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CLASSIFICATION OF IMAGE QUALITY OF TUBAN LEGEN BEVERAGES USING CONVOLUTIONAL NEURAL NETWORK (CNN) METHOD BASED ON RANDOM FOREST

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ABSTRACT

This study focuses on developing a classification method for the quality of Tuban legen beverage using a combination of Convolutional Neural Network (CNN) and Random Forest. The siwalan plant (Borassus flabellifer L.), commonly found in Tuban Regency, East Java, produces sap that is susceptible to fermentation and microbial damage. Therefore, it is essential to process legen properly to maintain its taste and quality.

The dataset used consists of 1280 images of legen beverage categorized into two classes: Steril and Campuran. The research process involves data collection, preprocessing, and splitting the dataset into training, validation, and testing sets with various ratios. CNN, specifically the VGG16 architecture, is used for feature extraction from images, while Random Forest serves as the classification algorithm. The model is optimized using GridSearchCV and evaluated with metrics such as accuracy, precision, recall, F1-score, and confusion matrix.

The results indicate that the combination of CNN and Random Forest can achieve optimal accuracy of up to 100% for certain data configurations, both for images with and without background, with a data ratio of 80% training, 10% validation, and 10% testing. Data augmentation is applied to enhance model variation and generalization, contributing to improved classification accuracy.

Although these results demonstrate the model's ability to recognize patterns, the study suggests potential for further improvement. It is recommended to explore other classification methods, conduct deeper hyperparameter optimization, and apply transfer learning to enhance model performance. Additionally, further research is needed to understand the impact of background on classification and how to address it.

This study makes a significant contribution to the development of a quality classification system for legen beverages by utilizing more robust and accurate deep learning technology. These findings can serve as an important reference for future research in image classification and food product quality, providing insights for developing more efficient and effective methods.

Keywords Image Classification; Convolutional Neural Network; Random Forest; Legen Drink;
Paper type Research paper

INTRODUCTION

The lontar palm (Borassus flabellifer L.) is a type of palm plant that has multipurpose properties, in Tuban Regency, East Java [1]. Lontar sap will undergo fermentation due to the presence of microorganisms in the sap, causing a sour taste due to the formation of acetic acid and making it a good medium for the growth of microorganisms [2]. Lontar sap has a relatively high sugar content and is sensitive to damage caused by microbial contamination, therefore the sap must be processed immediately after being taken from the tree, no later than 90 minutes after being removed from the trunk [3].

Legen is a liquid often referred to as lontar sap which is a raw material for making sugar, and can be used as a food ingredient such as alcoholic beverages (tuak), vinegar, and fresh drinks [4]. The process of processing lontar sap into legen is done by sterilizing it to make it safe to package and prevent microbial growth. Legen that has no added ingredients and whose container is clean is important to maintain its original taste, a blend of sweet and slightly sour. There are several types of legen that are mixed with various additional ingredients including vinegar, soursop juice, sugar in large quantities such as 1 kg, as well as artificial sweeteners and others, although these additions can affect the authenticity and characteristics of traditional legen drinks [5].

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Convolutional Neural Network (CNN) is a type of deep learning model for processing data that has a grid pattern, such as the internal features of data, and effectively generalizes these features to solve various general image problems, such as object recognition and other computer vision tasks [6]. One method that can be used is the decision tree method which is one of the decision-making methods, but this can lead to overfitting, so a method is needed that can overcome this problem. Methods that can be used to avoid overfitting are by pruning the tree or using the random forest (RF) method [7].

In this study, a Multi-Label Image Classification method with Convolutional Neural Network (CNN) was used as an algorithm to detect multiple defects in water bottles simultaneously. There are six class labels, namely less content, empty content, damaged cap, no cap, damaged label, and no label. Each of these class labels represents the possibility of defects in the bottle. Several combinations of feature learning layers and fully connected layers are used to extract patterns and classify input images. To facilitate this research, a large-scale dataset of water bottle images was collected, which represents the six predetermined class labels. When tested with a new dataset, the CNN model achieved a prediction accuracy of 98.526%, and an average accuracy of 97.71% when tested with 10-fold cross-validation [8].

