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Plant Recognition on Highway Slopes Based on Improved Prototype Network Integrated Classification

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***Abstract*—Automatic identification of highway slope plants is of great significance for highway safety and ecological protection. However, the classification task of slope plants faces problems such as small sample size and large category diversity. In order to improve the accuracy and robustness of highway slope plant classification, in this paper, an attention-enhanced prototype network integrated classifier (Attention Enhancement Prototype Network Integrated Classifier, AEPEC) is proposed. First, the attention mechanism is introduced to enable the prototype network to focus on important regions in the image and extract more discriminative features. Secondly, the integrated learning method is used to integrate multiple attention enhancement prototype network models to further improve the model performance. This paper verifies the actual slope plant image dataset, and the experimental results show that the proposed method has achieved significant performance improvement in the slope plant classification task.**

***Keywords*—slope plant classification, small sample learning, prototype network, attention mechanism and integrated learning**

I. Introduction

As an important part of ecological environment, slope plants play an important role in highway safety and ecological protection. The growth of plants directly affects the stability of soil and the safety of slope [1]. Therefore, the automatic identification and classification of slope plants is of great significance. However, the automatic classification of slope plants is challenging due to the wide variety of slope plants, the large morphological differences and the limited number of samples [2].

In recent years, deep learning techniques have achieved remarkable success in image recognition tasks. In particular, Convolutional Neural Network (CNN) has shown strong capability in image feature extraction [3]. However, deep learning models usually require large amounts of labeled data to be trained in order to achieve good performance. In slope plant classification task, due to the limited number of samples, direct application of deep learning model may lead to overfitting phenomenon [4]. Therefore, it is of great significance to study a classification method of slope plants that can achieve better performance under the condition of small samples.

To solve these problems, an Attention Enhancement Prototype Network Integrated Classifier (AEPEC) is proposed in this paper. Firstly, a pre-trained convolutional neural network is used as a feature extractor to extract high-level feature representations for slope plant images. Then, a multi-head attention mechanism is introduced to enable the prototype network to focus on important regions in the image in different subspace representations and extract more discriminative features. In addition, in order to further improve the performance of slope plant classification, this paper adopts ensemble learning method to fuse several attention-enhancing prototype network models with different data clipping sizes. In this way, the model can synthesize the advantages of each sub-model to improve the accuracy and robustness of the classification task.

The structure of this paper is as follows: The second part introduces the application of deep learning in plant classification; In the third part, the Attention Enhancement Prototype Network Integrated Classifier (AEPEC) method is described in detail. The fourth part shows the experimental design and result analysis; Finally, the fifth part summarizes the full text and looks forward to the future work.

II. Related Work

Traditional plant classification methods rely mainly on artificially extracted features, such as shape, texture and color, which are then classified using machine learning algorithms. In recent years, plant classification methods based on deep learning have achieved excellent performance and received wide attention. Abawatew *et al.* [5] designed attention-enhancing residual networks with good results in crop disease recognition. Hamid *et al.* [6] conducted a Fruit classification experiment using AlexNet and CNN and achieved superior performance in the Fruit-360 dataset. Ashwinkumar *et al.* [7] designed the OMNCNN model based on PlantDoc database. Chompookham *et al.* [8] faced with the problem of crop disease classification, five deep learning methods (MobileNetV1, MobileNetV2, NASNetMobile, DenseNet121 and Xception) are proposed to carry out comparative experiments. Wang *et al.* [9] proposed a trilinear convolutional neural network model by pre-training the model on ImageNet, and then carried out experimental studies on PlantVillage and PlantDoc datasets.

Existing studies rarely identify the plant types of highway slopes, and analyze the reasons. On the one hand, it is because there is a lack of open data set for slope plant identification, and the above-mentioned literatures are basically conducted model training and testing on open data sets such as PlantDoc and PlantVillage. The

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recognition performance of the correlation model can not be guaranteed under the condition of small samples. On the other hand, the existing studies mainly focus on the identification task of specific crop diseases or fruit types, such objects have large differences in appearance and morphology, significant differences in characteristics, and the classification difficulty is lower than that of slope plant recognition [10]. In view of the current research gaps in slope plant recognition tasks, especially under the condition of small samples, this paper proposes an attention-enhancing prototype network integrated classifier method, which will be introduced in detail below.

