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Confident Learning-Assisted Knowledge Distillation for Tongue Color Classification in TCM with Noisy Labels

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ABSTRACT_ Tongue tone is a significant tongue symptomatic file for conventional Chinese medication (TCM). Annotated samples frequently contain noisy labels due to the individual experience of TCM experts and the ambiguous boundaries between tongue color categories. Profound brain networks prepared with the loud named tests frequently have unfortunate speculation ability since they effectively overfit on boisterous marks. An original system named sure learning-helped information refining (CLA-KD) is proposed for tongue variety order with loud marks. In this structure, the educator network assumes two significant parts. From one viewpoint, it performs sure figuring out how to recognize, purge and right uproarious names. On the other hand, it learns the information from the clean labels, which it will then pass on to the student network to use as a training guide. In addition, to address the issue of insufficient data samples' unreliability and instability, we elaborately design an ensemble teacher network known as E-CA2-ResNet18. E-CA2 - ResNet18 takes on ResNet18 as the spine, and incorporates channel consideration (CA) component and initiate or not actuation capability together, which works with to yield a superior presentation. The trial results on three self-laid out TCM tongue datasets show that, our proposed CLA-KD can get a predominant characterization precision and great heartiness with a lower network model intricacy.

1.INTRODUCTION

Tongue tone is a significant tongue symptomatic file for conventional Chinese medication (TCM). Annotated samples frequently contain noisy labels due to the individual experience of TCM experts and the ambiguous boundaries between tongue color categories. Profound brain networks prepared with the loud named tests frequently have unfortunate speculation ability since they effectively overfit on boisterous marks. An original system named sure learning-helped information refining (CLA-KD) is proposed for tongue variety order with loud marks. In this structure, the educator network assumes two significant parts. From one viewpoint, it performs sure figuring out how to recognize, purge and right uproarious names. On the other hand, it learns the information from the clean labels, which it will then pass on to the student network to use as a training guide. In addition, to address the issue of insufficient data samples' unreliability and instability, we elaborately design an ensemble teacher network known as E-CA2-ResNet18. E-CA2 - ResNet18 takes on ResNet18 as the spine, and incorporates channel consideration (CA) component and initiate or not actuation capability together, which

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works with to yield a superior presentation. The trial results on three self-laid out TCM tongue datasets show that, our proposed CLA-KD can get a predominant characterization precision and great heartiness with a lower network model intricacy

2.LITERATURE SURVEY

2.1 G. Algan and I. Ulusoy, " Image classification with deep learning in the presence of noisy labels: A survey," Knowledge-Based Systems, vol.215, article no.106771, 2021.32.

ABSTRACT_ Image classification systems recently made a giant leap with the advancement of deep neural networks. However, these systems require an excessive amount of labeled data to be adequately trained. Gathering a correctly annotated dataset is not always feasible due to several factors, such as the expensiveness of the labeling process or difficulty of correctly classifying data, even for the experts. Because of these practical challenges, label noise is a common problem in real-world datasets, and numerous methods to train deep neural networks with label noise are proposed in the literature. Although deep neural networks are known to be relatively robust to label noise, their tendency to overfit data makes them vulnerable to memorizing even random noise. Therefore, it is crucial to consider the existence of label noise and develop counter algorithms to fade away its adverse effects to train deep neural networks efficiently. Even though an extensive survey of machine learning techniques under label noise exists, the literature lacks a comprehensive survey of methodologies centered explicitly around deep learning in the presence of noisy labels. This paper aims to present these algorithms while categorizing them into one of the two subgroups: noise model based and noise model free methods. Algorithms in the first group aim to estimate the noise structure and use this information to avoid the adverse effects of noisy labels. Differently, methods in the second group try to come up with inherently noise robust algorithms by using approaches like robust losses, regularizers or other learning paradigms.

2.2 N. Ma, X. Zhang, M. Liu, et al., "Activate or not: Learning customized activation," in Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Nashville, TN, USA, pp.8032–8042, 2021.

