Method for Hyperparameter Tuning of EfficientNetV2-based Image Classification by Deliberately Modifying Optuna Tuned Result

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***Abstract*—Method for hyperparameter tuning of EfficientNetV2-based image classification by deliberately modifying Optuna tuned result is proposed. An example of the proposed method for textile pattern quality evaluation (good or bad textile pattern fluctuation quality classification) is shown. When using the hyperparameters obtained by Optuna without changing them, the accuracy certainly improved. Furthermore, as a result of learning by changing the hyperparameter with the highest degree of importance, the accuracy changed, so it could be said that the degree of importance was certainly high. However, the accuracy also changes when learning is performed by changing the least important hyperparameter, and sometimes the accuracy is improved compared to when learning is performed using the optimal hyperparameter. From this result, it is found that the optimal hyperparameters obtained with Optuna are not necessarily optimal.**

***Keywords*—Hyperparameter tuning; EfficientNetV2; Optuna; textile pattern; optimal hyperparameter; learning process; pattern fluctuation**

I. INTRODUCTION

To optimize these hyperparameters, hyperopt, gpyopt, AutoML, PyCaret, Optuna, etc. have been proposed as black box optimization methods, which automate trial and error regarding hyperparameters and automatically discover optimal solutions. Similarly, as black box optimization methods, white box conversion of DL, binary decision trees, random forests, and mind maps using GNNs has also been proposed [1]. In particular, Optuna uses an algorithm called TPE (Tree-structured Parzen Estimator), which is a new method in Bayesian optimization, and is capable of parallel processing, and can be restarted midway by saving the results to the database.

Depending on the definition of the objective function and the validity of the importance of the parameters, hyperparameters that are not necessarily suitable for comparison with the evaluation criteria may appear. Therefore, in this paper, we introduce such a case and propose a method of intentionally changing the hyperparameters obtained through optimization with Optuna and selecting parameters with greater accuracy through trial and error.

As an application example of this method, we will show an example in which it was applied to the classification of pattern shifts in Kurume Kasuri. This is just one application example, and the proposed method can be widely applied to other classifications.

In Section II, research background and related research works are described followed by the proposed method for hyperparameter tuning by modifying Optuna tuned result in Section III. Then experiment of application of the proposed method given in Section IV followed by remarks in Section V. Conclusion and future research work is given in Section VI and Section VII respectively.

II. RESEARCH BACKGROUND AND RELATED RESEARCH WORKS

A. Research Background

Kurume Kasuri is a traditional cotton fabric handed down in the Chikugo region, and it is completed through over 30 steps, including design, binding, dyeing, and weaving. A major feature of Kurume Kasuri is that the yarn is pre-dyed and the patterned thread is woven while matching the patterns, resulting in subtle deviations and a unique faded pattern.

Regarding the degree of deviation, it is fine if the pattern shift is moderate, but if the deviation is too large, the product will not sell and will have to be sold at a low price. In addition, there is the problem that the evaluation criteria for the degree of deviation differ depending on the manufacturer. Therefore, in this study, we build an image recognition model that classifies whether the pattern shift of Kurume Kasuri is within an acceptable range (good or bad). At that time, Optuna searches for optimal hyperparameters and intentionally changes the most and least important parameters to improve accuracy.

B. Examples of Quality of Kurume Kasuri

Typical patterns of Kurume Kasuri are shown in Fig. 1. This Kurume Kasuri is woven with a rectangular pattern in mind. An example of pattern shift is shown in Fig. 2. Green indicates patterns within the acceptable range, and red indicates patterns outside the acceptable range. The red color has a shape that is almost different from the rectangular pattern, and it can be seen that the pattern is clearly too out of alignment.

