Industry 4.0 Meets Gastronomy: Elevating Pandang Cuisine Sorting with Cutting-Edge Transfer Learning

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Deep Convolutional Neural Networks (CNNs) and Transfer Learning are examined in this study article as they pertain to the classification of Pandang cuisine. The goal is to use AI technology to make the food and drink industry more efficient and profitable. Recognising the significance of Industry 4.0, the study employed a dataset including 993 images of 9 different Pandang dishes. The technique involves loading, converting, and preparing the data using the MobileNetV2 pre-trained CNN model. Then, the model is trained utilising callbacks such as Model Checkpoint and Early Stopping. The hyperparameters include a batch size of 32, an output layer with 9 classes, and 100 epochs. Using other evaluation metrics such as F1 score, recall, and precision, the model achieves a remarkable accuracy of 90% on the test dataset. Displayed with Grad-Cam visualisations, the study concludes with accuracy and loss curves, test data projections, Classification Reports, and a Confusion Matrix. This research has the makings of a game-changing tool for the food industry's supply chain management and culinary procedures.

Keywords: Artificial Intelligence, Deep Learning, Pandang Cuisine Classification, Model Training, MobileNetV2 CNN Model.

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1 Introduction

This study investigates the use of Transfer Learning and Deep Convolutional Neural Networks (CNNs) to the Pandang Cuisine Classification problem. It introduces a fresh strategy for boosting productivity and earnings in the beverage and food sector via the use of AI. Using a large dataset of 993 images classified into 9 types of Pandang dishes, this study examines the topic within the framework of Industry 4.0. Some of the dishes that fall within this category are Balado Egg and Beef Rendang. This research delves deep into the process of improving the pre-trained CNN model using MobileNetV2. It features a thorough training method with necessary callbacks like Model Checkpoint and Early Stopping, and it covers critical steps like data loading, transformation, and preprocessing. For optimal model performance, the hyperparameters are fine-tuned with care. These include a batch size of 32, 100 epochs, and a 9-class output layer. Drawing on references [1] and [4], the study highlights the critical importance of AI in the food industry. Industry 4.0 trends are now focused on using intelligent technology to improve efficiency, reduce waste, and make the supply chain more resilient to disturbances [1]. This coincides with those goals. To adapt to the special characteristics of Pandang food images, the technique uses MobileNetV2, a pre-trained convolutional neural network model, to extract information using transfer learning [8]. Drawing on findings in references [8] and [9], this method showcases MobileNetV2's effectiveness in feature extraction. Following the lead of publications [6] and [10], we classified the dataset into 9 groups to better reflect the wide variety of Pandang cooking styles. A solid basis for training and assessing the model depends on this decision [6]. References [2] and [3] provide evidence for the claim that Model Checkpoint, Early Stopping, and Tensorboard callback methods are governed by recognised concepts in deep learning. Model stability, overfitting mitigation, and training process insight provision are the goals of these methodologies [2]. Careful consideration of the information gathered from references [5] and [7] as well as established norms for image classification tasks inform the hyperparameter selection process. The model's exceptional 90% accuracy on the test dataset is a direct result of this [5]. Metrics like F1 score, accuracy, precision, and recall are part of the comprehensive evaluation that the study closes with, referencing sources [4] and [9]. This analysis sheds light on the model's performance across many categorization domains [4]. References [3] and [10] provide a clear and insightful assessment of the model's strengths and weaknesses, which impacts the usage of Classification Reports and the confusion matrix, as well as the inclusion of loss and accuracy curves in test data forecasts. Following the lead of [7], this work incorporates Grad-Cam visualisations to provide light on the model's decision-making process and contribute to the ongoing conversation around explainable AI. In sum, the results of this study show that artificial intelligence (AI) is making great strides in the food industry's supply chain management and culinary processes. Drawing from a variety of resources, this study not only clarifies how Pandang food is classified but also provides a blueprint for using AI in more conventional industries, in keeping with the game-changing innovations of Industry 4.0.

