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Grape leaf disease classification using efficientnet feature extraction and catboostclassifier

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ABSTRACT

Grapes are one of the most extensively cultivated crops worldwide due to their significant economic importance. However, the productivity of grape crops is often threatened by diseases caused by bacterial, fungal, or viral infections. Traditionally, the detection of infected grape leaves has been conducted through manual visual inspections, a method that is both time-consuming and prone to biases. Recent studies have leveraged transfer learning models to classify grape leaf diseases with high accuracy. Despite this progress, there is a notable gap in research exploring the integration of transfer learning for feature extraction and machine learning for feature classification in detecting grape leaf diseases. This study introduces a novel approach that combines transfer learning using EfficientNetB0 for feature extraction with a machine learning model, specifically Categorical Boosting (CatBoost), for feature classification. The proposed model demonstrates outstanding performance, achieving an accuracy of 99.56% on the test dataset, surpassing traditional transfer learning methods reported in previous studies.

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1. INTRODUCTION

Grapes are one of the most widely cultivated crops due to their high economic value [1]. Grapes are widely used for direct consumption, beverage ingredients and other processed products [2], [3]. However, problems such as fungal, bacterial and viral infections and unfavourable environmental conditions can affect the productivity of grapevines. Several grapevine leaf diseases such as powdery mildew, downy mildew [4], black rot [5] and grapevine leafroll [6] can damage the leaves, inhibit photosynthesis and reduce grape production and quality. Farmers or plant experts usually detect diseases on grape leaves by looking directly at the symptoms [7]. However, this method requires a lot of time, effort and expertise. It is also prone to error, especially when the disease is in its early stages and difficult to detect. Currently, technologies such as artificial intelligence are helping to identify grapevine leaf diseases more quickly and easily. These technologies, such as machine learning and deep learning, are good at identifying disease patterns in leaves. There are few researchs about classifying grape leaf disease using machine learning and transfer deep learning.

Research from [8] using CNN-VGG16 where VGG16 is used to extract the feature while using Fully-Connected Layer to classify the feature extracted from VGG16. The dataset used in their research are New

Plant Leaf Disease, where the dataset was based from PlantVillage with added augmentation to the dataset [9]. Result from their research, the CNN-VGG16 model reach test accuracy of 97.25%. This research also mentions the usage of 100 another test image collected from Google Image to further evaluate the model, resulting model accuracy of 95% in test data consist of 100 images collected from Google Image. Bin et al [10] use DICNN consist of Deep Separable Convolution Layer to reduce overfitting by reducing the parameters number, Cascade Dense Inception Module to extract feature from the dataset, and the use of Adam optimizer instead of Stochastic Gradient Descent (SGD) for its low memory requirement and simplicity, suitable for model with large data or parameter according to the author. Their research collects 4,023 images consist of 4 class such as anthracnose, brown spot, mites, black rot, downy mildew, leaf blight, and healthy leaves while 3,646 image are collected from publicly available dataset consist of 3 class such as brown spot, black rot, and leaf blight. They use augmentation technique such as brightness adjustment, contrast adjustment, sharpness adjustment, rotation adjustment such as 90 degrees to 270 degrees, symmetry adjustment, adding gaussian noise, and PCA jittering. 7,669 images are augmented into 107,366 image splitted into 60% for training, 20% for validation, 20% for test data. The DICNN model reach accuracy of 97.22% on test data with Deep Separable Convolution Layer reducing parameter count when compared into traditional convolution layer. The model appears more stable in training process with augmented data. Adam optimizer also improve the accuracy of the model slightly.

Another research using VGG also conducted by Thet, Htwe, and Thein [11], where they use VGG16 with Global Average Pooling after output layer to classify grape leaf disease. Global Average Pooling and Softmax layer implemented in this research to replace the Fully-Connected Layer of VGG16's model to improve the accuracy of grape leaf classification. Dataset used in this research are Myanmar Grapevine Dataset consist of 6000 images with 5 class of grape leaf disease such as 1200 anthracnose images, 850 downy mildew images, 930 nutrient insufficient images, 1200 black measles images, 1020 isariopsis leaf spot images, and 800 healthy leaf images from Pearl Grapevine Yard. The dataset was split with 80% for training and 20% for test data. Model from their research reach accuracy of 98.4% in test data. The research also mentions other method related to this research using VGG16 with Fully-Connected Layer and SVM Classifier, reached accuracy of 86.80%.