METHOD

The research stages used can be seen in Figure 1. This study adopts a machine learning-based approach using Convolutional Neural Network (CNN) for feature extraction from images of Legen beverages and Random Forest for classification. The research workflow comprises key steps: data collection and preprocessing, development of the CNN model for feature extraction, application of Random Forest as a classification model, and evaluation of model performance using several evaluation metrics [9].

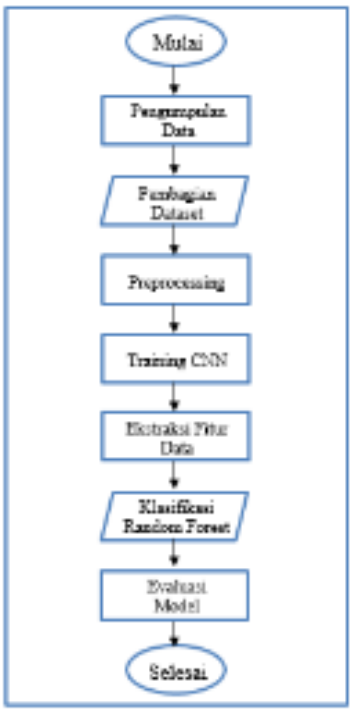

Figure 1. Flowchart Research Design

Data Collection

The initial stage of this research involves collecting images of Legen beverages. Data is gathered from multiple sources, including direct photography and available datasets [10]. The collected images must cover various quality conditions of Legen beverages, both Steril and Campuran, to ensure representative data.

Dataset Partitioning

The dataset used in this study consists of images of Legen beverages categorized by quality. The data is divided into three parts: training data, validation data, and test data, with various partition ratios explored to assess their impact on model performance [11]. The dataset is divided into three parts: training set, validation set, and testing set, using 8 split ratios (10:10:80, 20:10:70, 30:10:60, 40:10:50, 50:10:40, 60:10:30, 70:10:20, 80:10:10), where 10% of the data is used for model training, 10% for validation during the training process, and 80% for testing the model post-training. This step involves two main activities:

- Google Drive: To facilitate data access and management, Google Drive is used as the storage location for image data. This process involves mounting Google Drive to the working environment so that the dataset can be accessed directly.
- Dataset: The dataset is divided into three main subsets: training, validation, and testing. This division is crucial to ensure that the model can be effectively trained, validated, and tested.

Preprocessing

Once the image data is collected, the next step is image preprocessing [12]. Additionally, data augmentation is applied to expand the dataset's variation to enhance the CNN model's generalization ability. This stage involves several main processes:

- Resize: Adjusting the image size to uniform dimensions to facilitate further processing.
- Normalization: Scaling pixel values to a specific range, such as 0 to 1, to accelerate model convergence.
- Augmentation: Increasing data variation by transforming images, such as rotation, flipping, or adding noise, to avoid overfitting.
- Labeling: Assigning labels to each image based on the quality of the Legen beverage, with labels "Steril" and "Campuran"
- Generator: This generator will provide processed images in batches for training, validation, and testing, ensuring that data is fed into the model in a structured manner.

CNN Training

The research stages used can be seen in Figure 2. The Convolutional Neural Network (CNN) model is trained using the training data. The CNN model is used to extract important features from images of Legen beverages. The model used is VGG16, which has been pre-trained on the ImageNet dataset. This model is modified by adding a GlobalAveragePooling2D layer and several Dense layers for binary classification [13].

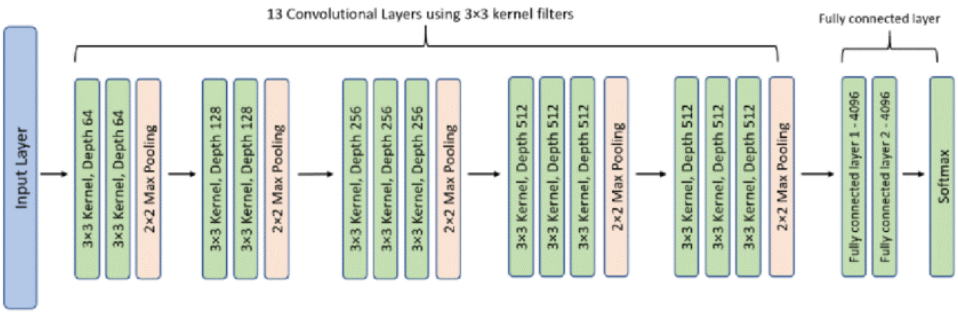

Figure 2. VGG16 Achitecture

The training process aims to optimize the weights in the CNN network so that the model can recognize patterns in images related to the quality of Legen beverages. The development and training of the Convolutional Neural Network (CNN) model for feature extraction include:

