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Deep Learning Agricultural Information Classification Combined With Internet of Things Technology in Agricultural Production and Economic Management

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ABSTRACT This study aims to explore the application of agricultural information classification combined with the Internet of Things technology in agricultural production and economic management in the context of deep learning (DL). The agricultural information classification system is built based on DL. In terms of experimental methods, qualitative and quantitative methods are used to compare the extractive forward and the generative reverse generation algorithm in the abstract generation method. Typical extraction methods that directly extract important sentences are relatively ineffective. The model parameter tuning and training of generative (regenerating new sentences) are difficult, and the effect does not reach the level of agricultural scientific research. Qualitative and quantitative evaluation practice proves that the effect is better. In the data training effect of Rice Digest, after nine days of iterative training for about 1400 steps, the loss value is 1.33, which is equal to the standard data set. In the data training effect of Wheat Digest, after nine days of iterative training for about 1400 steps, the loss value is 1.496, which is equal to the standard data set. Later, the existing original model is adjusted to fit the model of the agricultural dataset scale. Among them, the minimum learning rate is reduced from 0.01 to 0.003 to expand the learning rate drop rate. In the visual training comparison, when training to about 1400 steps, the cross-entropy loss function values are about 1.43 and 1.29, respectively. The curve smoothing factor is set to 0.97 to observe the overall change in target loss value. The results show that when the parameter settings remain unchanged, the loss value of the model starts to increase linearly at about 1400 steps, and the effect reaches the expected value. This study improves the relevance, completeness, and accuracy of information acquisition in the field of agricultural science and technology information and improves the utilization of agricultural information.

INDEX TERMS Deep learning, agricultural information classification, forward and reverse generation algorithm, economic management.

I. INTRODUCTION

Nowadays, more and more text content is generated by electronic media, and the important scientific and technological text information in agricultural research also shows this trend [1]. In the past, agricultural information users typically found a bunch of agricultural specialty articles through popular web search engines. Such search engines generally conduct relevant searches based on keywords and topic models, but the topics contained therein may not only be single agricultural topics. The interaction and relationship between different topics may be discussed in the article, which requires researchers to roughly browse the abstract and even the body part of each article to find the article information they really want to obtain [2]. This search method causes problems such as prolonged search time for relevant article information and low relevance, completeness, and accuracy of information acquisition [3]. How to grasp the key semantics of agricultural science and technology articles concisely and accurately, understand the theme of articles accurately,

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improve the relevance and integrity of agriculture-related user information and knowledge acquisition, and better provide knowledge services for researchers has become the focus of research, which should be paid attention to by agricultural researchers in the electronic information age [4].

In the field of deep learning (DL), there are still many scholars conducting research on agricultural information classification. Wang *et al.* (2021) made breakthroughs in obtaining agricultural information and detecting external or internal quality attributes of agricultural products using hyperspectral imaging technology. Compared with traditional machine learning, the DL architecture utilizes the spatial and spectral information of hyperspectral image analysis to improve the performance of hyperspectral image analysis. Applications of DL architecture in agriculture include maturity and composition prediction, different classification topics, and plant disease detection. The latest achievements in hyperspectral image analysis are comprehensively elaborated from two aspects of the DL model and feature network [5]. Saleem *et al.* (2021) plotted crop performance by implementing DL algorithms or architectures over the past decade to study the effectiveness of DL on traditional machine learning models for certain agricultural operations. The analysis of their famous study highlighted that DL-based models, such as region-based convolutional neural networks (CNN), achieved a more accurate area under the curve (94.84%) and outperformed traditional techniques in crop and weed discrimination. Finally, they also pointed out some important research gaps in previous studies and innovative future directions to help push agricultural automation to the next level [6]. Darwin *et al.* (2021) used remote sensing technology to provide accuracy and reliability for crop yield prediction and estimation. Image analysis automation with computer vision and DL models provides agriculture with accurate field and yield maps. The crops that DL technology is used for research are various agricultural and sideline products, such as grapes, apples, oranges, tomatoes and other fruits and sugarcane, corn, soybeans, cucumbers, corn, wheat, and other vegetables. Computer vision can be used as a product in applications such as robotic harvesting, weed detection, and pest infestation. DL techniques provide an average accuracy of 92.51% [7]. Ferrag *et al.* (2021) proposed an attack intrusion detection system based on DL. The system is based on three models, namely CNN, deep neural network, and recurrent neural network. Two new real traffic datasets are used, namely the variable dataset and the test dataset, and the performance of each model is investigated within two classification types (binary and multi-class). The two datasets contain different types of attacks. The results show that DL techniques give good results compared to other machine learning strategies (e.g., decision trees, random forests, naive Bayes, and logistic regression) on important performance metrics. These metrics include detection rate, false alarm rate, precision, F-score, recall, true negative rate, false acceptance rate, and accuracy [8]. Guillén *et al.* (2021) explored edge computing as a solution to bridge the gap between artificial intelligence and the Internet of Things (IoT) in rural settings, evaluating modern DL-based precision agriculture applications in terms of performance and power consumption training and inference stages. In rural IoT environments, the lack of connectivity (or low-bandwidth connections) and power has forced the search for efficient alternatives to provide computing resources to IoT infrastructure without increasing power consumption. Experimental results show that DL in the field of ground power unit connections contained in edge devices remains a challenging experiment. The cloud approach still has a long way to go in terms of performance [9]. Khan *et al.* (2021) built accurate detection and identification systems to identify weeds and crops for precise agrochemical treatment in real-time applications. Uncrewed aerial vehicles and other robots offer potential in precision agriculture applications by monitoring farmland plant by plant. Because they can acquire high-resolution images that provide detailed information on the distribution of crops and weeds in the field, they developed a DL system to identify weeds and crops in agricultural fields. The developed system was implemented and evaluated using high-resolution UAV images captured at two different target areas (peas and strawberries). The developed system was able to identify weeds with an average accuracy of 95.3%, while the overall average accuracy (crop and weeds) for both fields was 94.73%. The average kappa coefficient of the developed system is 0.89. The developed DL system outperforms existing machine learning and DL-based methods comparatively and can be embedded into precision sprayers for intelligent analysis strategies [10].