Uttam et al. [12] use EfficientNetB3 to classify grape leaf disease. The dataset used in their research are PlantVillage dataset consist of 4062 images consist of 423 healthly leaf, 1180 black rot infected leaf, 1383 ESCA infected leaf, and 1076 blight infected leaf. EfficientNetB3 model used in this research reach accuracy of 99.02% on test data, with 100% accuracy when classifying healthly and blight infected grape leaf. However, the model misclassify 1 instance of each Black Rot and ESCA infected leaf. In Kaur et al [13] researchs use EfficientNetB7 to classify grape leaf disease. Dataset used in this research is PlantVillage with 9027 images consist of 2115 healthly grape leaf image, 2360 black rot infected grape leaf image, 2400 black measle infected grape leaf image, 2152 blight infected grape leaf image. The data then splitted with ratio 80% for training and 20% for testing. Accuracy from this model reach 98.7% on test image with total epoch 92.

Currenly, there are limited research about using Transfer Learning model as Feature Extractor and Machine Learning model as feature classification to classify grape leaf disease. Most of the reseach mentioned in section before are either using Convolution Neural Network (CNN), Transfer Learning model such as MobileNet and EfficientNet, or by adding modification to the CNN and Transfer Learning model's layer. There are some researchs about using Transfer Learning model as feature extraction and Machine Learning model as feature classification in different topic such as research by Dutta and Wahab Sait [14] to classify speech disorder from Mel-Spectogram using EfficientNetB7 and MobileNetV3 to extract feature and CatBoost model to classify the feature. Using CNN feature engineering and CatBoost model as feature classification, Sait and Awad [15] use the model to detect Coronary Artery Disease (CAD) from computer tomograpy image. Both researchs achieved high accuracy outperform CNN and Deep Transfer Learning model mentioned on their research. Based on their research, this research will be focused on using Transfer Learning model as feature extractor and Machine Learning model as feature classification. EfficientNetB0 will be used in this study as feature extraction and CatBoost will be used as feature classification. This objective of this research is to improve the accuracy of the grape leaf disease classification model from the past research.

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2. METHOD

The study contain research from dataset collection, pre-processing method using ImageDataGenerator, model building consists of Feature Extractor model and Classification Model, and model evaluation using metric such as accuracy, precision, recall, f1-score. Figure 1 is the flow of this research.

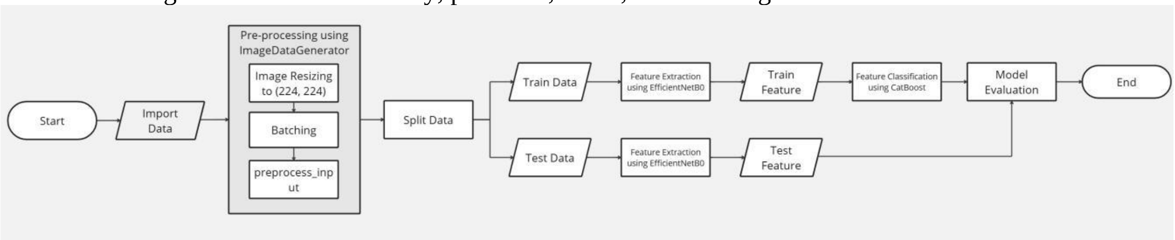

Figure 1. Flow of the research

Dataset

Dataset used in this research is Grapevine Disease Dataset (Original) collected from kaggle by Rajarshi Mandal [16]. Dataset contain 9027 images with 7222 images for training and 1805 image for testing. There is 4 class in this dataset, namely ‘Black Rot’, ‘ESCA’, ‘Healthly’, and ‘Leaf Blight’. Each of the image have resolution of 256 x 256 and come in .jpg format. Example of image can be seen on Figure 2 while number of images each class is shown on Table 1.