- CNN Model with VGG16: VGG16, a CNN architecture proven effective in image classification tasks, is used in this research. This model has several convolutional and pooling layers that enable deep feature extraction from images.

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- CNN Model Training: The CNN model is trained using preprocessed training data to optimize model weights and biases, allowing it to recognize important patterns in images.

Feature Extraction

After training the CNN model, relevant features from the images are extracted using the final layers of the CNN model [14]. These features are then used as input for the subsequent classification model. Feature extraction from training and validation data involves:

- Feature Prediction Using CNN Model: Using the trained CNN model, features from training and validation data are predicted. These features represent a more compact and informative representation of the images.
- Reshape Features for Random Forest: Extracted features are reshaped into a suitable format for input into the Random Forest model.

Random Forest Classification

The research stages used can be seen in Figure 3. The next stage involves classification using Random Forest. Random Forest is an ensemble algorithm consisting of multiple decision trees. In this study, Random Forest is used to classify the quality of Legen beverages based on features extracted by the CNN. This research employs GridSearchCV for hyperparameter tuning, resulting in the best Random Forest configuration that provides optimal accuracy [15].

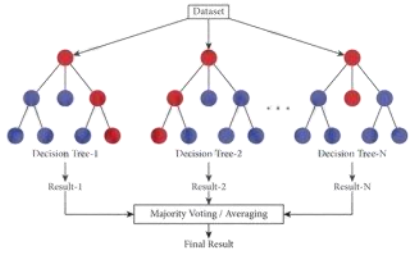

Figure 3. VGG16 Architecture

DISCUSSION

In this study, we explored the use of Convolutional Neural Networks (CNNs) through a transfer learning approach with the VGG16 model for feature extraction, which was then integrated with Random Forest for image classification. Various data splitting configurations were tested to evaluate the model's performance in classifying images into two classes: sterile and mixed.

Data Splitting and Model Accuracy

Table I shows the experimental results showed that different data splitting configurations significantly affected the model's performance. Using 80% of the data for training, 10% for validation, and 10% for testing resulted in the highest validation accuracy of 100% with and without background. This indicates that the model was able to recognize patterns very well when given a sufficient amount of training data. However, this extremely high accuracy also suggests the potential for overfitting, especially if the model struggles to generalize to unseen data.

TABLE I. VALIDATION ACCURACY WITH AND WITHOUT BACKGROUND

	Precision	Recall	F1-Score	Support
campuran	1.00	1.00	1.00	64
steril	1.00	1.00	1.00	64
accuracy			1.00	128
macro Avg	1.00	1.00	1.00	128
weighted Avg	1.00	1.00	1.00	128

Overfitting Challenges

The research stages used can be seen in Figure 4. Although the validation accuracy reached 100% in some configurations, there were strong indications that the model might be overfitting. This was evident from the significant difference between the training loss and validation loss, especially when the validation loss approached zero too quickly. Overfitting can be caused by insufficient training data or a model that is too complex for the dataset used.