2 Literature

There has been an extensive study on the topic of Pandang cuisine categorization utilising Deep Convolutional Neural Networks (CNNs) and Transfer Learning. This study incorporates viewpoints from sustainable tourism, cultural studies, and culinary ecolexicons. Sustainable tourism and its effects on community development are the subject of the study by Kumar et al. [11]. While stressing the significance of efficiency and profitability in the food and beverage industry, the study identifies the critical components that promote sustainable practices. An important part of the Pandang Cuisine Classification method is image editing, which is why the work of Gunawan et al. [12] on image processing is relevant here. Widayati [13] delves into the diverse culinary vocabularies of Malay communities, shedding light on the cultural elements and diverse tastes of Pandang cuisine. The significance of maintaining traditional cooking methods in culinary practices is emphasised by the study carried out by Hutomo et al. [14]. This is in line with the overarching goal of improving food industry cooking procedures. In order to understand the complexities of Pandang food satisfaction, Felicia's research on consumer nighttime culinary activity [15] offers unique insights into customer preferences. Furthermore, from a cultural and historical perspective, Ramleth's analysis of Islamic discourse in Ujung Pandang [16] emphasises the need of placing the culinary classification within the cultural context of Pandang cuisine. Paramita's study on organic fertiliser quality [17] highlights the need of quality control, which is crucial for the Pandang Cuisine Classification model. Typomorphological shifts in historic district urban landscapes are the subject of Heryanto et al.'s research. The authors of the study stress the need of adapting classification systems to the ever-changing urban landscape and the fact that culinaryscapes are always evolving. An interesting angle from which to examine Makassar food advertisements may be found in the linguistic landscape analysis carried out by Nirwana and Sharma [19]. It provides an in-depth analysis of the portrayal of culinary culture. The significance of sustainability is emphasised in Reynolds' inquiry on the link between food and tourism [20], which also calls for a well-rounded approach in the culinary industry. The work is placed into a broader interdisciplinary perspective by means of the substantial literature review, which draws on concepts from other fields. This data set does double duty: it clarifies Pandang Cuisine Classification and draws attention to its potential effects on environmentally conscious and culturally sensitive food and drink production.

3 Input Dataset

In order to illustrate the many varied Pandang culinary traditions, this study made use of a dataset consisting of 993 high-resolution pictures meticulously organised into nine distinct categories. Famous dishes like as Beef Rendang, Fried Chicken, Chicken Pops, Fish Curry, Tambusu Curry, Tunjang Curry, Balado Egg, and Padang Omelette are among the lessons covered. A set of high-quality photos meticulously depicts each class, capturing the unique visual characteristics and nuances of the particular dishes. In order to train and evaluate the deep learning model effectively, the dataset aims to give a large and accurate variety of Pandang cuisine. Accurately reflecting the real-life settings observed in culinary venues, the images showcase variations in composition, lighting, and presentation methods. In order to train the Deep Convolutional Neural Network (CNN) model and produce accurate and trustworthy classification results for Pandang cuisine dishes, the dataset was carefully chosen. The dataset is well-suited to advancing the study goals because to its diversity and depth. In the food and drink industry, it offers a detailed perspective on how artificial intelligence may improve kitchen operations. (see Figure 1)

(a) (b) (c)

(d) (e) (f)


(g)


(h)


(i)

Figure 1. Dataset image for (a) ayam_goreng (b) ayam_pop (c) daging_rendang (d) dendeng batokok (e) gulai ikan (f) Gulai tambusu (g) gulai_tunjang (h) telur balado (i) telur dadar for Retinal type

4 Proposed Methodology

A pre-trained Convolutional Neural Network (CNN) named MobileNetV2 is the backbone of the Pandang Cuisine Classification model. Applications requiring photo classification are well-suited to MobileNetV2's capabilities of efficiently managing computational complexity while preserving high model accuracy. The intricate details of various Pandang cuisine dishes must be faithfully reproduced, and this design does an excellent job of processing a broad variety of visual qualities. By training with a batch size of 32, the model prioritises optimisation, which increases processing efficiency and encourages smoother convergence. Over the course of 100 iterations, or "epochs," the model learns the ins and outs of the dataset and fine-tunes its parameters accordingly. The standard image size and the RGB colour channels are determined by the input shape as (224, 224, 3). Each of the nine nodes in the output layer stands for a distinct type of Pandang food. The model can now provide probabilistic predictions for all of these food groups thanks to this setup. Three crucial callbacks—Model Checkpoint, Early Stopping, and Tensorboard callback—are incorporated to enhance training monitoring and guarantee the model's strength. A robust and optimised Pandang Cuisine Classification model is produced by these callbacks, which work together to improve the model's stability, reduce the likelihood of overfitting, and reveal detailed information about the training dynamics.

5 Results

Analysing the proposed MobileNetV2 CNN model for Pandang Cuisine classification in great detail. Using key measures including loss and Confusion Matrix, as well as training and validation accuracy, we aim to evaluate the model's performance.