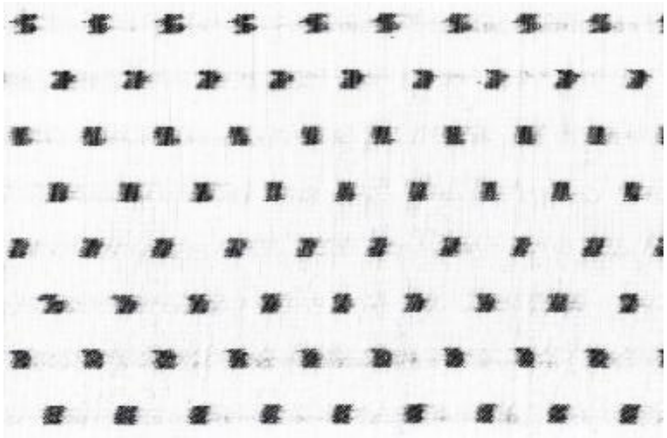


Fig. 1. Typical kurume kasuri image. (sideways)

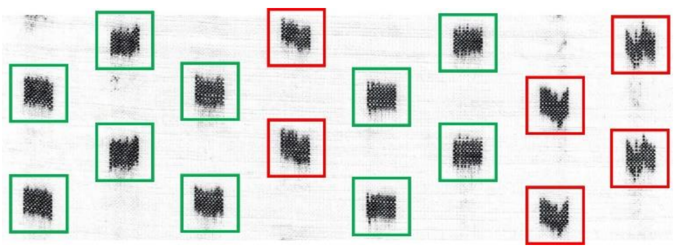


Fig. 2. Example of kurume kasuri pattern shift. (Green: Within the acceptable range, Red: Outside the acceptable range).

C. Related Research Works

It has been proposed a method to evaluate the quality of pattern shifts in Kurume Kasuri by considering them as 1/f fluctuations [2]. Other than this, there are image classification method related research works as follows,

EfficientnetV2: Smaller models and faster training are proposed [3] together with deep neural network configurations of network is network [4].

Classification by re-estimating statistical parameters based on auto-regressive model is proposed [5]. Meanwhile, multi-temporal texture analysis in Landsat Thematic Mapper: TM classification is also proposed [6]. On the other hand, maximum likelihood TM classification taking into account pixel-to-pixel correlation is proposed [7] together with a supervised TM classification with a purification of training samples [8]. Meantime, TM classification using local spectral variability is proposed in [9]. Also, classification method with spatial spectral variability is proposed in [10] together with TM classification using local spectral variability [11].

Application of inversion theory for image analysis and classification methods is proposed [12]. Meanwhile, polarimetric Synthetic Aperture Radar: SAR image classification with maximum curvature of the trajectory in Eigen space domain on the polarization signature is proposed [13].

A hybrid supervised classification method for multi-dimensional images using color and textural features is proposed [14]. On the other hand, polarimetric SAR image classification with high frequency component derived from wavelet Multi Resolution Analysis: MRA is proposed [15].

Comparative study of polarimetric SAR classification methods including proposed method with maximum curvature of trajectory of backscattering cross section in ellipticity and orientation angle space is proposed [16].

Human gait gender classification using 2D discrete wavelet transforms energy is attempted [17] together with human gait gender classification in spatial and temporal reasoning [18]. Meanwhile, comparative study on discrimination methods for identifying dangerous red tide species based on wavelet utilized classification methods is conducted [19].

Multi spectral image classification method with selection of independent spectral features through correlation analysis is proposed [20]. Meanwhile, image retrieval and classification method based on Euclidian distance between normalized features including wavelet descriptor is proposed [21].

Gender classification method based on gait energy motion derived from silhouettes through wavelet analysis of human gait moving pictures is proposed [22] together with human gait skeleton model acquired with single side video camera and its application and implementation for gender classification [23]. Meantime, gender classification method based on gait energy motion derived from silhouette through wavelet analysis of human gait moving pictures is proposed [24] together with human gait gender classification using 3D discrete wavelet transformation feature extraction [25].

Image classification considering probability density function based on Simplified beta distribution is proposed [26]. Maximum likelihood classification based on classified result of boundary mixed pixels for high spatial resolution of satellite images is proposed [27]. On the other hand, context classification based on mixing ratio estimation by means of inversion theory is proposed [28].

Optimum spatial resolution of satellite-based optical sensors for maximizing classification performance is found [29]. Meanwhile, the combined non-parametric and parametric classification method depending on normality of Probability Density Function: PDF of training samples is proposed [30]. In recently, method for hyperparameter tuning of image classification with PyCaret is proposed and well validated [31].

III. Proposed Methods

A. Image Recognition Model

In order to classify whether the pattern shift is within an acceptable range, we used the pre-trained model EfficientNetV2 [3]. EfficientNetV2 is a model that achieves both learning efficiency and high classification accuracy by using NAS (Neural Architecture Search) and model scaling.

