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Sri Lankan Leafy Tea Quality Grades Classification Using Deep Learning

Tharushi Amarabandu
Faculty of Computing
Informatics Institute of Technology
Colombo, Sri Lanka
tharushi.20211525@iit.ac.lk

Sulochana Rupasinghe
Faculty of Computing
Informatics Institute of Technology
Colombo, Sri Lanka
sulochana.r@iit.ac.lk

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I. Introduction

Tea is a popular beverage in almost every corner of the world because of its unique taste and aroma. Tea originates from the leaves of the Camellia sinensis plant. Tea grading involves analyzing different parameters to identify the quality grades of tea, including the size and appearance of the tea leaf, colour, aroma, flavour, texture, uniformity and liquor. Manual methods and Sifter machines are used for the current grading process. Colour sorter machines classify tea grades by analyzing the colour of tea leaves and sifter machines grade tea leaves by analyzing the size of tea particles. Current tea grading methods are time-consuming, laborious, expensive and sometimes inaccurate.

To address these challenges, machine learning approaches have been introduced as effective solutions. In the past few years, many researchers introduced different machine learning algorithms to classify tea grades, including artificial neural network (ANN), K-nearest neighbors (KNN) and Support Vector Machine (SVM) [1]. Deep learning provides powerful algorithms for computer vision tasks including image classifications. This study aims to propose a novel approach for the Sri Lankan tea grading process using deep learning as AI is still rarely used in this domain.

II. Literature Review

The most relevant existing work by Zhu [2] presented a deep learning approach to classify oolong tea varieties. Images were recognized using computer vision and predictions were obtained using Convolutional Neural Network (CNN) that had been trained. Three CNN models including MobileNetV1, MobileNetV2 and ResNet50 were employed by the authors. This study classified 5 different grades of oolong tea including Shuixian, Gaoshan, Dongding, Rougui and Tieguanyin. The dataset of oolong tea images was created carefully cropped and enhanced to produce datasets suitable for several research fields. The initial count of over 50,000 images expanded to over 300,000 by utilizing various data augmentation techniques including translations, scaling and rotations. This study showed that CNNs work well for classifying tea. However, it mainly focused on Chinese oolong tea limiting its applicability to other tea varieties such as Sri Lankan leafy tea grades.

Bakhshipour introduced two approaches to improve the tea grading process. In the first study [3], a decision tree-based system was proposed to classify Iranian green and black tea into five grades each, using 83 image-based features. J48 and REP decision tree algorithms were used for classification. In the second study [4], the authors used support vector machine (SVM), decision trees, artificial neural networks (ANN) and Bayesian networks (BN) to classify four varieties of Iran black tea including Flowery Broken Orange Pekoe (FBOP), Orange Pekoe (OP), Flowery Orange Pekoe (FOP) and Dust One (PD-ONE). Unlike these existing studies, the proposed approach in this study focuses solely on deep learning-based models, eliminating the need for manual feature extraction. In recent decades, the developments of Internet of Things (IoT) devices, such as E-nose and E-tongue combined with machine learning have increased the efficiency of the tea grading process. Yu implemented a system combining E-nose and artificial neural networks to classify different grades of green tea[5].These techniques are costly and difficult to use.

The next section will discuss the proposed methodologies for classifying Sri Lankan leafy tea grades using deep learning.

III. Methodology

A. Dataset

The dataset includes 2,500 images captured using a mobile phone camera. It consists of 500 images for each of the five Sri Lankan tea grades (BOP1, OP1, OPA, Pekoe and Chunmee). Tea industry professionals then verified the dataset. The images were captured by arranging tea particles on a white background and photographing them from different angles.