Whether the agricultural science and technology literature information can be further semantically mined, extended to the literature information objects without condensed information, to provide condensed knowledge with high correlation and concise and coherent semantics, and provide agricultural information users with a better knowledge service experience. Therefore, the experimental comparison uses traditional methods in agricultural science and technology information semantic mining and new technical methods based on DL to carry out research in agricultural science and technology literature information and discusses the rationality and existence of agricultural science and technology information semantic mining based on DL. Finally, the research goal is determined to carry out semantic information mining of agricultural scientific research abstracts based on DL. The prototype of agricultural science and technology information extraction system was tried to build. Unconcentrated information in agricultural science and technology literature is used for semantic extraction and mining.

II. RESEARCH METHODS

A. CONSTRUCTION OF AGRICULTURAL INFORMATION CLASSIFICATION SYSTEM BASED ON DEEP LEARNING

In DL, Automatic Text Categorization (ATC) refers to the process of using a computer program to determine the category of text according to the content of the text in each category [11]. Generally, the method of machine learning is used for automatic text classification, that is, automatic text classification based on the training set. The purpose of text classification is to obtain an estimate of the dependencies between the input and output of the system based on the given known training samples, so that it can make as accurate predictions as possible for the unknown output [12]. The specific structure is shown in Figure 1:

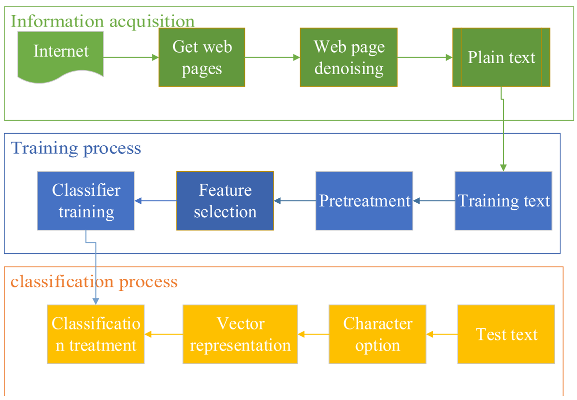

FIGURE 1. Construction of agricultural information classification system in DL.