Regarding the implementation, using TensorFlow in Python, we added Global Average Pooling [4] and dropout to the final layer of EfficientNetV2, which is a model that has already trained ImageNet, and built a model that changed to binary classification (see Fig. 3). Global Average Pooling is a layer that takes the average value for each feature map obtained in the previous layer. By using this, it is possible to reduce the number of parameters compared to the case of a fully connected layer.

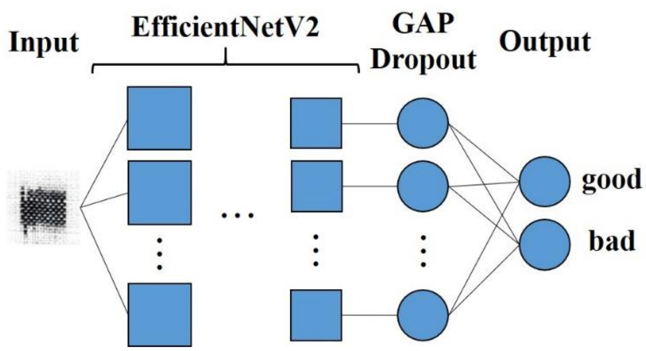


Fig. 3. Model architecture.

With this model, we performed two types of learning: transfer learning only and transfer learning + fine tuning.

B. *Hyperparameter Tuning*

Hyperparameter tuning was performed using the following three methods, and the accuracy of each method was compared.

1) Manual setting.

2) Optimization using Optuna.

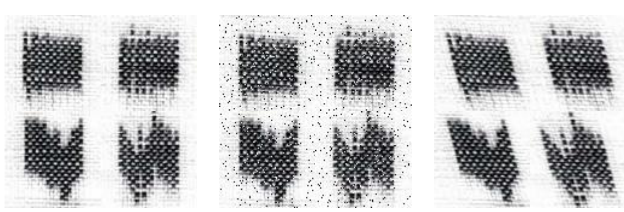
3) Deliberately changing the most important (lowest) hyperparameter among the hyperparameters obtained by Optuna.

In addition, in (2) Optimization using Optuna, specify TPE as the Sampler.

IV. Experiment

A. *Data Used*

From the scanned Kurume Kasuri images, contour extraction and other operations were performed using OpenCV, and a total of 70 pattern images of 80 × 80 pixels were extracted. Then, based on the results obtained from the pattern evaluation questionnaire to weavers, patterns with pattern shift within the acceptable range were classified as good, and patterns outside the acceptable range were classified as bad [2]. After that, we used a total of 210 image data (training: 180 images, test: 30 images) that was created by applying data augmentation to all of them by adding salt-and-pepper noise and skew (see Fig. 4).



(a) Original (b) Salt and pepper noise (c) Skew

Fig. 4. Sorted Kurume Kasuri pattern image. (upper - good, lower - bad).

B. *Transfer Learning*

Table I shows the hyperparameters and prediction accuracy for test data when optimizing manually and using Optuna in transfer learning. The two hyperparameters searched were dropout rate and batch size, and the results showed that learning using the optimal hyperparameters obtained by Optuna resulted in better accuracy.

TABLE I. Hyperparameters and Prediction Accuracy for Test Data when Optimized Manually and with Optuna

	Manual	Optuna
Dropout Rate	0.5	0.129 [0 ~ 0.5]
Batch Size	16	32 [16, 32, 64]
Accuracy	76.67%	90%

※The hyperparameter search range is in []

The importance of hyperparameters obtained through optimization using Optuna is shown in Fig. 5. The dropout rate is 0.77 and the batch size is 0.23, indicating that the dropout rate is more important.