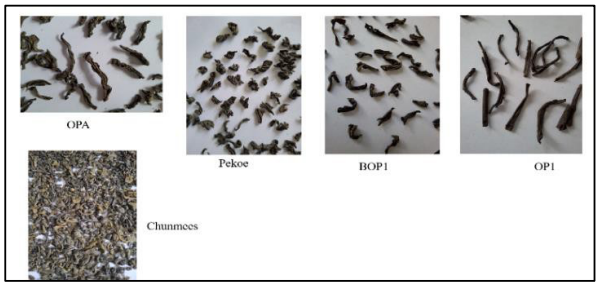

Fig. 1. Sample images of five Sri Lankan tea categories

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B. Data Preprocessing

The captured images were labeled and resized into 224 × 224 pixels. The dataset was then divided into 80% training and 20% testing.

C. Data Augmentation

Dynamic augmentation techniques including flipping, rotation and zooming were used during training to reduce model overfitting.

D. Proposed CNN Model

The custom CNN architecture begins with data augmentation layer. This architecture includes three convolutional blocks. In the first block, a Conv2D layer with 32 filters applies ReLU activation and L2 regularization, followed by max pooling layer and dropout layer to reduce overfitting. The second block increases the model's complexity by using 64 filters while maintaining the same structure as the previous block, including max pooling and dropout. The third block uses 128 filters, max pooling and a 40% dropout rate to significantly improve feature extraction. After these blocks, a Global Average Pooling layer reduces dimensionality, followed by a dense layer with 128 units and dropout to prevent overfitting. Finally, the output layer uses softmax activation to classify the input into multiple categories based on the number of classes defined.

E. Transfer Learning with MobileNetV2 and VGG16

MobileNetV2 and VGG16 were used for transfer learning, with pretrained weights to improve feature extraction and classification performance on the tea grade dataset. VGG16 consists of 16 layers, primarily using 3×3 convolutional filters and max-pooling layers to extract hierarchical features. The VGG16 model was pretrained on the ImageNet dataset. A VGG16-based transfer learning model begins with the VGG16 base model, which serves as the feature extractor. After that, it includes a Flatten layer, a fully connected layer with 256 neurons activated using ReLU and a dropout layer with a rate of 0.5 to reduce overfitting. The final softmax layer classifies the images into tea grades.

The MobileNetV2 architecture is also pretrained on ImageNet. In this proposed approach, MobileNetV2 is used as the base model for extracting features with frozen weights. Initially, input images are augmented. The model then processes these images through two convolutional layers: the first with 128 filters and the second with 64 filters, both utilizing a 3×3 kernel, followed by Batch Normalization and ReLU activation. After that, a global average pooling layer, a dense layer, and a dropout layer are added. Similar to VGG16, the architecture ends with a softmax layer.

Each model was trained multiple times using various hyperparameters and epochs to determine the optimal configuration for tea grade classification. To enhance performance, different combinations of batch sizes, learning rates and optimizers were tested. After training, each model was compared with the others. The next chapter discusses the testing phase.

IV. Results and Discussion

Performance metrics, including accuracy, precision, recall, and F1-score, were used to evaluate the results. A confusion matrix was also utilized to assess the models. VGG16 achieved the highest accuracy, with 99.48% on the training data and 98.60% on the validation data. The following table presents the results of all models.

TABLE I. Results Table

model	Accuracy	precision	recall	f1-score
Custom CNN model	88%	0.99	0.98	0.98
MobileNetV2	85%	0.85	0.85	0.84
VGG16	99%	0.99	0.98	0.98

V. Conclusion

This study proposes a deep learning-based approach for classifying Sri Lankan leafy tea grades. The dataset includes 2,500 tea particle images, focusing on five Sri Lankan tea grades: OPA, OP1, BOP1, Pekoe and Chunmee. The author proposed a novel CNN architecture and utilized two additional pre-trained models. A model comparison was conducted with CNN, MobileNetV2 and VGG16 achieving overall accuracies of 88%, 85%, and 99%, respectivelyVGG16 was selected as the best classifier for the tea grading system. This study highlights that deep learning can be used to improve the efficiency of the tea grading process in the tea industry.

Future work can expand the dataset and develop real-world applications, such as mobile applications with real-time capturing capabilities.

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