In Figure 1, text information classification is essentially a pattern recognition process. Its design and development can be divided into four main links: (1) text preprocessing includes the process of word segmentation of the training and test corpora and the frequency statistics of the segmented words. (2) Text feature description mainly includes model establishment, feature selection, and text feature expression. (3) The training stage of the text classification algorithm. (4) The new text real-time classification stage is mainly responsible for the realization of Internet short text information classification, but information acquisition must be carried out before information classification. The information acquisition module is mainly responsible for the acquisition of web page information. Information classification is mainly responsible for the information classification of short texts on web pages. The short text information classification module classifies the retrieved text, and the process is like the ordinary text classification, including the training process, the testing process, and the feedback process. The main goal of the training process is to train the training samples with a text classification algorithm to construct a classifier [13], [14]. The process includes text segmentation, feature selection, weight sets, and classifier construction. The text segmentation algorithm is shown in Figure 2:

In Figure 2, ABCDEFG represents a short sentence, and each letter represents a Chinese character. Text word segmentation algorithms mainly represent long strings of text in the form of words or phrases. This study not only deals with Chinese but also deals with English words, such as the phonetic alphabet [15]. Feature selection is mainly to select

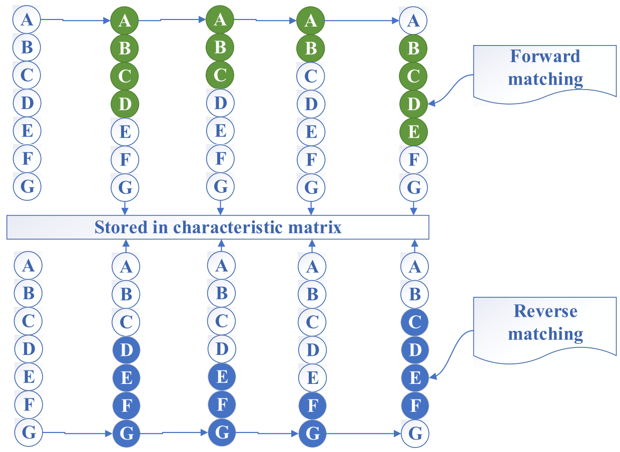

FIGURE 2. Matching algorithm for text segmentation.

words or phrases that are sufficient to express the general idea of the text from the results of text segmentation to form a vector representing the text. The weight setting is mainly to set the magnitude of each word or phrase in the vector to distinguish the importance of different words or phrases in the feature vector. The construction of the classifier is mainly based on the improvement of the traditional classification algorithm in this paper, which makes the classifier more scalable and universal [16]. The training process is roughly the same as the classification process, but a feedback process is introduced at the end. The feedback process is mainly to apply the results obtained after classification to the classifier to improve the accuracy of the classifier. Short text information classification is a branch of shallow natural language processing, and its processing objects are various forms of short text corpus [17], [18]. The length of a single short text is too short, and it is difficult to mine effective features and valuable information. Therefore, short text language calculation is generally aimed at the entire short text corpus, useful for mining information from many short text sets rather than performing natural language processing on a short text. The unique linguistic characteristics of short text corpus make short text language computing very different from regular text language computing, and the corresponding key technologies are also quite different [19], [20]. The running speed of both forward and reverse algorithms is tested on 9 document sets of different sizes. The experimental comparison is shown in Table 1:

In Table 1, the execution time of the two-word segmentation algorithms increases as the file size increases. However, the time for reverse matching of files of the same size is significantly lower than that for bidirectional matching. Not only that, its growth rate is much lower than that of two-way matching [21], [22]. This is mainly because the two-way match does two scans, which will inevitably increase the execution time. In addition to proving that reverse matching has an advantage in execution time, the accuracy gap between reverse matching and bidirectional matching is

TABLE 1. Iterative speed table for forward and reverse algorithms.

File size	4.11	7.64	9.44	9.5	9.8	10
Time/s	4.96	6.78	9.26	11.56	12.97	15.87
Time/s	5.28	7.43	10.32	13.39	15.74	18.21

verified against the usage environment. The specific word segmentation algorithm process is shown in Figure 3:

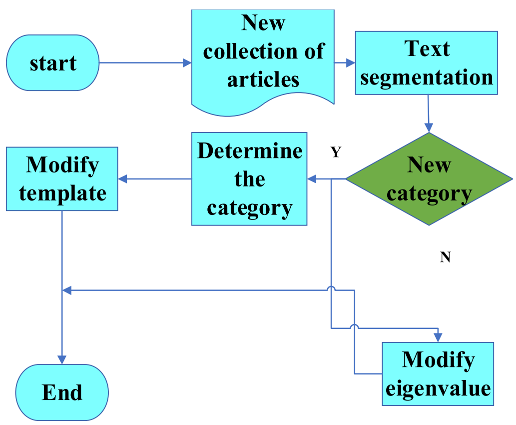

FIGURE 3. Flowchart of agricultural information classification system.

