IJITCE

ISSN 2347- 3657

International Journal of
Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 12, Issue 2, 2024

AGRICULTURAL TEXT CLASSIFICATION METHOD BASED ON DYNAMIC FUSION OF MULTIPLE FEATURES

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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 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.

I.INTRODUCTION

The "Agricultural Text Classification Method Based on Dynamic Fusion of Multiple Features" project introduces an innovative approach to address the challenges of information retrieval and classification in agricultural domain texts. With the proliferation of digital agriculture and the abundance of agricultural data sources, there arises a need for robust methods to classify and analyze textual information effectively. Traditional text classification techniques often rely on single-feature models, which may not fully capture the diverse characteristics of agricultural texts. In response to this challenge, this project proposes a dynamic fusion method that integrates multiple features, including lexical, syntactic, semantic, and contextual information, to improve the accuracy and robustness of agricultural text classification. By leveraging advanced machine learning algorithms and feature fusion techniques, the project aims to develop a comprehensive classification framework capable of accurately categorizing agricultural texts into relevant domains and topics. The implementation of this dynamic fusion approach has the potential to enhance information retrieval, knowledge discovery, and decision-making processes in the agricultural sector, ultimately contributing to improved productivity, sustainability, and innovation in agriculture.

II.EXISTING SYSTEM

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

International Journal of
Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 2, 2024

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.

Disadvantages

- The system doesn't implement deep learning models which will lead less effective and accuracy.
- The system doesn't implement Rule-based Methodology for supporting ML Algorithms.

PROPOSED SYSTEM

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

(2) 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.

(3) 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

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 12, Issue 2, 2024

scope and the constructed feature vector are dynamically fused to improve the accuracy of agricultural text classification with phenotypic values.

Advantages

- The system is more powerful since it is using TEXT CLASSIFICATION MODEL BASED ON DYNAMIC FUSION OF MULTIPLE FEATURES

- 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.

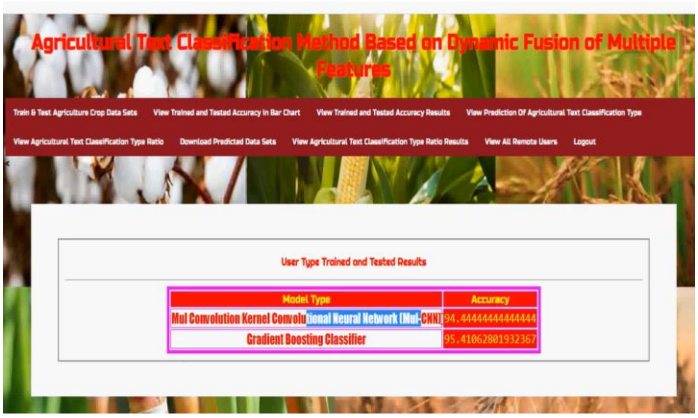
MODULES

- **Service Provider**

In this module, the Service Provider has to login by using valid user name and password.

After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart,

View Trained and Tested Accuracy Results,



View Predicted Type, View Type Ratio, Download Predicted Data Sets, View Type Ratio Results,

ISSN 2347–3657
Volume 12, Issue 2, 2024

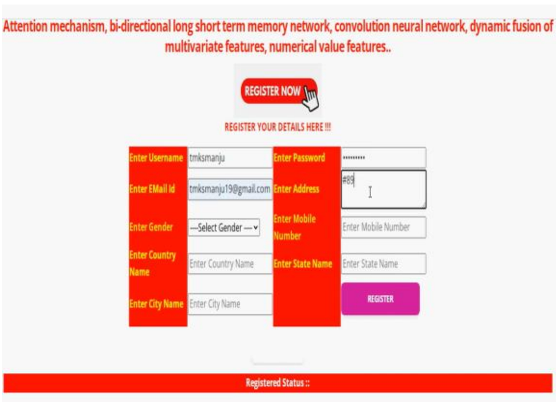
View All Remote Users.

- **View and Authorize Users**

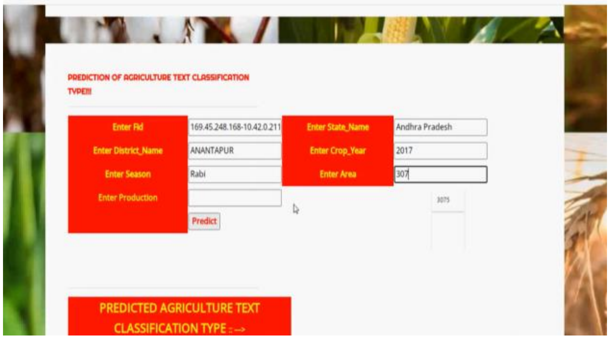
In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

- **Remote User**

In this module, . User should register before doing any operations. Once user registers, their details will be stored to the database.



After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, after login we have to Predict Type,



VIEW YOUR PROFILE.

CONCLUSION

In conclusion, the "Agricultural Text Classification Method Based on Dynamic Fusion of Multiple Features" project presents a novel approach to address the challenges of text classification in the agricultural domain. By leveraging dynamic fusion techniques to integrate multiple features, the project offers a comprehensive solution for accurately categorizing agricultural texts and extracting relevant information. The development of robust classification models capable of handling diverse textual data sources is essential for advancing knowledge discovery and decision-making processes in agriculture. Through the implementation of the proposed method, stakeholders in the agricultural sector can benefit from improved information retrieval, enhanced data analysis capabilities, and better insights into agricultural trends and developments. Ultimately, the outcomes of this project have the potential to facilitate innovation, sustainability, and productivity in agriculture, thereby contributing to the advancement of the agricultural industry.

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