with insufficient number of characteristic words, and cut the sample with excessive number of characteristic words to ensure the consistency of the input length of the sample. After cleaning the experimental data, the cold resistance or non-cold resistance labels of each wheat variety classification are marked. In the experiment, the data were divided into training set, verification set and test set at the ratio of 6:2:2 according to the labels with and without cold resistance.

B. PARAMETER SETTINGS

In the process of network model training, the parameter settings of Bi-LSTM and Mul _ CNN are shown in Table 1.

TABLE 1. Parameter setting.

Parameters	Setting
Word vector dimension	100
Maximum length of text	150
Size of convolution kernel	3,4,5
Number of convolutional kernels	100
Pooling value	2
Bi_LSTM hidden unit	64
Structural feature dimension	14

To speed up the learning speed and improve the efficiency of parameter adjustment, the model training adopts the method of Early-Stopping termination training to adjust the network parameters. The training optimization function uses RMSprop to update the network parameters. The learning rate η is set to 0.001, the batch size of the training is 32, and the number of training is 200. Dropout mechanism is used to reduce the over-fitting degree of the model. Dropout layer is added after Bi-LSTM and Mul_CNN to reduce the over-fitting degree of the model, and the discard rate p is set to 0.5.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. DIFFERENT METHODS OF AGRICULTURAL TEXT CLASSIFICATION RESULTS

The model is trained on the training set, the network parameters are adjusted and optimized using the validation set, and the model performance is tested on the test set. The accuracy and consistency test Kappa coefficient were selected as the standard to verify the performance of the model. The experimental results on the test set with other text classification methods are shown in Table 2.

TABLE 2. Comparison of the results of different methods.

Methods	Accuracy	Kappa
CNN	81.28%	0.5669
Mul_CNN	83.55%	0.6292
Bi-LSTM	79.64%	0.5315
Bi-LSTM_ATT	82.92%	0.6061
CNN + Bi-LSTM	83.58%	0.6212
CNN + Bi-LSTM_ATT	85.55%	0.6677
MulCNN + Bi-LSTM	88.34%	0.7354
MulCNN + Bi-LSTM_ATT	90.15%	0.7678
Method of this paper	**91.13%**	**0.7911**

The comparative analysis of table 2 shows that the local semantic features extracted by single convolutional neural network are better than the global context semantic features extracted by bidirectional long-term and short-term memory network in the performance of wheat cold resistance text classification and recognition. The Accuracy value and

Kappa coefficient of CNN are 1.64 % and 0.0354 higher than those of Bi-LSTM, respectively. The multi-scale convolution Mul_CNN is 5.91 % and 0.1377 higher than that of Bi-LSTM, indicating that different levels of local semantic feature combinations calculated by different convolution kernel convolution are suitable for agricultural text classification tasks in this paper.

The performance of the combined neural network model is better than that of the single model, and the accuracy and Kappa coefficient of CNN + Bi-LSTM are higher than those of the single CNN and Bi-LSTM models. In particular, the accuracy of Mul_CNN + Bi-LSTM is 88.34 %, 4.79 % and 8.70 % higher than that of Mul_CNN and Bi-LSTM, respectively. The consistency test is 0.7354, 0.1062 and 0.2039 higher than that of Mul_CNN and Bi-LSTM, respectively. This shows that the local semantic features captured by CNN and the global context semantic features captured by Bi-LSTM can effectively improve the performance of agricultural text classification in this paper.

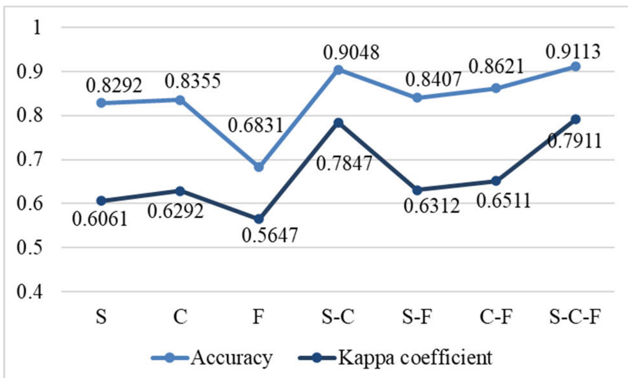
After introducing attention mechanism into Bi-LSTM, the accuracy value and Kappa coefficient of Bi-LSTM-ATT method were increased by 3.28 % and 0.0746 compared with single Bi-LSTM method. The Accuracy and Kappa coefficient of Mul_CNN + Bi-LSTM_ATT method reached 90.15 % and 0.7678. Further comparative analysis shows that the accuracy value is not significantly improved, and the Kappa coefficient is relatively large. This shows that the Bi-LSTM with attention mechanism can capture important information in the global range, which can not only improve the overall accuracy of text classification, but also improve the consistency of text classification prediction results and actual results.

Compared with the results of different methods in agricultural text classification, the proposed multi-feature dynamic fusion method has better experimental performance than other comparison methods. The Accuracy value and Kappa coefficient of agricultural text classification task are 91.13 % and 0.7941, Bi-LSTM_ATT can get the key semantic feature representation of agricultural text in the global range, Mul_CNN can get the local semantic feature representation of agricultural text at different levels of phrase level, and manual extraction of numerical features can get the feature representation of agricultural text with actual semantic numerical information. Using the attention mechanism to dynamically calculate the importance of the three semantic features, the key features in the global range obtained by the neural network, the local features at different levels and the constructed feature vector are dynamically spliced and fused, which can improve the accuracy of agricultural text classification with phenotypic values. The experimental results show that the multi-feature dynamic fusion method proposed in this paper can improve the recognition ability of agricultural text classification containing phenotypic numerical value with substantive semantic information.