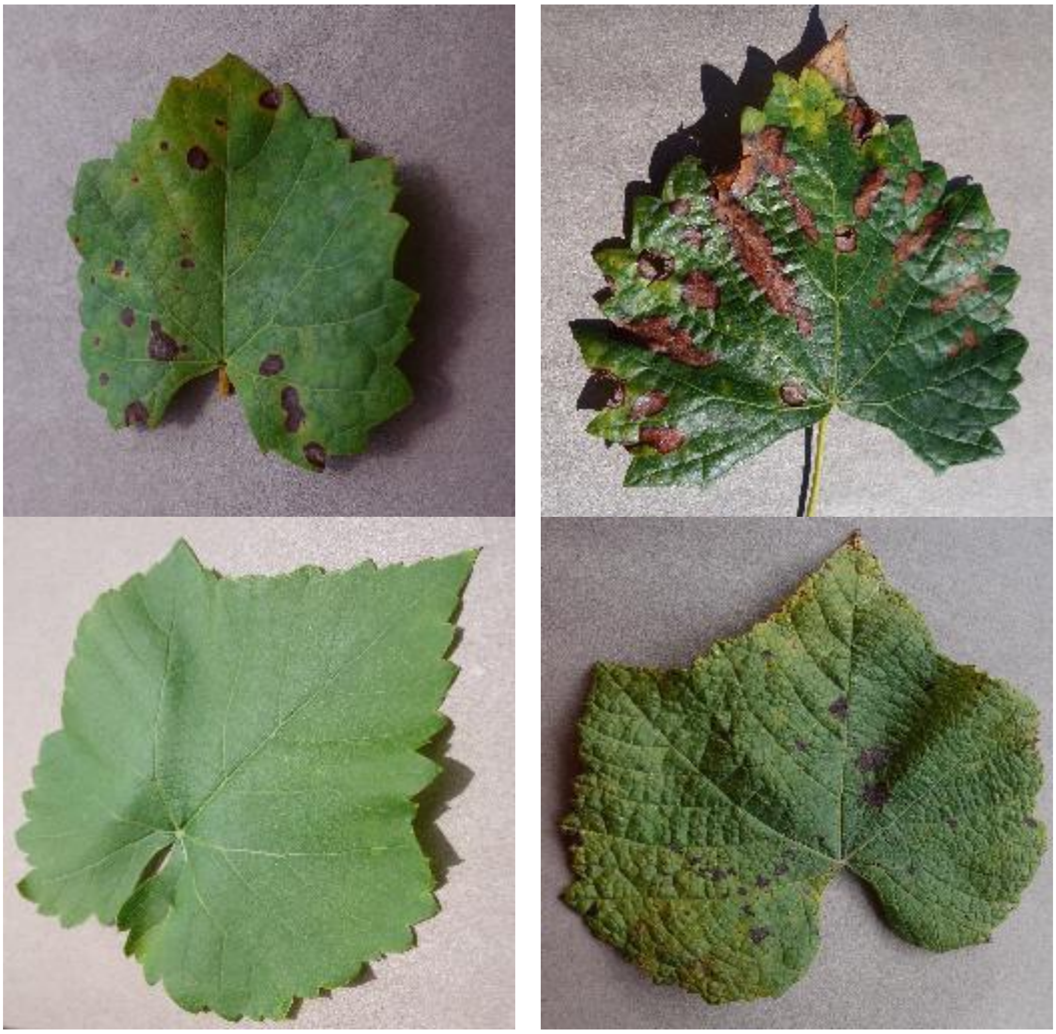

Figure 2. **(**Upper left) black rot, (upper right) ECSA, (bottom left) healthly, (bottom right) leaf blight.

Table 1. Training and test images data count.

Class	Training Images	Test Images
Black Rot	1888	472
ESCA	1920	480
Healthly	1692	423
Leaf Blight	1772	430

Pre-processing Method

Preprocessing method in this study consist of Image resizing, where each of image in the dataset are resized from original 256x256 to more smaller 224x224, since EfficientNetB0 by default accepting input size of 224x224. After resizing each image in the dataset, the data then is batched with batch_size is 32. This mean every time the model EfficientNetB0 extracted the feature in one-go, there are 32 image that are processed by EfficientNetB0 model [17]. This batching process ensure the feature extraction process is fast enough while retaining the good quality of feature extracted [18]. Last process is applied preprocess_input function to check whether the image have the pixel with accepted range for EfficientNetB0. The pixel range accepted by EfficientNetB0 are [0, 255].

Model Building

Model building is a process to build the model for grape leaf classification. There are 2 processes used to classify grape leaf disease, Feature Extraction and Feature Classification. Feature Extraction is a process to extract feature from data, either image or text-based data [19]. For this task, EfficientNetB0 is used in this study due to relative compact yet powerful feature learning using compound scaling method [20]. Compound scaling is a method to proportionaly scale resolution, depth, and wide of the network to ensure the network are optimized, therefore achieve improved accuracy and efficiency [21]. Figure 3 is the construction of EfficientNetB0 used as feature extractor.