III. Attention Enhancement Prototype Network Integration Classifier (AEPEC) Method

The attention enhancement prototype network integrated classifier method proposed in this paper is shown in Fig. 1, which consists of three main modules: feature extraction, prototype generation module and integrated learning module. The principles of the core module are described below.

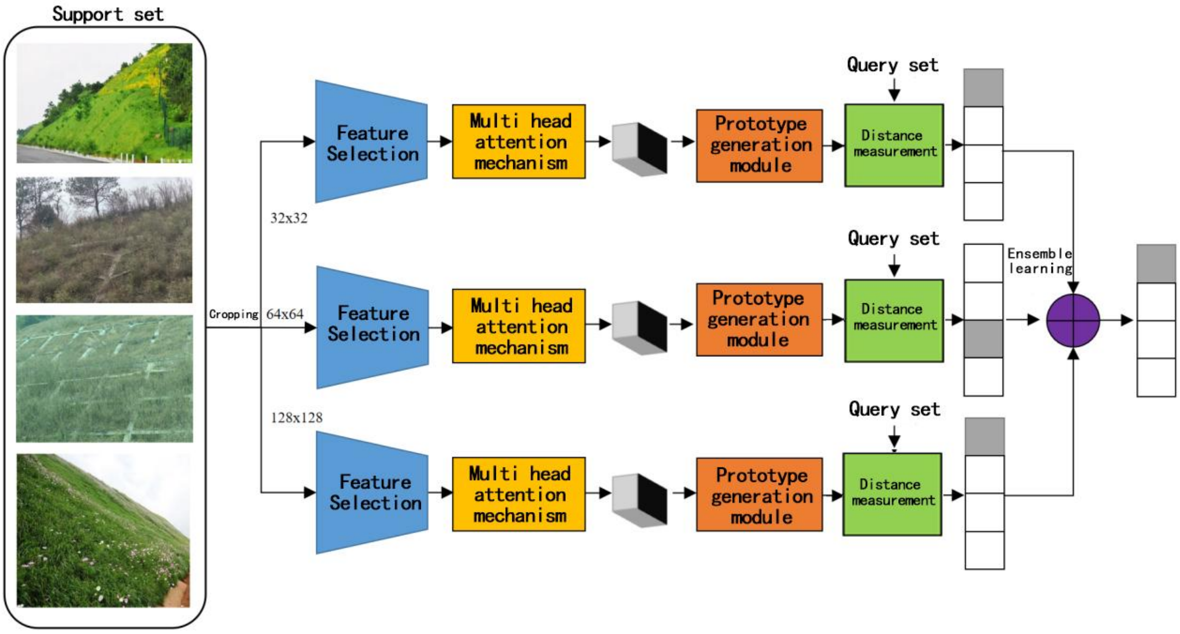


Fig. 1. Architecture of integrated classifier of attention enhanced network.

A. Prototype Network (ProtoNet)

ProtoNet is a prototype based metric learning method, whose main idea is to represent each category as a prototype vector and classify it by calculating the distance between the sample and the prototype. Given a support set S and a query set Q, the prototype network first uses a Convolutional Neural Network (CNN) as a feature extractor to extract feature representations for the images in the support set S and query set Q. Let the CNN feature extractor be function f , and input the highway slope image I into the CNN feature extractor to obtain the feature vector: $x = f(I)$.

For each category c, Calculate the mean of the feature vectors of the samples belonging to this category in the support set S, and obtain the prototype vector P_c . Assuming there are N_c samples for category c in support set S, the feature vectors of each sample are represented as x_i ,Where i=1, 2, N_c , the formula for calculating the prototype vector P_c of category c is as follows:

$$P_c = \frac{1}{N_c}\sum_{i=1}^{N_c} x_i$$

For each sample q in the query set Q, Calculate the distance P_c between its feature vector and the prototype vector $d(q,P_c)$ of each category in the support set. Distance calculations can be performed using Euclidean, Mahalanoban, or other appropriate distance measures. The Euclidean distance is used, and the distance calculation formula is as follows:

$$d(q,P_c) = \|q - P_c\|_2$$

For each sample q in the query set Q, Classify based on its distance from the prototype vectors P_c of each category in the support set. Specifically, assigning q to the nearest category. Let the distance metric be $d(q,P_c)$, where c = 1, 2, ..., C, C are the total number of categories, The formula for calculating the predicted category $\bar{c}$ of sample q is as follows:

$$\bar{c} = \arg\min_c d(q,P_c)$$

B. Attention Enhancement Prototype Network

To enable the prototype network to focus on important areas in the highway slope image and extract more discriminative features, we introduce a multi-head attention mechanism. Specifically, we incorporate a multi-head attention layer in the feature extraction phase of the prototype network, whose output is a weighted sum of the input features. The multi-head attention mechanism enables the model to focus on important regions in the image in different subspace representations and to extract more discriminative features.

Firstly, calculate the self attention score of the input feature, which is the dot product of the input feature and itself. Let the input feature matrix be $X \in R^{n \times d}$, where n is the number of features and d is the feature dimension. Firstly, map the X-ray properties to Q (query matrix), K (key matrix), and V (value matrix), and the calculation formula is as follows:

$$Q = X \cdot W_Q \in R^{n \times d_k}$$
$$K = X \cdot W_K \in R^{n \times d_k}$$
$$V = X \cdot W_V \in R^{n \times d_v}$$

Among them W_Q, W_K ,and W_V are the weight matrices of the query, key, and value matrices, respectively, d_k and d_v are the dimensions of the query, key matrix, and value matrix, respectively.

The self-attention score matrix is calculated by the following formula: $S \in R^{n \times n}$

$$S = QK^T / \sqrt{d_k}$$

Applying the Softmax function to each row of S to obtain the attention weight matrix the calculation formula is $A \in R^{n \times n}$, as follows:

$$A_{ij} = e^{S_{ij}} / \sum_{j=1}^{n} e^{S_{ij}}$$

The weighted sum of the input features and attention weights is calculated to obtain the output of the multi-level attention layer:

$$Z = AV \in R^{n \times d_v}$$

The above computational procedure describes the single-head attention mechanism. To implement the multi-head attention mechanism, we can compute H different heads in parallel and then connect their outputs together. Let the output of the multi-head attention layer be M, and the calculation formula is as follows:

$$M = Concat(Z_1, Z_2, ..., Z_H) W_O$$

where Concat represents the connection operation, W_O is the output weight matrix, and Z_i is the output of the i th head.

By introducing a multi-head attention mechanism, the prototype network can focus on important areas in the highway slope image and extract more discriminative features to achieve better plant recognition performance in small sample learning scenarios.

C. Integrated Learning Methods

To further improve the performance of the slope plant classification task, we used an integrated learning approach to fuse multiple attention-enhanced prototype network models with different data cropping sizes. In this way, the model is able to synthesize the advantages of each sub-model and improve the accuracy and robustness of the classification task. The specific integrated learning process is as follows:

Datasets with different cropping sizes were generated from the raw image data. Let the original dataset be D to generate K datasets with different trimmed sizes $\{D_1, D_2, ..., D_K\}$. For each trimmed-size dataset D_i , Train an independent attention enhancing prototype network model $AEPEC_i$, for each attention enhanced prototype network model, calculate its performance metrics on the validation set, such as accuracy, F1 score, etc. Let the performance metric function be $T(AEPEC_i, V)$, where V represents the validation set, and calculate the performance metric $T_i = T(AEPEC_i, V)$ of each model on the validation set. Assign weights to each model based on their performance metrics on the validation set. The strategy adopted in this article is to normalize the performance indicators so that the sum of weights is 1:

$$w_i = T_i / \sum_{j=1}^{M} T_j$$

In the testing phase, for a given test sample x, calculate its prediction results on each attention enhancing prototype network model separately. Let $AEPEC_i$ predict the result of the test sample x as $y_i(x)$, where $y_i(x)$ represents the class probability vector. Calculate the weighted average prediction result by combining the prediction results and weights of each model:

$$y(x) = \sum_{i=1}^{M} w_i \cdot y_i(x)$$

The category corresponding to the maximum probability was selected as the final prediction category of the test sample, namely:

$$c(x) = \arg\max_c y_c(x)$$

Through the above computational process, the integrated learning of the attention-enhanced prototype network model trained on the datasets with different trimmed sizes can be realized, and the final prediction results can be obtained.