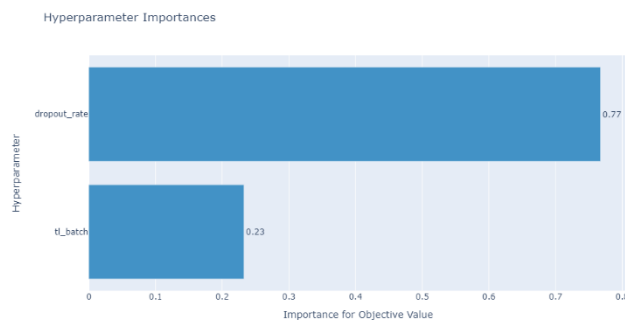
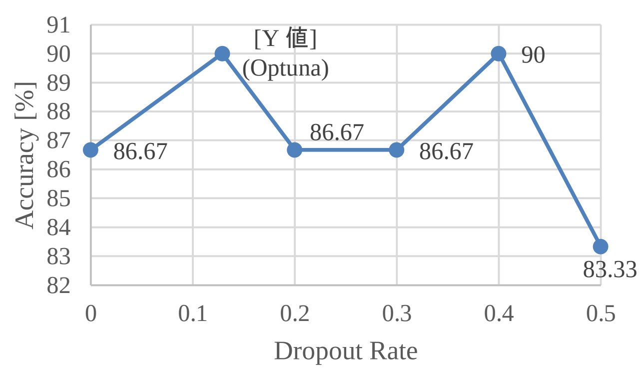
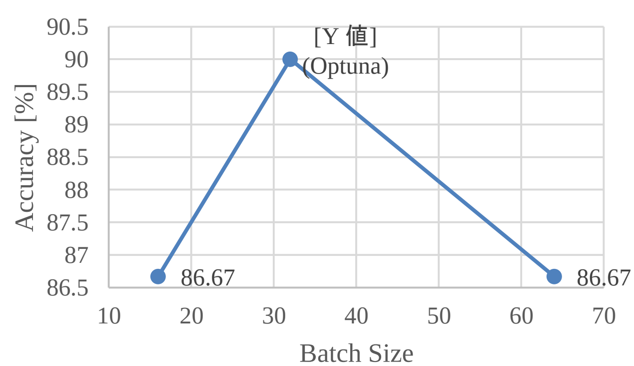


Fig. 5. Importance of hyperparameters when transfer learning was performed.



(a) Changed only the dropout rate, which had the highest importance.



(b) Changed only the batch size, which had the lowest importance.

Fig. 6. Change in accuracy when changing hyperparameters of high (low) importance among the hyperparameters obtained by optimization with Optuna.

Fig. 6(a) shows the change in accuracy when only the dropout rate, which was highly important, was changed. Accuracy changed to some extent, but not regularly, and never exceeded the 90% accuracy in Optuna.

Fig. 6(b) shows the change in accuracy when only changing the batch size, which was of low importance. Accuracy changed little and never exceeded the accuracy of Optuna of 90%, as was the case when only the dropout rate was changed.

C. Transfer Learning and Fine Tuning

Table II. shows the hyperparameters and prediction accuracy for test data in transfer learning + fine tuning when optimized manually and with Optuna. The searched hyperparameters were the dropout rate, the learning rate, the number of epochs and batch size for transfer learning, and the batch size for fine tuning.

TABLE II. HYPERPARAMETERS AND PREDICTION ACCURACY FOR TEST DATA WHEN OPTIMIZED MANUALLY AND WITH OPTUNA

	Manual	**Optuna**
Dropout Rate	0.5	0.124 [0 ~ 0.5]
Learning Rate	0.001	0.001 [0.001, 0.0005, 0.0001]
Epoch (Transfer Learning)	10	15 [10, 15, 20]
Batch Size (Transfer Learning)	16	32 [16, 32]
Batch Size (Fine Tuning)	16	32 [16, 32]
Accuracy	50%	80%

※The hyperparameter search range is in []

As with the case where only transfer learning was performed, the optimal hyperparameters obtained by Optuna were used. The result was that the accuracy was better when learning was performed. The importance of hyperparameters obtained through optimization using Optuna is shown in Fig. 7. The dropout rate was the most important at 0.49, and the batch size (transfer learning) was the lowest at 0.05.