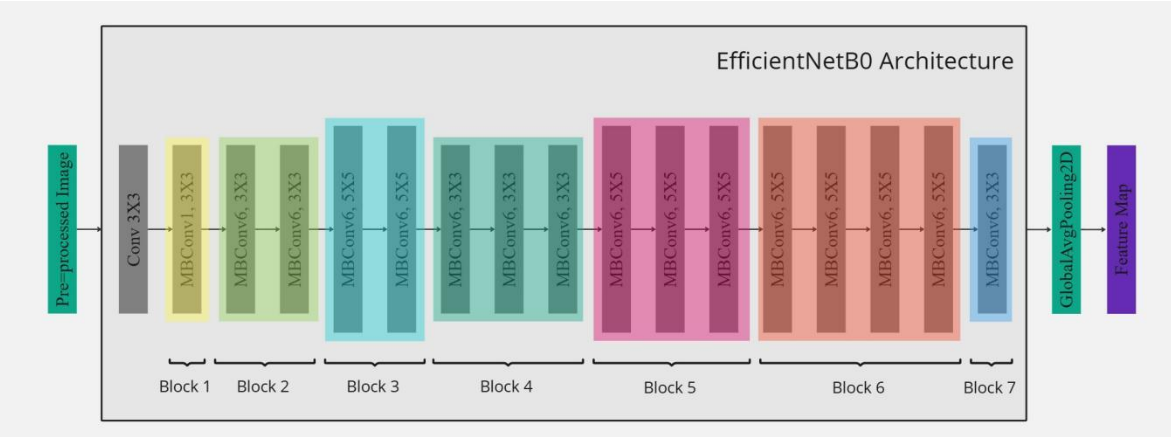

Figure 3. Construction of EfficientNetB0 as a feature extractor

EfficientNetB0 consist of Mobile-Inverted Convolutional Block (MBConv Block) inspired by MobileNet Construction with Squzeze-and-Excitation optimization [22]. The Mobile Inverted Convolutional Block in EfficientNet uses inverted residuals, depthwise separable convolutions, and Squeeze-and-Excitation to improve efficiency and performance [23]. While Squzeze-and-Excitation unit employs an adaptive recalibration process that models the interdependencies between channels, thereby enabling the recalibration of channel-wise feature responses [24].

CatBoost or Categorical Boosting is an algorithm created by Prokhorenkova et al. in 2018 based on Gradient Boosting Algorithm where the algorithm uses binary decision tree as base predictor [25]. Notable feature of CatBoost is Ordered Boosting, which uses a permutation-driven approach to mitigate prediction shifts caused by target leakage, which is a common issue in traditional gradient boosting algorithms [25]. Another feature of this algorithm is the handling of categorical features without the necessity for one-hot encoding and handling imbalanced data by employing an objective function that considers the class distribution of the data. The base model used by CatBoost is a fully symmetric tree, and the same splitting criteria are applied at every layer [26]. Additionally, CatBoost utilizes categorical characteristics, which significantly increase the dimensionality of the features and enhance prediction stability and speed [26].

Model Evaluation

Model will be evaluated using metric such as accuracy, precision, recall, f1-score. Formula (1), (2), (3), (4) are used to calculate each of the metric used to evaluate the model in this study.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)} \quad (4)$$

3. RESULTS AND DISCUSSIONS

Experiment Result

The experimentation and result of the experiment of proposed EfficientNetB0 as Feature Extractor and CatBoost as Feature Classification to classify grape leaf disease with dataset mentioned in section before will be discussed in this section. The model will be trained and tested using Grapevine Disease Dataset consist of 9027 images split into 7022 images for training and 1805 image for testing. There are 4 class in this dataset, namely 'Black Rot', 'ESCA', 'Healthly', and 'Leaf Blight'. Preprocessing of the data consist of resizing the image from the original size 256x256 into smaller 224x224. Then the dataset will be batched with each batch will consist of 32 images. After that, the preprocess_input function for Keras library will be applied to the image to check whether the pixel of the image is in range between 0 and 255 as EfficientNetB0 only accept image with those pixels range as input. The dataset is already splitted into training and testing from the dataset source itself, so in this study, it doesn't need to be splitted.

EfficientNetB0 is used to extract the feature from the dataset. Feature extracted from last layer of EfficientNetB0 then passed to Global Average Pooling layer to be flatten into 2-dimensional data consist of amount of data and feature extracted, usually the amount of feature extracted from last layer of EfficientNetB0 after passed into GAP layer is 1280 feature. After feature extraction process by EfficientNetB0, next process is classification process using CatBoost Algorithm.