As the banana industry develops, the demand for intelligent banana crown cutting is increasing. To achieve efficient crown cutting of bananas, accurate segmentation of the banana crown is crucial for the operation of a banana crown cutting device. In order to address the existing challenges, this paper proposed a method for segmentation of banana crown based on improved DeepLabv3+. This method replaces the backbone network of the classical DeepLabv3+ model with MobilenetV2, reducing the number of parameters and training time, thereby achieving model lightweightness and enhancing model speed. Additionally, the Atrous Spatial Pyramid Pooling (ASPP) module is enhanced by incorporating the

Shuffle Attention Mechanism and replacing the activation function with Meta-ACONC. This enhancement results in the creation of a new feature extraction module, called Banana-ASPP, which effectively handles high-level features. Furthermore, Multi-scale Channel Attention Module (MS-CAM) is introduced to the Decoder to improve the integration of features from multiple semantics and scales. According to experimental data, the proposed method has a Mean Intersection over Union (MIoU) of 85.75%, a Mean Pixel Accuracy (MPA) of 91.41%, parameters of 5.881 M and model speed of 61.05 f/s. Compared to the classical DeepLabv3+ network, the proposed model exhibits an improvement of 1.94% in MIoU and 1.21% in MPA, while reducing the number of parameters by 89.25% and increasing the model speed by 47.07 f/s. The proposed method enhanced banana crown segmentation accuracy while maintaining model lightweightness and speed. It also provided robust technical support for relevant parameters calculation of banana crown and control of banana crown cutting equipment

3.PROPOSED SYSTEM

In olden days diseases will be identified based on tongue colour and this technique mostly used in Traditional Chinese medicines (TCM). To predict disease experts will analyse tongue colour and later this task was automated using deep learning algorithms but this algorithms performance was not up to the mark because of tongue images scarcity or presence of Noisy labels. To overcome from this issue author of this paper employing two different modules such as Teacher and student.

Teacher module get trained on Noisy and clean images and then assigned threshold to each image features and if image features are clear then it will have high threshold and this will be input to Student module which will get trained on threshold based features. After training student module will predict labels with maximum probability and ignore feature which has less threshold so noisy images and their labels will be avoided.

In propose work author using Resnet18 as the backbone teacher module for features threshold calculation and then using Activation function to filter out noisy label features and then applying Attention model (activation and attention will get run through student module) to select optimize features for label prediction and this model is called as E-CA2-ResNet18.