In Figure 3, the essence of the algorithm is to readjust the center vector and threshold of the feedback class. The input to the algorithm is the new text vector and the corresponding category (which may not appear in the classification system). The specific steps include five steps. Step 1: determine whether the new text is a new category. If it is a new category, determine the weight of the category feature value and modify the classification template; if it is an existing category C, go to step 2. Step 2: read out the center vector of class C and the number of occurrences of all eigenvalues contained in this class. Step 3: according to the weight calculation formula, recalculate the center vector of the adjusted category C. Step 4: adjust the weights of relevant feature values in the classification template. Step 5: feedback ends here.

B. FEEDBACK OPTIMIZATION OF AGRICULTURAL INFORMATION CLASSIFICATION SYSTEM IN DEEP LEARNING

Experiments have shown that the classification system has greatly improved the classification accuracy [23], [24]. However, the commonly proposed classification algorithms are not scalable. It cannot easily add new categories of texts but also difficult to add new texts of the same category [25], [26]. Feedback optimization is added based on the agricultural information classification system. The specific process is shown in Figure 4:

In Figure 4, the document vocabulary vector is obtained from the text to be segmented, which is mainly carried out in

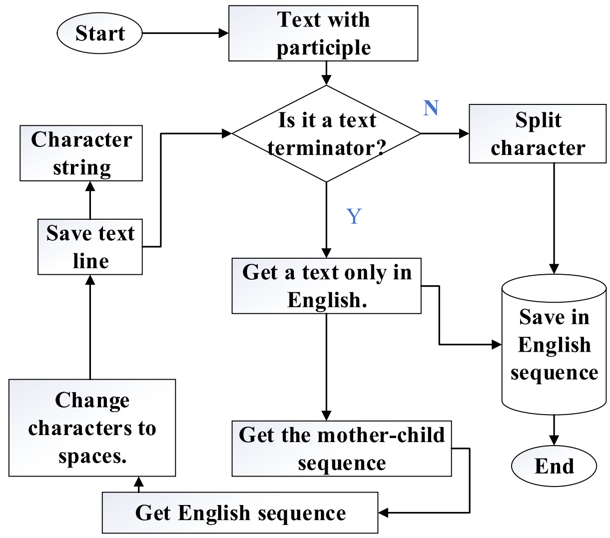

FIGURE 4. Flow chart of feedback optimization of the agricultural information classification system.

three steps [27], [28]. The first step is to read all characters of the text to be segmented word by word and check; if it is a non-Chinese or English character, replace it with a space; if it is a space and the previous character is also a space, delete the space; if it is Chinese or If it is an English character, it will not be processed, and the next character will be read; if it is a text terminator, the text will be passed to the second step, and the next character will be read again, and the above steps will be repeated. So far, the obtained text contains only Chinese and English characters, and spaces are used as separators between Chinese phrases and English words [29]. The second step is to read the text obtained in the first step word by word and determine whether it is a space. The second step is to read the text obtained in the first step verbatim and determine whether it is blank. If it is a space, the sequence of characters is read. The character sequence is passed to the third step, which itself re-reads the next character until a new space is encountered. In the third step, the reverse maximum matching algorithm is used to perform word segmentation on the Chinese sequence obtained in the second step, and the obtained English character sequence is converted into lowercase characters (since spaces are used as delimiters between English words, word segmentation is not required. Convert to lowercase characters, mainly to facilitate character matching). Vectors containing both English and Chinese words in the document are obtained [30]. In the Chinese word segmentation part of the third step, although most researchers prefer to use the two-way maximum matching algorithm, considering the speed and accuracy of word segmentation, it can be proved by the experiments in this paper that the reverse maximum matching algorithm is slightly better. The feedback learning process can be divided into two categories. One is semi-automatic feedback, that is, human participation in the feedback judgment process to determine whether the classification results can be fed back.

At this time, the system displays the classification result, and the human judges whether the classification result is correct; if it is correct, it means that the classification result can be fed back to the training process. That is, the training result can be strengthened and improved; if it is not correct, simply give up the feedback and no longer pursue the cause of the error. The other type is called fully automatic feedback. That is, the machine scores itself, and the scoring standard is a threshold. If the correlation between the new text and the category is greater than the closed value, the machine will be confident that the classification is correct and give feedback on the training process to improve and strengthen the training results.

III. RESULTS

A. DEEP LEARNING AGRICULTURAL INFORMATION SYSTEM SAMPLE SELECTION AND CROP CLASSIFICATION

A DL agricultural information system is used to crawl featured agricultural web pages and categorize them. The specific data is shown in Figure 5.