This study uses CatBoost as feature classification where after feature from the image extracted by EfficientNetB0, the feature extracted passed into CatBoost Classifier. Library CatBoostClassifier from CatBoost is used for feature classification task in this study. Hyperparameter of CatBoostClassifier was manually-tuned as shown in Table 2.

Table 2. Hyperparameter of catboostclassifier

Hyperparameter	Default value	Picked value	Explanation
iterations	1000	3000	The maximum number of trees that can be built when solving machine learning problems.
learning_rate	0.1	0.075	The learning rate used for training.
l2_leaf_reg	None	10	Coefficient at the L2 regularization term of the cost function.
depth	None	6	Depth of the trees.

After hyperparameter tuning, the model will be trained using train feature extracted from train image using EfficientNetB0. Model evaluation will be carried on test feature extracted from test image also using EfficientNetB0. Model will be evaluated using metric such as accuracy, precision, recall, F1-score. Classification Report consist of precision, recall, and F1-score of each class, macro average and weighted average can be seen on Table 3 while Confusion Matrix can be seen on Figure 4.

Table 3. Performance comparation of the model

Model	Accuracy	Precision		Recall		F1-score	
		Macro	Weighted	Macro	Weighted	Macro	Weighted
Original CatBoost	99.22%	99.26%	99.22%	99.26%	99.22%	99.26%	99.22%
Manually-Tuned CatBoost	99.56%	99.58%	99.56%	99.58%	99.56%	99.58%	99.56%

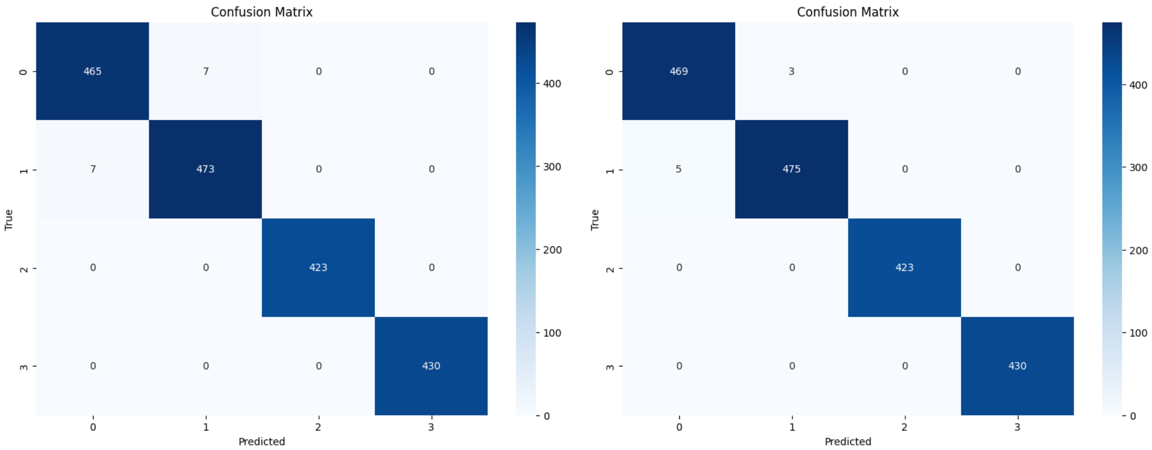

Figure 4. Confusion matrix of the original (left) and manually-tuned catboost (right) model.

Both model perfectly classify both healthly and leaf blight grape leaf from the dataset. However Black Rot and ESCA grape leaf disease are not perfectly classified. There are 7 instances where Black Rot Image predicted as ESCA and 7 instance where ESCA image predicted as Black Rot and other model have less missclassification, with 3 instances where Black Rot Image predicted as ESCA and 5 instance where ESCA image predicted as Black Rot. Both diseases visually might look exactly same, with difference are Black Rot infected leaf will have black spot in their leaf while ESCA infected leaf will have striped black spot in their leaf. Other research also faced similar issue, such as research by Uttam et al [12] where their model also suffers the same issue as this research's proposed model. Figure shown both example of misclassification. Example of misclassification can be seen on Figure 5.

