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Ensemble Learning Development Based on Transfer Learning for Indonesian Traditional Food Detection

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ABSTRACT

Development of traditional food competes with other traditional foods now. They must compete with fast food and food from abroad. In 2013, the food and beverage sector were the second highest contributor to tourist expenditure after accommodation. This shows its very important role in the economy. That caused, we need a model that can predict traditional Indonesian foods and snacks. We used ensemble learning. It had 2 transfer learning methods, namely VGG-19 and Xception. They will be combined to improve the performance of the existing model. The research result shown output. It has found that the ensemble learning model achieved accuracy of up to 97% on training data and 91% on testing data. It is hoped that this prediction model can help people recognize typical Indonesian food and increase interest in and preserve the food around them.

Keywords : *transfer learning; ensemble learning; xception; VGG-19;*

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1. INTRODUCTION

Indonesia has a rich and unique culture spread throughout its islands. One aspect of this wealth lies in the variety of traditional foods that every region in Indonesia has. Traditional food is a type of food that has been passed down from generation to generation and is an important part of a region's cultural identity [1]. Each region has different human characteristics and habits, so traditional foods also differ in terms of shape, taste and variety. By looking at the traditional food in an area, we can understand the natural conditions, habits, values and beliefs held in that area. As ancestral relics, traditional food is also considered a valuable cultural heritage.

Broadly speaking, traditional food can be categorized into 3 types, namely [2]:

a. Endangered food

This food is rarely found on the market and has a high level of rarity. Several factors that cause this food to be scarce include the limited number of people who make it. Apart from that, this food is also threatened by competition with other types of food.

b. Less popular food

This food is still often found and available on the market but has few fans and is less well known by the public.

c. Popular food

This food is very common and easy to find and popular among people from various backgrounds.

The globalization of era, traditional food not only competes with other traditional foods, but also must compete with fast food and food from abroad. The increasing public interest in trying imported foods has led to the widespread spread of these foods. As a result, people are slowly starting to abandon traditional food and prefer fast food or food from abroad [3].

This will have various long-term consequences. The lack of interest in traditional food has resulted in a decline in sales, which in turn can encourage sellers to switch professions from making traditional food to other jobs. If the number of traditional food makers decreases, the preservation of traditional food will also be hampered because no one makes and enjoys it. Without realizing it, foods that were once common in society can disappear over time. When these foods are lost, future generations will not know the shape, taste, or even the existence of traditional foods that should be cultural heritage [4].

Conservation considerations aside, the food sector has enormous potential. In Indonesia, in 2013, the food and beverage sector were the second highest contributor to tourist expenditure after accommodation. This shows that is very important role in the economy. Its mean the food and beverage sector contributed 17.7% of the total average expenditure of $1,142 USD spent by foreign tourists, while accommodation costs contributed 48.9% [5].

Preserving traditional foods has enormous benefits, both culturally and economically. we can maintain the existence of our ancestral heritage and maintain cultural richness by preserving traditional food. Economically, preserving traditional food can provide various benefits, such as increasing income in the surrounding area, creating new jobs, and developing the economic and tourism sectors.

After considering the things above, I was finally motivated to contribute to the preservation of traditional food through the IT sector. To introduce traditional food to various groups of society, we created a model that can detect traditional food in Indonesia. We developed a transfer learning model consisting of various types of traditional food and snacks by utilizing Machine Learning technology. This model is trained to automatically recognize traditional food names based on images entered by the user.

It is hoped that this research will make it easier for people to identify various types of traditional food around them and can introduce the diversity of food found in Indonesia to various groups of society, especially the younger generation. Furthermore, it is hoped that this research will be able to improve the tourism sector as people's knowledge and interest in traditional food increases.

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2. LITERATURE REVIEW

A study on traditional Indonesian food was carried out in 2022 by Grendion Prajena et all. This study uses convolutional neural networks to provide a reliable classification for recognizing 10 types of traditional Indonesian food. The system proposed by this study can achieve 90% accuracy [1].