B. DYNAMIC FUSION RESULTST OF MULTIVARIATE FEATURES

In order to explore the influence of dynamic fusion of multiple features on agricultural text classification, the experimental results of text classification with different semantic features are compared and analyzed. The results of multi-feature dynamic fusion are shown in Figure 3.

It can be seen from Figure 3 that the effects of different semantic features on the accuracy of text classification and the kappa coefficient of consistency test are basically the same. Local semantic feature C captured by convolution kernels of different sizes is more representative and has a slight advantage over key semantic feature S captured by Bi-LSTM_ATT in classification performance. On the contrary, the feature F constructed by the numerical values in the text is far less effective than S and C on this task. The experimental results of S-F, C-F, S-C and S-C-F show that the deep abstract features automatically obtained by deep neural network and the dynamic fusion of artificial phenotypic features can improve the results of text classification in this study. However, the influence of automatic extraction of deep semantic features on agricultural text classification in this paper is significantly higher than that of traditional phenotypic features. In particular, the results of S-C-F show that the method of dynamic fusion of multiple features proposed in this paper can obtain more comprehensive semantic feature expression of agricultural texts and improve the effect of text classification.



Note: S: Key semantic features in global scope;
C: Local Semantic Features of Multi - Size Convolution;
F : Numerical characteristics of the structure.

FIGURE 3. Experimental results of multi feature dynamic fusion.

C. ANALYSIS AND DISCUSSION

In the experimental data, the number of cold-resistant and non-cold-resistant samples is 1 019 and 2 030. The experiment uses the multi-feature dynamic fusion of agricultural text classification method in this paper, and selects the accuracy, recall and F1 of two cold-resistant labels as evaluation criteria. Different label results are shown in Figure 4.

The experimental results of Figure 4 show that the Precision, Recall and F1 values predicted by the proposed

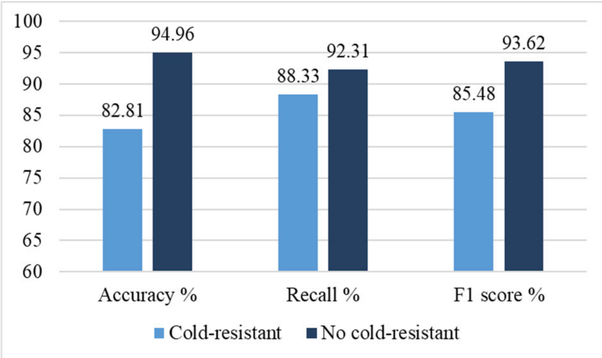


FIGURE 4. Comparison results of different labels.

multi-feature dynamic fusion method for non-cold samples are 94.96 %, 92.31 % and 93.62 % respectively, while the Precision, Recall and F1 values predicted by the cold samples are reduced by 12.15 %, 3.98 % and 8.14 % respectively. In order to further explore the reasons for poor identification of cold-resistant samples, the confusion matrix results of cold-resistant text classification are shown in Figure 5.

It can be seen from Figure 5 that the number of no cold-resistant samples misidentified as cold-resistant samples are 23, and the number of cold-resistant samples misidentified as no cold-resistant samples are 31. There are higher proportion of cold-resistant samples were identified as no cold-resistant samples. Comparing the number of two types of samples in the experimental data, it can be seen that the reason for this phenomenon is that the ratio of the number of cold-resistant samples and the number of cold-resistant samples in the data set is 2:1, and some characteristics of the cold-resistant samples that are not dominant in the number will be ignored in the process of model training, resulting in a small number of cold-resistant samples being mistakenly identified as cold-resistant samples.

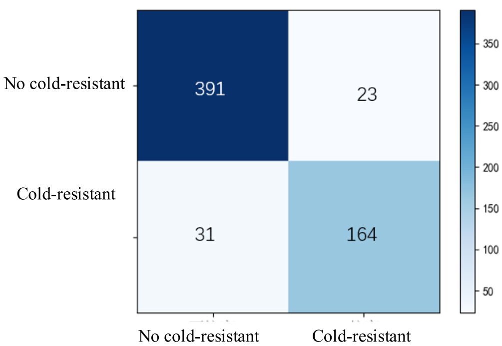


FIGURE 5. Confusion matrix of text classification.

The prediction results of different cold resistance labels show that the identification performance of this method for non-cold resistance samples is better than that for cold resistance samples. Through the analysis of the results of confusion matrix, it can be found that the proportion of cold-resistant samples wrongly identified as non-cold-resistant samples is higher. The imbalance between the number of cold-resistant samples and the number of non-cold-resistant samples in the dataset leads to the failure of the recognition model to fully learn the feature information of the cold-resistant samples, which makes the model to determine the non-cold category relatively more.

VI. CONCLUSION

In this paper, since the phenotypic numerical features contained in agricultural texts have practical significance, combined with the experimental tasks of this study, we proposed a classification method of agricultural texts based on dynamic fusion of multiple features. Firstly, three convolution kernels with different sizes are used to obtain more abundant local semantic features at different levels of wheat cold resistance text, and Bi-LSTM with attention-fusion mechanism is used to obtain important semantic expressions between contexts in the global scope. Then independent numerical features are constructed by using the text of wheat traits with numerical expression. Attention mechanism is introduced again in the process of multi-feature dynamic fusion to dynamically adjust the weights of different semantic expressions in the process of feature fusion and capture the key information beneficial to text classification in different levels of features. The performance of agricultural text classification shows that the proposed multi-feature dynamic fusion method fully excavates the potential semantic features in the text data, which is effective for the agricultural text classification task with phenotypic values. The next work will expand the data set and sample equalization to improve the performance of wheat cold resistance text classification and recognition.

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