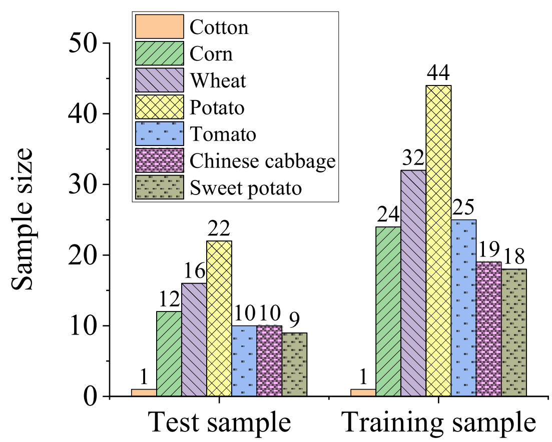

FIGURE 5. DL data sample selection diagram.

In Figure 5, the seven groups of data categories are agricultural science and technology as 1, cotton as 2, corn as 3, wheat as 4, walnut as 5, red dates as 6, and grapes as 7. There are seven categories. Thirty web pages with a total of 300 pieces of information are selected for agricultural information classification experiments, with training samples accounting for 66% and test samples accounting for 33%. Specifically, the data classification diagram is shown in Figure 6:

In Figure 6, this test classifies the dataset. This experiment is divided into six groups in total, namely (1) a machine learning information system is used to classify the original data; (2) 300 center vectors are retained; (3) 600 center vectors are retained; (4) 900 center vectors are retained vector; (5) 1200 center vectors are retained; (6) adjacent samples of 300 center vectors are retained. The size of the training set greatly affects the size of the training time. As the training set increases, the training time grows significantly faster than the F1 measure. Again, the appropriate sample set pruning will

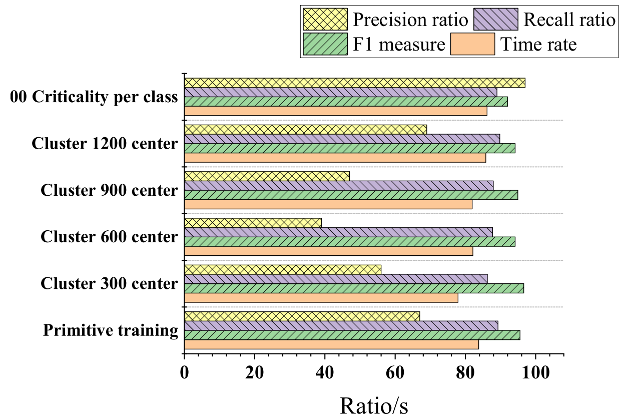

FIGURE 6. DL agricultural data information classification diagram.

also affect the performance of the classifier a little. Finally, the methods of retaining the center vector and retaining the adjacent text of the center vector can improve the classification speed. Still, the accuracy will also decrease accordingly, so only a compromise between the two is taken. Both methods can be used in classification applications with large training sets, but special attention should be paid to the degree of reduction of training samples.

B. LOSS TREND OF INFORMATION CLASSIFICATION MODEL TRAINING IN DEEP LEARNING

The preliminary experiment tests the agricultural information classification model in DL based on the traditional extractive abstract generation algorithm. Figure 7 visualizes the training error of the loss function.

In Figure 7, the original training steps of the model are 2000 steps. If the amount of data is not large enough, training with so many steps is likely to overfit. Training is run for a week on ten servers, each with a 4-core K-series graphics card. In view of the inability to reach its experimental environment, this study put the original code on a small standard experimental dataset, temporarily adjusted the training steps to 1400 steps, and the final training cross loss value was 1.321. The classification training effect of crop wheat and rice abstracts is shown in Figure 8:

In Figure 8, in the data training effect of Rice Digest, after nine days of iterative training for about 1400 steps, the loss value is 1.33, which is equal to the standard data set. In the data training effect of Wheat Digest, after nine days of iterative training for about 1400 steps, the loss value is 1.496, which is equal to the standard data set.