In 2020 Ari Wibisono et all. conducted a study on an automatic Indonesian traditional food recognition system. This study uses several types of convolutional neural networks such as Densenet121, Resnet50, InceptionV3, and Nasnetmobile. The results of this study show that when using a high-quality dataset, the Indonesian traditional food recognition system is automatic with accuracy, precision and recall of 0.95[2].

Another study that uses convolutional neural networks for automatic classification of traditional Indonesian food. This study uses ResNet50 architecture and 200 images for classification of traditional Indonesian food. The model used in this study achieved an accuracy of 96% [3].

In 2022, Vijaya Kumari G. et all, used Efficientnetb0, a transfer learning technique. The model developed by researchers can classify 101 types of food with an accuracy of 80% [4]. Amritto Sarker Sagor et all, used ensemble learning to classify 58 local Bangladeshi foods. Using transfer learning this researcher was able to get an accuracy of 86% [5].

In 2022 Puteri Khatya Fahira et all, showed that the Random Forest classifier achieved the best accuracy compared to other classifiers. From the experimental results, it can be concluded that the standard of the data acquisition process influences the high accuracy achieved by the classifier. In the future, obtaining data on different Javanese traditional foods from the internet could be useful to test the performance of this method on datasets with different image conditions [6].

In 2024 Ajeng Wulandari, this experiment uses a Padang cuisine dataset consisting of 993 images from 9 classes for the training and testing phases. Several pre-trained CNN models, namely VGG-16, InceptionV3, MobileNetV3, and DenseNet-201, were compared to find out the best model for this experiment. The results show that DenseNet-201 achieves the highest scores in accuracy, precision, recall, and f1-score. This means DenseNet-201 is the most suitable model for automating this food recognition [7].

a. Transfer Learning

Transfer learning is when an existing model is reused to solve a new challenge or problem. Transfer learning is not a different type of machine learning algorithm, but rather a technique or method used when training a model. Knowledge developed from previous training is recycled to help perform new tasks. The new task will be related to a previously trained task, which could be categorizing objects in a particular file type. Pre-trained models typically require a high level of generalization to adapt to new, never-before-seen data.

Transfer learning means that training does not need to start from scratch for each new task. Training a new machine learning model can be very resource-intensive, so transfer learning saves both resources and time. Accurate labeling of large datasets also takes a lot of time. Most of the data organizations encounter is often unlabeled, especially with the extensive datasets required to train machine learning algorithms. With transfer learning, a model can be trained on an available labeled dataset, then applied to a similar task that may involve unlabeled data.

The first step in transfer learning is to choose a pre-trained model, such as VGG-19 or Xception. The second step is to create a basic model. We can download the existing network weights to save additional model training time. In the third step, we freeze the layer so as not to lose all the learning that has occurred. The fourth step adds a training layer. The fifth step we train the newly added layer. Finally, we fine-tune the model that we have trained

Transfer learning, a category under machine learning, has received a lot of attention from the research community in recent years. Transfer learning has been recognized as having connectivity between additional testing and training samples that produces faster and more efficient output [8]. The use of transfer learning also helps speed up the creation of machine learning model prototypes with models that have been trained by other people, because training a good machine learning model can use time and expensive GPUs. [9].

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b. Xception Pre-trained Model

The Xception architecture has 36 convolutional layers that form the basis of feature extraction from the network. The 36 convolution layers are organized into 14 modules, all of which have linear residual connections around them, except the first and last modules. This makes the architecture very easy to define and modify, requiring only 30 to 40 lines of code using a high-level library such as Keras [10].

The choice of the Xception architecture stems from its attractive attributes, including its ability to adapt to complex image datasets and its computational efficiency. The separable depth-wise convolutions and shortcuts between convolution blocks in this model contribute to its lightweight yet powerful nature. [11].