IV. EXPERIMENTS AND THE RESULTS

In order to verify the effectiveness and superiority of the proposed attention-enhanced prototype network integrated classifier (AEPEC) method in the slope plant classification task, the experimental verification is carried out.

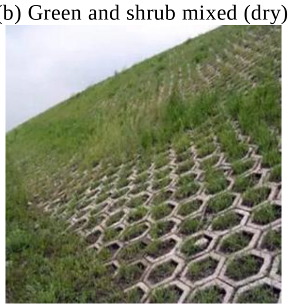
A. Data Set and Preprocessing

The experiment used an actual slope plant image dataset of multiple slope plants, including four categories: hay grass, grass shrub and dry grass shrub (as shown in Fig. 2). Each category consists of 10, 10, 22, and 11 images in turn. To enhance the diversity of the data, we performed data enhancement operations on the original images, including random cropping, horizontal flipping, rotation, etc. In addition, in order to realize the integrated learning method, this paper made K=3 and finally obtained three data sets with different cropping sizes, which are 32×32, 64×64 and 128×128.

(a) Grass and shrubs (green)

(b) Green and shrub mixed (dry)

(c) cured hay



(d) green grass

Fig. 2. Example of the four side slope plants.

B. Experimental Setting and Evaluation Index

To verify the effectiveness and superiority of the AEPEC method in the highway slope plant classification task, we first divided the experimental dataset. Under the setting of small sample learning, the data set is divided into training set, validation set and test set as follows:

Training set: For each category, 5 images are randomly selected as the training sample. There are four categories in the data set, so the training set has an image.

$$5\times4=20$$

Validation Set: For each category, 2 images are randomly selected from the remaining images as the validation sample. In this way, the validation set has the one common image.

$$2\times4=8$$

Test set: The remaining images are used as the test set to evaluate the performance of the model. Assuming there are M images for each category, then the test set has $(M-7)\times4$ images.

Accuracy (Accuracy), precision (Precision), recall (Recall) and F1 score (F1-Score) were used as evaluation indicators.

C. Results and Analysis

The loss function trained by the method of this paper is shown in Fig. 3. Visible, in all pictures the model almost converged after being trained for 70 cycles. After training convergence, the confusion matrix of model classification on the dataset is shown in Fig. 4. The AEPEC model presented here has a recognition accuracy of 85.5%.

The results of the highway slopes are shown in Table 1. We found that the Attention Enhancement Prototype Network Integrated Classifier (AEPEC) method achieved significant performance improvement in the slope plant classification task.

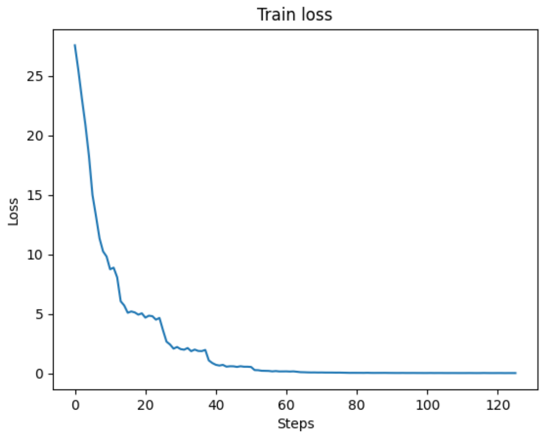


Fig. 3. Changes in the loss function during model training.