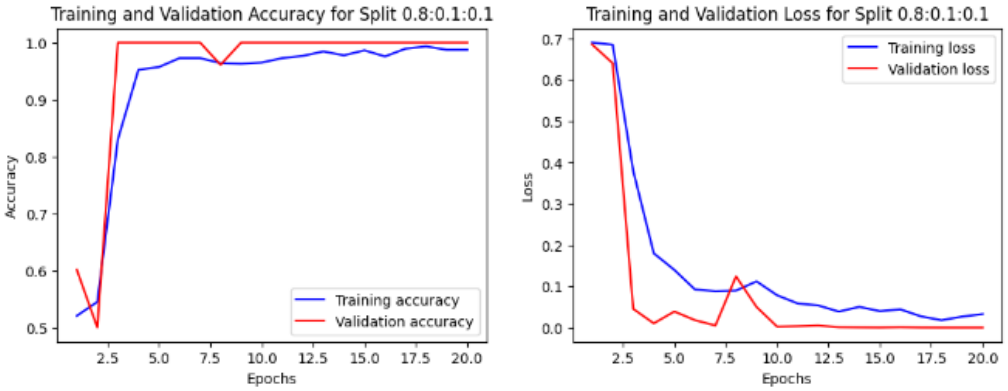

Figure 4. Training and Validation Accuracy Loss

Random Forest Performance

The Random Forest model trained using features extracted from the CNN showed varying performance depending on the data splitting ratio. Although the highest validation accuracy was achieved, performance in some configurations indicated that the model was not optimal in handling larger data variations. This suggests that the model may require further adjustments, such as better hyperparameter tuning or increased model complexity.

Evaluation using Confusion Matrix

The research stages used can be seen in Figure 5. The analysis using the confusion matrix provided in-depth insights into the model's performance in classifying the two classes. Although the model was able to classify many images correctly, there were some classification errors that indicated the model might struggle to distinguish between similar features in the two classes. This suggests the need for further improvements in terms of data quality and quantity.

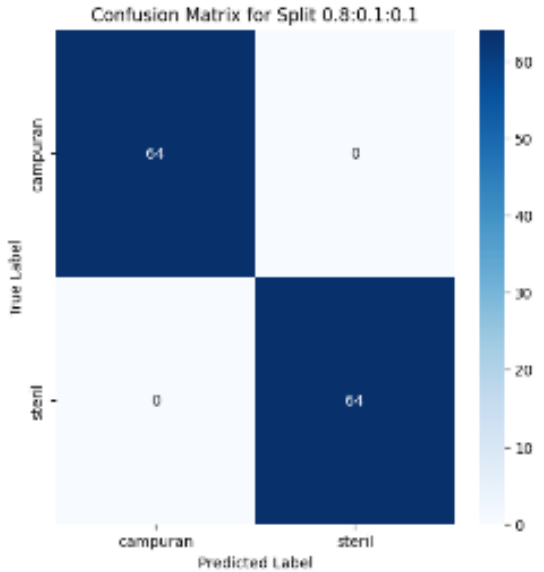

Figure 5. Confusion Matrix

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Implications and Recomendations

The results of this study show that although the transfer learning approach and integration with Random Forest can achieve high accuracy, there are significant challenges in terms of overfitting and generalization. To improve model performance, it is recommended to:

- Increase the amount and variety of training data to help the model recognize more diverse patterns.
- Use regularization techniques to reduce overfitting.
- Explore simpler or more complex model architectures depending on the dataset used.
- Perform more extensive hyperparameter tuning to find the optimal configuration.

This study provides a solid foundation for further development in image classification using the combination of CNN and Random Forest, but also highlights the importance of thorough evaluation of potential overfitting and generalization capabilities of the model.

CONCLUSION

This study investigated the effectiveness of combining CNN and Random Forest for classifying the quality of Tuban's legen drink, specifically differentiating between sterile and mixed beverages. Utilizing a dataset of 1280 images across two classes (Sterile and Mixed), we explored eight different data split ratios to determine the optimal configuration for model training and evaluation.

Our findings demonstrate that the CNN-based Random Forest method significantly improved classification accuracy compared to previous studies. Notably, data split ratios of 80%:10%, 70%:20%, 60%:30%, 40%:50%, 30%:60%, and 10%:80% consistently achieved the highest accuracy of 100% for images with backgrounds. Similarly, for images without backgrounds, the same split ratios, excluding 50%:40%, also yielded the highest accuracy of 100%, specifically with the 80%:10% split.

These results suggest that this approach holds strong potential for classifying legen drink quality. However, considering the high accuracies achieved, future research should consider expanding the dataset or employing more complex data augmentation techniques to further validate and enhance the model's robustness and generalization capabilities. Furthermore, exploring alternative methods or further optimization strategies could lead to even more accurate and reliable classification systems for this specific application.

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