Therefore, the Xception model has been used to detect Covid-19 with an F1 score of 0.818 [11], waste type classification with an accuracy of 88% [12], and scene image classification with an accuracy of 91.20% [13]. We can conclude that the Xception model can be used on many datasets and produces good results.

c. VGG-19 Pre-trained Model

VGG-19 is a well-known CNN model, and has been successfully applied in image classification, pattern recognition, and speech recognition. VGG-19 is made of a Stack of convolutional layers (which have different depths in different architectures) followed by three Fully Connected (FC) layers: the first two have 4096 channels each, the third one performs ILSVRC classification with 1000 classes and thus contains 1000 channels (one for each class). The final layer is the softmax layer. The fully connected layer configuration is the same in all networks [14].

Many VGG-19 model studies have been carried out such as fault diagnosis which has a final accuracy of 99.175% [15], Sentiment analysis of images resulting in 99% accuracy [16], and diagnosing skin cancer resulting in an accuracy of 98.18% [17]. We can conclude that the VGG-19 model can also be used on many datasets and produces good results.

d. Ensemble Learning

Ensemble Learning is a technique used to combine two or more machine learning algorithms to obtain superior performance compared to when the constituent algorithms are used individually [18].

Ensemble learning methods train many basic machine learning or deep learning models and combine their predictions to obtain improved performance and better generalization capabilities than individual basic models [19].

Ensemble methods are divided into two broad categories, namely sequential ensemble techniques and parallel ensemble techniques. Sequential ensemble techniques generate basic learners sequentially, for example Adaptive Boosting (AdaBoost). The sequential formation of basic learners encourages dependencies between basic learners. The model's performance is then improved by giving higher weights to previously underrepresented learners.

In parallel ensemble techniques, the underlying learner is generated in a parallel format, for example a random forest. The parallel method utilizes the formation of basic learners in parallel to encourage independence between basic learners. Basic learner independence significantly reduces errors due to the application of averaging.

To improve the performance of ensemble learning we will use the averaging voting method. Each member of the ensemble contributes equally by voting using their predictions. Therefore, it introduces the concept of diversity when each model is combined. This diversity will reduce variance and increase the ability to generalize beyond the training data.

3. METHODS

To create this model, I will first create a simple model using a Convolutional Neural Network to get initial accuracy and benchmarks. After that, to improve the performance and accuracy of this model, I will adopt a transfer learning method using a pre-trained model which is then modified by adding several additional layers and then trained again with a dataset containing a collection of types of traditional food and snacks.

3.1. Data Acquisition and Preprocessing

The saved dataset will be in .zip format because it can accommodate a lot of photo data at once. However, a .zip dataset cannot be processed directly because image processing requires an appropriate format, namely .png or .jpg format for data in the form of images so that in processing it needs to be unzipped or opened first. After successfully opening each part. The dataset it will be saved in a directory called /jajanan_indonesia_final. This directory will consist of 3 large folders, namely:

- /jajanan_indonesia_final/Training
- /jajanan_indonesia_final/Validation
- /jajanan_indonesia_final/Testing

Where each section will contain 16 categories of traditional Indonesian food and snacks that will be trained. The training folder contains a collection of images that will be used to train and create the model. Meanwhile, the validation folder will be used in the model validation process. The testing folder will be used after the training process is complete. The images contained in this folder serve as material for testing the model that was previously successfully created, whether the model is able to carry out its duties in the image classification task or not.

The latest dataset has a total of 960 images, which is the total amount of training, validation, and testing. The existing dataset is considered insufficient because ideally a dataset would have at least 1000 images. Then caused data addition is carried out, namely by taking new data from the internet. The source of the added data comes from kaggle, a leading data science community platform. In Kaggle there are many datasets that can be used to research something, including image data about traditional Indonesian food and snacks. This dataset includes 8 traditional Indonesian cakes: Kue Lumpur, Kue Risoles, Kue Dadar Gulung, Kue Lapis, Kue Kastengel, Kue Klepon, Kue Putri Salju, Kue Serabi.