E refers to activating Activation Function

CA2 refers to Attention module

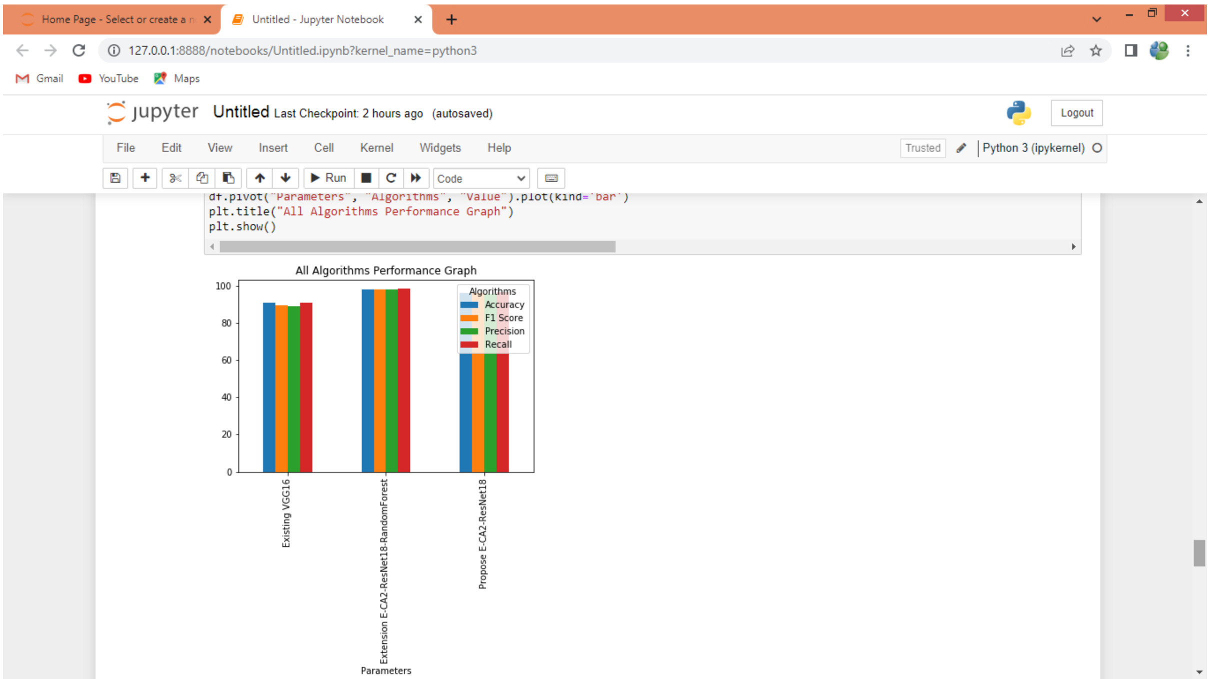
ResNet18 as the backbone model

Author has compare propose E-CA2-ResNet18 performance with many existing algorithms such as VGG16, MobileNetV2 and many more but training all this algorithms may take much time so we have implemented VGG16 as the existing and E-CA2_ResNet18 as the propose work.

3.1 IMPLEMENTATION

In propose work after employing ResNet18, Activation and Attention algorithms author has manage to get accuracy between 93 to 96%. Propose E-CA2-ResNet18 has already achieved optimized features by segregating Noisy and clean labels, so as extension we have extracted all optimized features from propose E-CA2-ResNet18 and then retrain with Random Forest to form hybrid model and this hybrid model giving more accuracy compare to propose and existing algorithms.

4.RESULTS AND DISCUSSION



Above is the performance graph of all algorithms where x-axis represents algorithm names and y-axis represents Precision, accuracy, recall and FSCORE in different colour bars