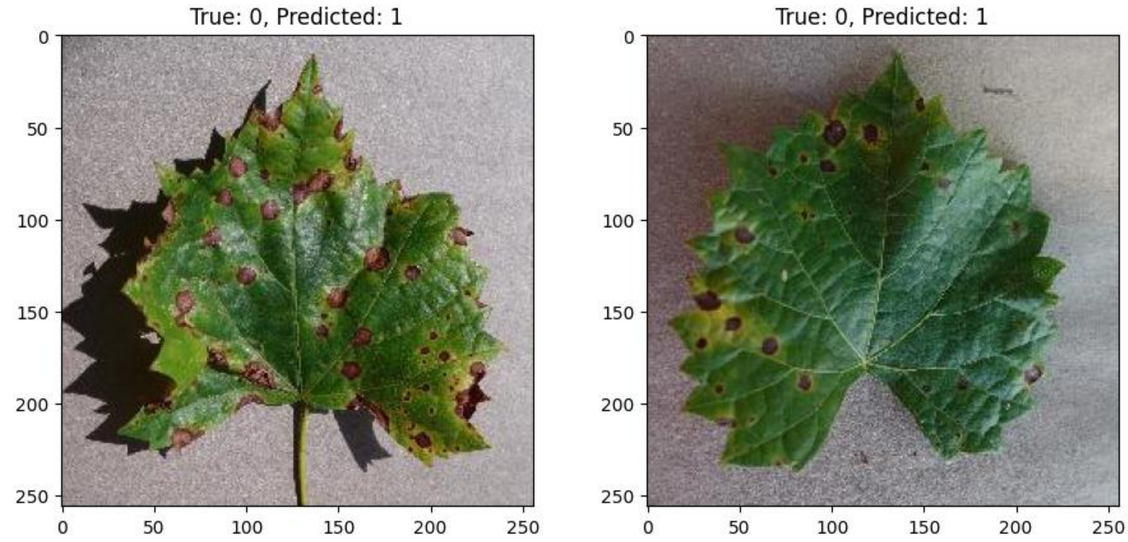

Figure 5. Example of misclassification from the model

Discussion

With the result from section before, the proposed model will be compared to others research before. Table 4 shown the comparation between proposed model with other similar past research.

Table 4. Comparation with others similar research

Author	Method	Dataset Description	Result
M. A. Hasan, Y. Riyanto, and D. Riana. [8]	CNN-VGG16	4000 images, 4 class	Reached Classification Accuracy of 97.25% on test data
B. Liu, Z. Ding, L. Tian, D. He, S. Li, and H. Wang. [10]	Improved-DCNN	7669 images, 7 class	Reached Classification Accuracy of 97.22% on test data with noticeable decrease in parameter count
K. Z. Thet, K. K. Htwe and M. M. Thein. [11]	CNN-VGG16-GAP	6000 images, 5 class	Adding GAP layers improve accuracy of VGG16 from 90.2% to 98.4%
A. K. Uttam. [12]	EfficientNetB3	4062 images, 4 class	Using EfficientNetB3, classification accuracy reachs 99.02%.
Kaur, P. et al [13]	EfficientNetB7	9027 images, 4 class	Reach Classification accuracy of 98.7%
Proposed Method	**EfficientNetB0 + CatBoost**	**9027 images, 4 class**	**Reach classification accuracy of 99.56% on test data**

Based on the comparation with other method in Table 4, it can be said that the proposed model outperforms other complex model such as EfficientNet and VGG16 by accuracy metric, therefore it can be said that using transfer deep learning as feature extraction and machine learning as feature classification can improve the accuracy of grape leaf disease classification.

4. CONCLUSION

Grape is the most widely cultivated crop due to high economic value. However, grape disease caused by bacterial, fungi, or virus infection can affect the productivity of grape crop. Most of the infected grape's inspection are done manually by visual which can be time consuming and produce some bias. There are some researches utilize transfer learning model to classify grape leaf disease with high accuracy. However, there is noticable lack of research utilizing combination of transfer learning for feature extraction and machine learning for feature classification to classify grape leaf disease. This research proposed a new model using transfer learning model, namely EfficientNetB0 to extract the feature from grape leaf dataset and machine learning model, namely Categorical Boosting or CatBoost to classify the feature extracted by EfficientNetB0. The proposed model performs really well, achieving 99.56% accuracy on test data, outperform other traditional transfer learning method from the past research. This paper also found out the issue with the model where the model cant fully accurate classify Black Rot and ESCA infected grape leaf. Future research can be focused on improving classification accuracy on both Black Rot and ESCA infected grape leaf disease using different combination of deep transfer learning model and machine learning model.

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