This traditional cake also consists of 3 main folders: Training, validation, and testing. The training folder the number of images varies from 170 to 200 images. the validation and testing folders, each cake has 20 images. This dataset can be accessed on the kaggle repository: https://www.kaggle.com/datasets/ilhamfp31/kue-indonesia.

Then we merging the data. The dataset now includes a total of 16 types of traditional food. Apart from increasing categories, the existing dataset has also increased in terms of number. Initially this dataset had 960 images, but now there has been an addition of 1,845 images to the data for a total of 2,805 images.

Figure 1. *Preview of indonesian food dataset gathered*

The image above shows the current appearance of the dataset after adding data. It had in the training folder, namely the folder that acts as a place to store training data, the number of images there is 2201 which cover 16 classes/categories of traditional Indonesian food. The aim of adding data is so that the neural network can carry out the learning process more easily because it has more training data.

3.2. Modelling

The deep learning model will be built in 3 stages, namely creating an initial CNN model, using transfer learning, then combining the 2 selected transfer learning models into 1 ensemble model.

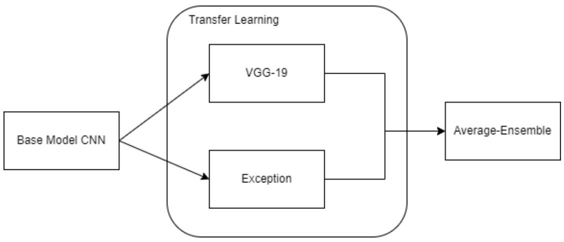

Figure 2. *Ensemble learning conceptual model: combining transfer learning*

The basic CNN model will be used as an initial benchmark, to see how much accuracy can be obtained with a regular CNN model. The transfer learning will be used as a form of model improvisation. In this research, there are 2 pre-trained models used, namely VGG-19 and Exception. we created of the transfer learning model has completed. Those 2 models will be combined and merged into 1 ensemble model using the Averaging method. The results of this

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ensemble will then be used as the final model which is ready to be used for the prediction process.

The CNN architecture that is formed will be divided into 4 experiments. This is intended to find a model with the best accuracy that can be produced. The first experiment consists of basic components. For feature extraction, there are a total of 4 convolutional layers with a pattern of 64-128-64-128 which are equipped with a pooling layer for every 2 convolutional layers.

The second experiment will focus on adding convolution layers to improve the feature extraction process from the model. Previously the architecture used had a 64-128-64-128 pattern. However, in the second experiment a model was created with a repetition pattern of 64-64-128-128-256-258 and equipped with a pool layer for every 2 convolution layers. In the third experiment, a different approach was taken, namely by adding a dropout layer. Dropout is a layer whose role is to delete neurons randomly during training. This layer is expected to reduce the overfitting conditions that occurred in the previous 2 experiments.

In the third experiment, the model architecture used will be the same as the architecture in the first experiment, namely with a 64-128-64-128 pattern with a pooling layer in every 2 convolution layers. In fourth experiment, which is the last experiment. We modifications will be made to the hidden layer, namely by adding a new hidden layer which has 1024 neurons and adding a dropout layer.

In general, so far, several ways have been carried out to improve the performance and accuracy of the model being built, such as carrying out the augmentation process twice on the data. However, this step is not the only way to increase accuracy. After conducting various experiments on the model, the best way to further improve the performance of this model is:

- Developing Transfer Learning Model
- Building Ensemble Learning with Transfer Learning as the Base Learner

3.3. Evaluation

Table 1. *Experiment result using convolutional neural network with 4 different models*

Experiment	Training Accuracy	Validation Accuracy
First Model	0.58	0.48
Second Model	0.56	0.47
Third Model	0.48	0.41
Fourth Model	0.48	0.43

Based on the 4 experiments that have been carried out, it can be concluded that none of the CNN models that have been built have achieved 60% accuracy, this means that the models that have been made cannot be said to be capable of carrying out the classification process because their accuracy values are small. The biggest change is the addition of dropouts.