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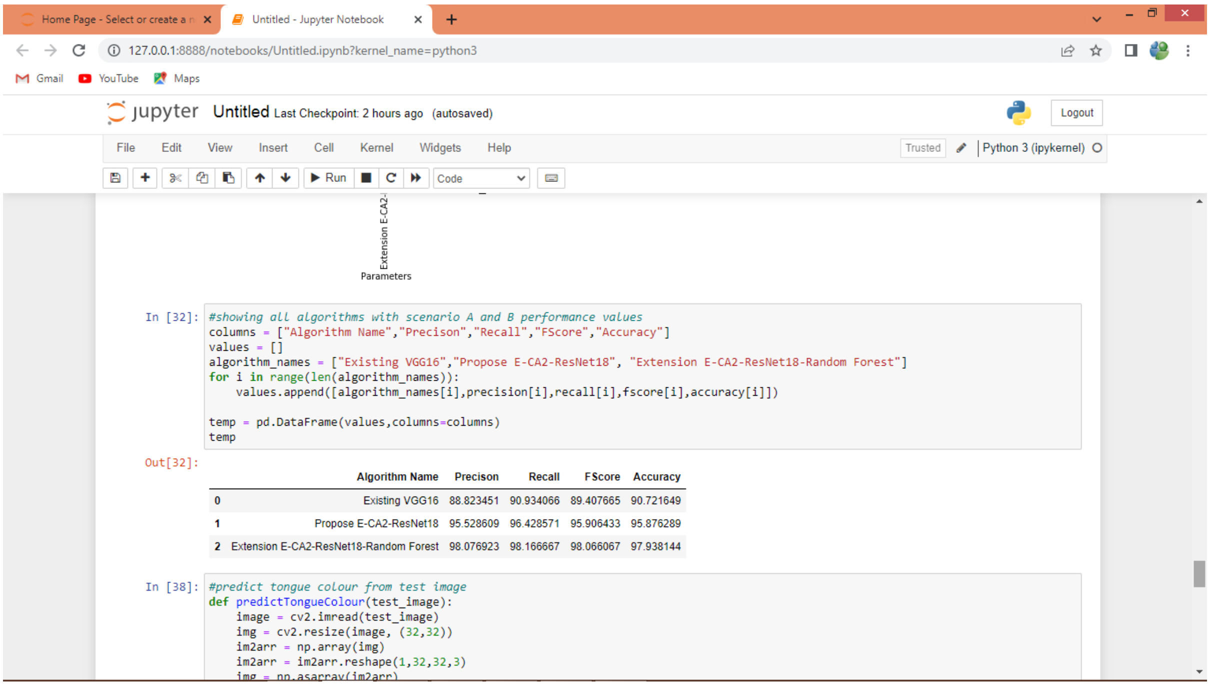
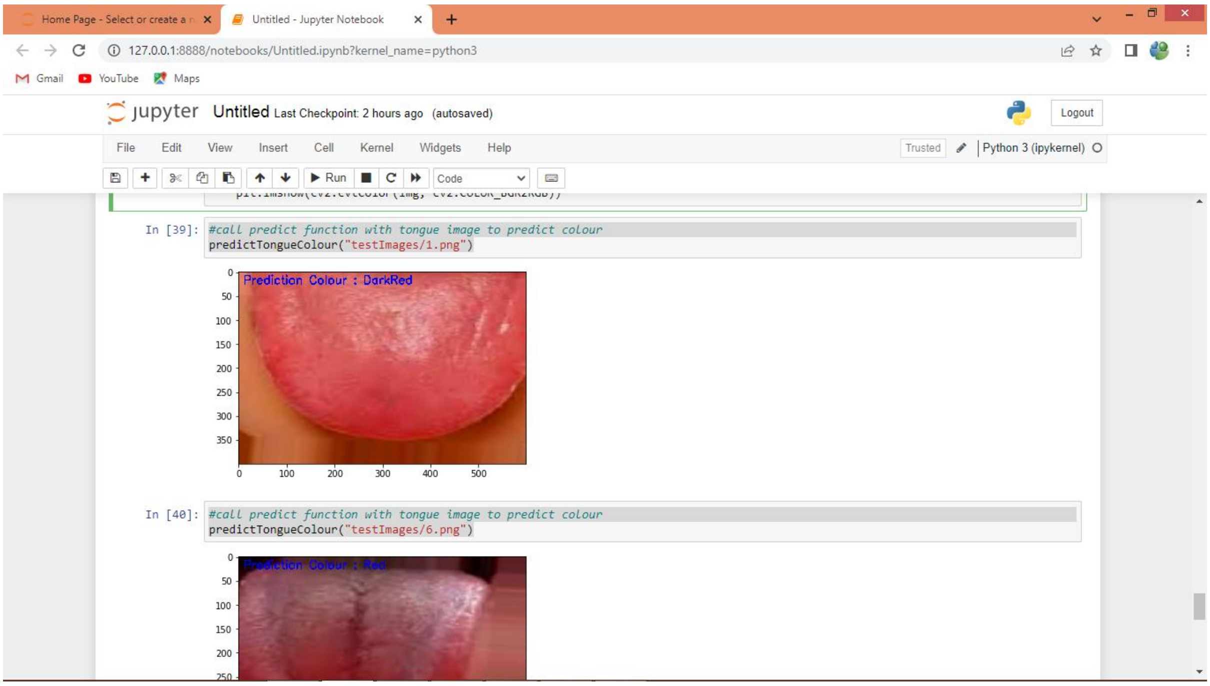
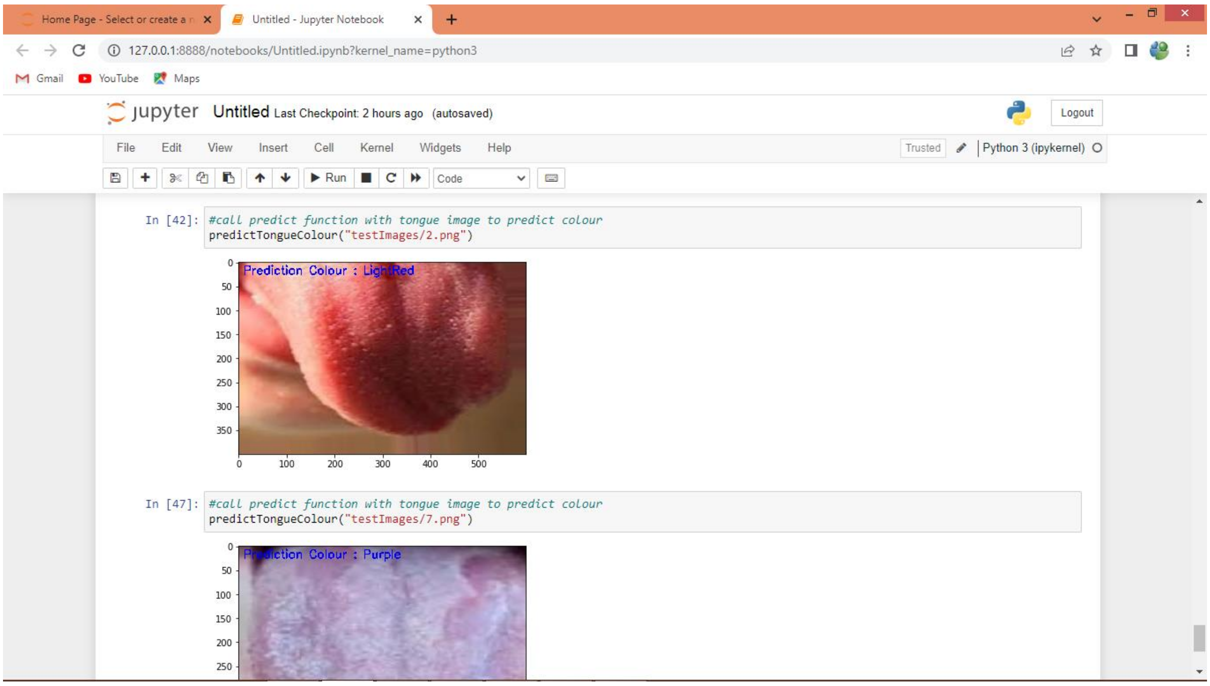