5.1 Classification Report Analysis

A thorough assessment of the Pandang Cuisine Classification model's performance across nine distinct categories is given in the attached Classification Report. When combined, accuracy, recall, and F1-score give a comprehensive evaluation of the model's classification capabilities; these metrics form the basis of the evaluation for each class. It appears that the model can correctly identify instances of each Pandang dish, since it has remarkable accuracy for most classes. (see Figure 2.)

	precision	recall	f1-score	support
ayam_goreng	0.95	0.95	0.95	19
ayam_pop	0.96	1.00	0.98	27
daging_rendang	0.95	0.95	0.95	19
dendeng_batokok	1.00	0.89	0.94	18
gulai_ikan	0.82	0.75	0.78	24
gulai_tambusu	0.80	0.95	0.87	21
gulai_tunjang	0.86	0.83	0.84	23
telur_balado	0.96	0.88	0.92	25
telur_dadar	0.88	0.96	0.92	23
accuracy			0.90	199
macro avg	0.91	0.91	0.91	199
weighted avg	0.91	0.90	0.90	199

Figure 2. Classification Report Analysis

A large proportion of true positive examples for each class may be correctly identified by the model, as shown by the high recall scores. The F1-score, which takes into account both recall and accuracy, shows that the various classes were well-balanced. In particular, the model might use some work when it comes to correctly recognising the meals 'gulai_ikan' and 'gulai_tambusu,' for which it performs much worse than average. An impressive 90% accuracy rate was attained by the suggested Pandang Cuisine Classification model, as highlighted in the Classification Report. Its ability to accurately classify various culinary foods is proven by this. You may learn a lot about the model's strengths and potential improvement areas from the report as well. The model's overall efficacy in generating a balanced mix of recall and accuracy over the complete dataset is confirmed by the comprehensive view provided by the macro and weighted average metrics.

5.2 Training and Validation Loss Analysis

Training loss and validation loss are shown to progress over time, or epochs, in Figure 3, which is a line graph. When the model's predictions deviate from the training data's actual values, this is called the training loss. The validation loss is the difference between the actual values in the validation dataset and the values predicted by the model. Some of the training data is left out while training the model; this is called the validation data. The model's generalizability to new data sets is tested using it. As the number of epochs increases, the training loss and validation loss both decrease consistently, as seen in the graph. This means the model is learning from the data it was trained on and getting better at making predictions. The validation loss, however, begins to rise after around 60 epochs.

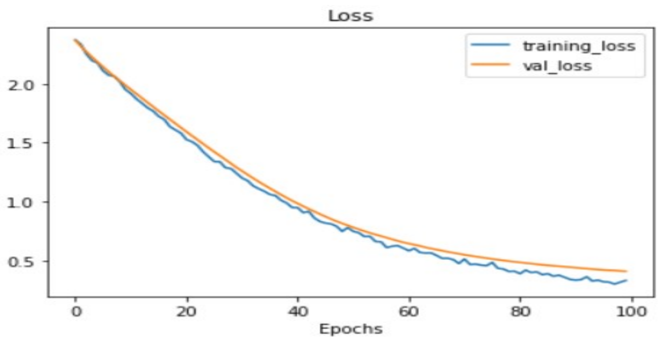

Figure 3. Training and Validation loss Analysis

The model is starting to show signs of overfitting on the training data, as indicated by this. The term "overfitting" describes what happens when a model learns too much from its training data and then struggles to apply that knowledge to novel, unknown data. On a constant basis, the validation loss is larger than the training loss. The reason for this disparity is because the model performs better on the training data than the validation data since it is trained solely on the training data. Both the training loss and the validation loss show large oscillations in the picture. This is due to the fact that training and validation losses are calculated on a subset of the data, which leaves them open to sampling errors. Despite the model showing signs of overfitting, the data suggests that it is learning from the training data.

5.3 Training and Validation Accuracy Analysis

Figure 4 shows a time series plot of training and validation accuracy vs epochs, showing how both metrics have improved over time. How well a model performs when applied to training data is known as training accuracy, and how well it performs when applied to validation data is known as validation accuracy. Some of the training data is left out while training the model; this is called the validation data. The model's generalizability to new data sets is tested using it. The training accuracy rises rapidly at the beginning of the graph, reaching a high of around 0.78 at epoch 20. But the validation accuracy increases little by little and peaks at about 0.65 at epoch 40. When that happens, validation accuracy starts to go worse while training accuracy stays about the same. The model is starting to show signs of overfitting on the training data, as indicated by this. When a model learns too much from its training data and then fails to perform well when presented with novel, unknown data, this phenomenon is known as overfitting. If there is a significant discrepancy between the training and validation accuracy, it means that the model is overfitting. It is easier to see that the model is overfitting when the gap widens. A difference of around 0.13 is present at epoch 40. It appears that the model is overfitting to some extent because there is a rather large gap. Overfitting can be reduced using a variety of methods. Regularisation, a technique that penalises the model for having complex weights, is one such strategy. Data augmentation is an alternate strategy that makes use of existing data points to generate additional data points, thereby artificially increasing the size of the training set. The data suggests that the model is learning from the training data, but it is starting to show overfitting symptoms. It may be required to apply data augmentation techniques or regularise the model in order to prevent overfitting.