Although the amount of accuracy decreases when adding dropout, overfitting conditions also decrease. This can be a reference in creating advanced models using transfer learning.

Table 2. *Accuracy comparison between transfer learning models*

Experiment	Training Accuracy	Validation Accuracy
VGG-19 Model	0.8428	0.8428
Xception Model	0.9421	0.9421

Based on the results of the transfer learning experiment, it was found that the use of transfer learning had a significant change in accuracy. In making the previous CNN model, it can be seen that of the 4 experiments carried out, not a single model was able to achieve an accuracy of more than 60%. Meanwhile, using a transfer learning model can achieve accuracy of up to 90%.

Table 3. *Precision comparison between transfer learning models*

Experiment	Training Precision	Validation Precision
VGG-19 Model	0.8868	0.8412
Xception Model	0.9547	0.9126

Based on performance improvements can also be seen from precision and recall results. In the VGG model, the precision is 88%. The xception model is even able to penetrate precision values of up to 95%. It can be said that these two models are considered good to be used as base learners for ensemble learning later.

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Table 4. *Ensemble learning model result based on accuracy (training and validation)*

Experiment	Training Accuracy	Validation Accuracy
Average-Ensemble	0.9754	0.9238

After the process of combining the 2 transfer learning models is successful, an ensemble model is created by calculating the overall average of the combined predictions of the 2 models. The table shown Enthought transfer learning has good accuracy, the use of ensembles can improve the overall model performance results. With the ensemble, the model now has a training accuracy of 97% and validation accuracy of 93%. Apart from that, there was also a decrease in loss function, which is a good sign. Previously both transfer learning models had numbers above 1, but combining the 2 models succeeded in reducing the loss function value so that now the model has a loss function of 0.2371 for training data and 0.3490 for validation data.

The same thing also happens to the precision and recall values. Even though the ensemble learning validation recall value is still lower than the Xception model, the overall value of the ensemble model is still superior to previous models. With precision values of 99% in training and 96% in validation, as well as recall values of 93% respectively in training data and 84% in validation data, it can be said that the ensemble learning experiment was successful in improving the overall performance of the prediction model for typical traditional foods and snacks. Indonesia.

Table 4. *Comparison between models based on test data (accuracy and loss function)*

Experiment	Test Accuracy	Test Loss Function
VGG-19 Model	0.8154	0.5328
Xception Model	0.8725	0.4475
Average Ensemble Model	0.9128	0.3790

After all models have been successfully created, comparisons can be carried out. If previously the results were displayed on training and validation data, performance comparisons will be made on the testing dataset. Based on the testing results, it was found that the ensemble learning model was in first place in all aspects. Both the VGG-19 and Xception models were unable to achieve 90% accuracy, but the ensemble model had 91% accuracy. The ensemble model also has the smallest loss function among the three, so it can be said that the ensemble model has the smallest error value. The ensemble precision and recall also show good numbers. With a precision value of 95% and recall of 87%, it can be concluded that the ensemble testing data has the best performance.

CONCLUSION

Based on the research results, evidence was obtained that among other models the ensemble learning model can be used for traditional food detection processes because it has high accuracy above 90% for training data (97%), validation (92%) and testing (91%). Apart from that, ensemble learning also produces a low loss function/error rate so that combining 2 transfer learning models into ensemble learning can be said to be successful. It is hoped that this ensemble learning model can help people recognize traditional food around them and increase people's interest in preserving traditional Indonesian food. It is also hoped that this model can be used as a reference for the next development. Its namely a real-time traditional food detection application. It can detect traditional food directly.

The research conducted, several suggestions can be formulated:

- Building applications to make real-time predictions
- Addition of traditional food types to increase the diversity of types in the dataset

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