In above screen displaying all algorithm performance in tabular format



In above screen calling predict function with image path and then displaying predicted tongue colour output in blue colour text



Above is another image output.

5.CONCLUSION

In this study, we addressed the challenges of noisy labels and insufficient data in tongue color classification for Traditional Chinese Medicine (TCM) by proposing a novel framework, Confident Learning-Assisted Knowledge Distillation (CLA-KD). The CLA-KD framework effectively integrates a Teacher module trained on both noisy and clean images, with a Student module that focuses on reliable, high-threshold features to avoid overfitting on noisy labels.

Our proposed model, E-CA2-ResNet18, utilizes ResNet18 as the backbone and incorporates activation functions and attention mechanisms to filter out noisy features, thereby enhancing the accuracy and robustness of the classification. Experimental results demonstrate that E-CA2-ResNet18 achieves superior classification performance, with accuracy rates ranging from 93% to 96%.

Additionally, by extracting optimized features from E-CA2-ResNet18 and retraining with a Random Forest classifier, we developed a hybrid model that further improved accuracy, outperforming existing algorithms such as VGG16 and MobileNetV2. This hybrid model highlights the effectiveness of combining advanced deep learning techniques with traditional machine learning methods to enhance model performance.

In conclusion, the CLA-KD framework and the E-CA2-ResNet18 model provide a robust and accurate solution for tongue color classification in TCM, demonstrating significant improvements over traditional deep learning approaches. This study underscores the potential of integrating

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confident learning, knowledge distillation, and ensemble methods to tackle challenges in medical image classification, offering a promising direction for future research and practical applications in TCM diagnostics.

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