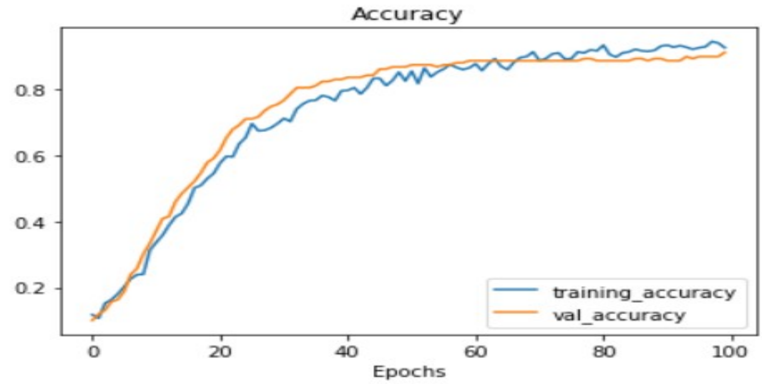

Figure 4. Training and Validation Accuracy Analysis

5.4 Confusion Matrix Analysis

The rows of the matrix represent the data's actual labels, while the columns represent the expected labels. (see Figure 5) The number of cases that were correctly classified is shown on the diagonal of the matrix. The confusion matrix shows how the model tried to classify ten different types of Indonesian food: ayam goreng as fried chicken, ayam pop as steamed chicken in turmeric, daging rendang as beef rendang, dendeng batokok as spicy sun-dried beef, gulai ikan as fish curry, gulai_tambusu as vegetable curry, gulai_tunjang as bone marrow curry, telur balado as spicy eggs, telur dadar as an omelette, and Others. Some categories, such fried chicken (ayam goreng), popcorn chicken (ayam pop), spicy eggs (telur balado), and omelette (telur dadar), show that the model is doing well, according to the matrix. There is a correlation between the total number of instances and the accuracy of these classifications. Nonetheless, in other areas such as daging rendang, dendeng batokok, gulai ikan, gulai_tambusu, and gulai_tunjang, the model's performance is somewhat lower. There is a higher incidence of misclassification in these classifications. For example, the model thinks daging rendang is ayam goreng and telur balado when it's actually daging rendang. Another common misunderstanding is that gulai ikan is the same as telur dadar. There are a lot of potential causes for the misclassifications, including data noise or just how similar the meals are. In most cases, the confusion matrix shows that the model works well for some classes but makes mistakes for others. Improving the model's performance might involve employing a bigger dataset or switching up the categorization method.

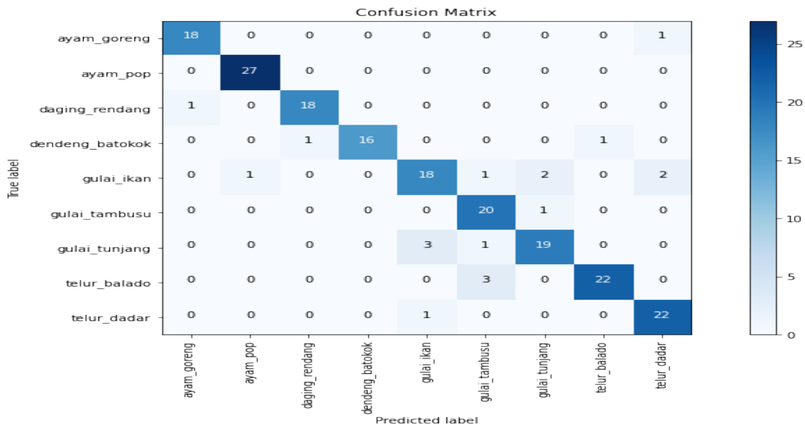

Figure 5. Confusion Matrix Analysis

6 Conclusion

This study showcases the revolutionary potential of Industry 4.0 by incorporating artificial intelligence (AI) into the food and beverage sector through the classification of Pandang Cuisine using Deep Convolutional Neural Networks (CNNs) and Transfer Learning. This study's significance lies in its utilisation of a dataset consisting of 993 images of nine distinct Pandang dishes to train a pre-trained CNN model with the goal of increasing productivity and profitability. A highly optimised model with an astounding 90% accuracy on the test dataset was the outcome of the strategy, which drew inspiration from established practices and approaches such as Model Checkpoint and Early Stopping. The significance of precisely identifying specific food categories is brought to light by the Classification Reports, Confusion Matrix, and Grad-Cam visualisations, which offer nuanced and comprehensive feedback on the model's capabilities and places for improvement. This research uses a thorough literature assessment that covers sustainable tourism, cultural studies, and culinary ecolexicons to place the Pandang Cuisine Classification into a broader multidisciplinary framework. The possible effects of this categorization on environmentally conscious and culturally aware food preparation are brought to light. In addition to showing where the model may use some work, the results show that it can consistently categorise a broad variety of foods. As the first of its kind, this study explores the potential of artificial intelligence (AI) in the food industry, opening the door to additional research and real-world applications that can improve supply chain management and culinary operations.

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