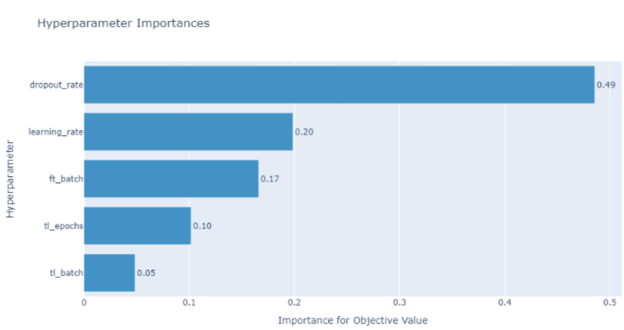
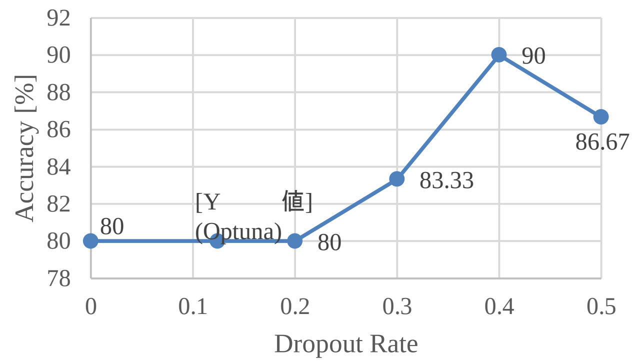


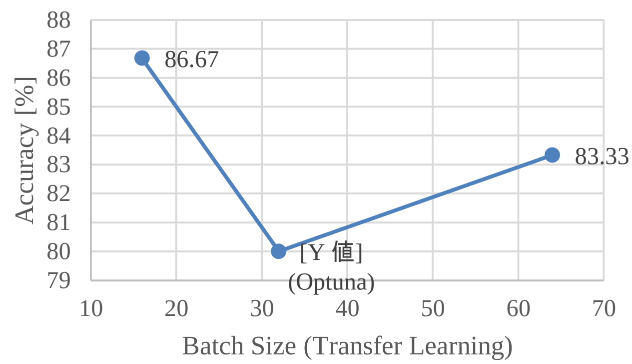
Fig. 7. Importance of hyperparameters when transfer learning and fine tuning were performed.

Fig. 8(a) shows the change in accuracy when only the dropout rate, which was highly important, was changed. Unlike the case of only transfer learning, the accuracy changed significantly, and when the dropout rate was 0.4, the accuracy was 90%, which exceeded the accuracy of Optuna of 80%.

Fig. 8(b) shows the change in accuracy when only changing the batch size (transfer learning), which was of low importance. Unlike the case of only transfer learning, the accuracy changed to some extent, and exceeded the accuracy of Optuna of 80%, which is the same as when changing only the dropout rate.



(a) Changed only the dropout rate, which had the highest importance.



(b) Changed only the batch size in the transfer learning, which had the lowest importance.

Fig. 8. Change in accuracy when changing hyperparameters of high (low) importance among the hyperparameters obtained by optimization with optuna.

V. REMARKS

In both the case of transfer learning only and the case of performing fine tuning after transfer learning, the dropout rate was the most important. This is thought to be because only the dropout rate had a continuous search range and the widest search range, while the other hyperparameters had a categorical search range.

The reason why the accuracy change was not regular when only the dropout rate was changed is because the nodes deleted by Dropout are random, so if a node with features that have a large impact on classification is deleted. This is thought to be due to the fact that there were cases where this was not done. In order to measure accuracy more accurately, it is necessary to perform verification using K-fold cross validation.

In transfer learning + fine tuning, by changing the hyperparameters with the highest (lowest) importance, the accuracy was improved compared to the results with Optuna. This is because Optuna's search algorithm used this time, TPE, is based on Bayesian optimization and does not exhaustively search all hyperparameters like grid search, so a locally optimal solution was reached. This is thought to be the cause.

VI. Conclusion

We proposed a method of intentionally changing the hyperparameters obtained through optimization using Optuna and selecting parameters with greater accuracy through trial and error. As an application of the proposed method, we classified pattern shifts in Kurume Kasuri.

In both cases, whether it's transfer learning alone or fine-tuning after transfer learning, learning with hyperparameters obtained through optimization with Optuna clearly improved accuracy compared to setting them manually. In transfer learning + fine tuning, by changing the hyperparameters with the highest (lowest) importance, the accuracy was improved compared to the results with Optuna.

From this result, we found that the optimal hyperparameters obtained with Optuna are not necessarily optimal.

VII. Future Research Works

Further study is required for validation of the proposed method for hyperparameter tuning with a variety of examples of image classifications. Also, the other method for optimization of automate hyperparameter search has to be investigated in the near future.

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