C. VISUALIZATION EFFECT OF DEEP LEARNING AGRICULTURAL INFORMATION CLASSIFICATION SYSTEM

Later, the original model is adjusted to fit the model of the scale of the agricultural dataset. Among them, the minimum learning rate is reduced from 0.01 to 0.003 to expand the learning rate drop rate. After being adjusted, the visualization of model training and validation results is shown in Figure 9:

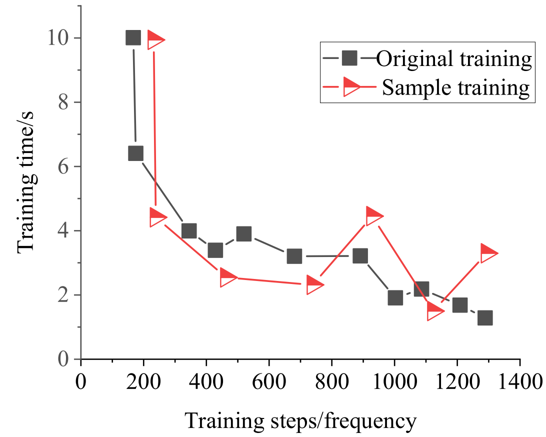

FIGURE 7. DL sample data function training diagram.

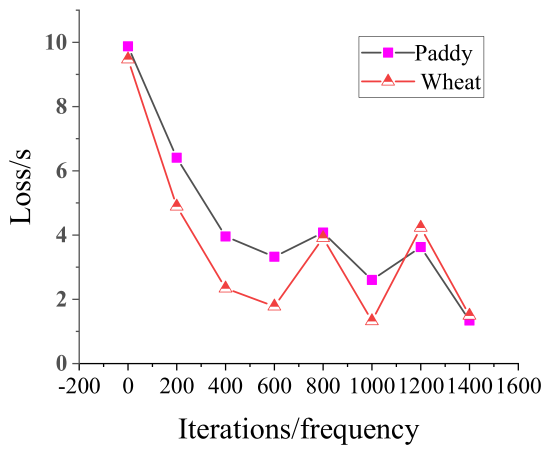

FIGURE 8. Rice and wheat training graph in DL.

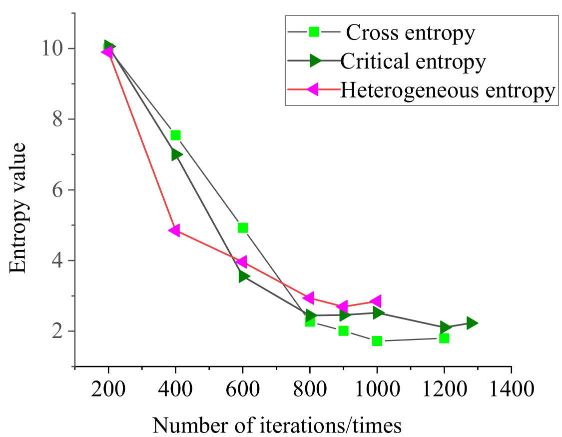

FIGURE 9. Visualization of the DL agricultural information classification system.

In Figure 9, when training to about 1400 steps, the cross-entropy loss function values are about 1.43 and 1.29, respectively. At this point, the loss value of the objective function on the training set begins to decrease significantly, while the loss value of the objective function on the validation set begins to increase. The training starts to pause at this step to prevent overfitting. In order to test the scalability of the model on new datasets, the model at the time node is tested on the entire validation set. It tests the cross-entropy loss value of the objective function on the validation data set, also uses the visual detection tool and sets the curve smoothing coefficient to 0.97 to observe the overall change in the target loss value. When the parameter settings are unchanged (in the case of training), the model starts to increase the loss value linearly at about 1400 steps. At this time, combined with the fact that the loss value of the training target is decreasing, there will be overfitting in the retraining, and the training should be stopped.

IV. CONCLUSION

This study focuses on efficiently extracting key arguments from a dataset of agricultural science and technology literature and composing semantically coherent knowledge. The experiment compares the traditional extractive abstract generation algorithm and the emerging DL-based generative abstract generation algorithm. The experimental results can be summarized from the following three aspects. 1. Based on supervised learning, a large amount of labeled text is needed to train neural networks. In the current situation where there are massive document datasets that are difficult to digest and utilize effectively, large-scale neural network training and learning is a good research direction; 2. based on the research model, the needs of agricultural information users are accurately grasped, and a practical system suitable for agricultural application demand scenarios is developed; 3. combined with the basic technology of natural language processing, the DL method is used to improve the information acquisition in the field of agricultural science and technology information. Relevance, completeness, and accuracy improve the utilization rate of agricultural information and improve the level of knowledge services. However, shortcomings still exist, such as reducing the sample to an ideal level, and there is still room for improvement. Currently, the number of training texts and test texts is limited. The algorithm's performance when dealing with large-scale data needs further practical verification. Although the DL classification model has been implemented, it is still necessary to observe the performance and performance of the classification model in practical applications and make corresponding optimizations and improvements.

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