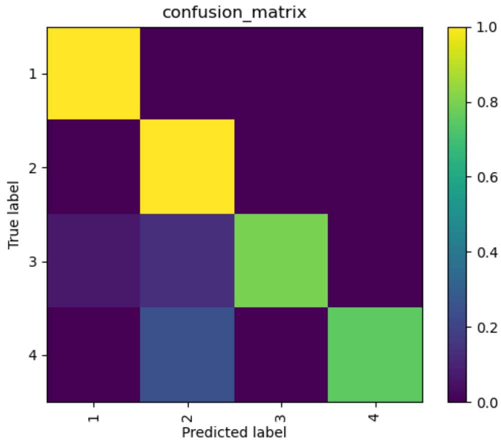


Fig. 4. Classification confusion matrix.

Table 1. Comparison experiment of highway slope

Method	Precision	Accuracy rate	Recall	F1-score
ProtoNet	75.0%	75.5%	74.7%	75.1%
Attention-Enhanced ProtoNet	80.5%	81.0%	80.1%	80.5%
AEPEC	85.5%	86.2%	85.1%	85.6%
CNN	70.0%	70.6%	69.9%	70.2%
LSTM	65.5%	65.8%	65.3%	65.5%

In order to verify and analyze the effectiveness of the model in more detail, we have discussed deeply from the following aspects:

- **The role of attention mechanism:** By comparing the single size attention enhancement prototype network (single Attention-Enhanced ProtoNet) with the basic prototype network (ProtoNet), we found that the model with the attention mechanism showed significant improvement in accuracy, precision, recall and F1-score. This shows that the attention mechanism can help the model to focus on important areas in the image and extract more discriminative features, thus improving the classification performance.

- **Role of the ensemble learning method:** We further analyzed the performance differences between the AEPEC method and a single Attention-Enhanced ProtoNet. The experimental results show that through the ensemble learning method, AEPEC fully utilizes the information extracted from different trimmed size datasets, which further improves the accuracy and robustness of the classification task. This indicates that the ensemble learning method has a significant effect in this task.
- **Inter-category difference analysis:** To further validate the performance of the AEPEC method on different categories, we statistically and analyzed the precision, recall, and F1 scores of each category, and the results are shown in Table 2. The results showed that AEPEC method achieved good performance in most categories, indicating that it has strong generalization ability for slope plant classification task.
- **Compared with other deep learning methods:** The experimental results also show that AEPEC method, compared with other deep learning methods, such as Convolutional Neural Network (CNN) and Long and Short-Term Memory network (LSTM), has a higher accuracy, precision, recall and F1 score on the slope plant classification task. This indicates that the AEPEC method has stronger advantages and potential in dealing with such problems.

Table 2. Identification performance of the AEPEC method for different plant categories.

Class	Accuracy Rate	Recall	F1-Score
Class 1	88.0%	86.5%	87.2%
Class 2	83.5%	85.0%	84.2%
Class 3	84.5%	83.1%	83.7%
Class 4	87.0%	88.5%	87.7%

In conclusion, the experimental results show that the original strong prototype network integrated classifier (AEPEC) method has significant effectiveness and superiority in the slope plant classification task. The introduction of attention mechanism and integrated learning method enables the model to show better generalization ability and robustness when handling learning tasks with small samples.

V. Summary

In this paper, we propose an innovative method——Integrated Classifier (AEPEC) for the slope plant classification task. The AEPEC approach combines prototype networks, attention mechanisms and ensemble learning to meet the challenges of small sample learning and improve the model performance on slope plant classification tasks. Through experimental analysis, we found that AEPEC method shows obvious superiority in slope plant classification task, indicating its effectiveness and applicability in small sample learning scenarios. The introduction of the attention mechanism helps to improve the generalization ability and robustness of the model, enabling it to focus on important regions in the image and extract more discriminative features. The application of ensemble learning methods further optimizes model performance, exploiting the prediction results of multiple weak classifiers, and improves the accuracy and robustness of the classification task. The AEPEC method shows high innovation in the experiment and is expected to achieve more extensive application in other related fields such as plant classification of highway slopes. In the future, the performance of the AEPEC method will be validated on larger scale and more categories of slope plant datasets to further demonstrate its generalization ability.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Zhai and Kang conducted data collection and methodological research; Tang was responsible for preparing the initial draft, conceptualizing, reviewing and editing, verifying, visualizing, and supervising, as well as conducting validation and formal analysis; all authors have approved the final version.

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