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PADANG CUISINE CLASSIFICATION USING RESNET FEATURES AND TRANSFER LEARNING

Victor Saputra Ginting[1], Daniel Zalukhu[2], Leon Batee[3]
[1]Program Studi Teknologi Informasi Universitas Deli Sumatera,
[2]Program Studi Teknologi Informasi, Universitas Deli Sumatera
[3]Program Studi Teknologi Informasi, Universitas Deli Sumatera
[1]victorsaputraa@gmail.com, [2]danielzalukhu35@gmail.com, [3]leonvebrian@gmail.com
[2].

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ABSTRACT

Padang cuisine is a renowned Indonesian culinary heritage with diverse dishes that are often challenging to identify visually due to their similarities and variations. This study proposes a digital image-based classification system to accurately recognize five types of Padang dishes: Rendang, Dendeng Batokok, Ayam Pop, Gulai Tambusu, and Gulai Tunjang. Feature extraction was performed using a pre-trained ResNet model to leverage its deep residual architecture, which effectively captures rich visual information. The extracted features were then used to train and compare two classifiers: Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel, and Multi-Layer Perceptron (MLP) with three hidden layers and ReLU activation optimized by Adam. The dataset comprised 548 images collected from Kaggle, evenly distributed across the five dish categories. Evaluation metrics included accuracy, precision, and recall. Experimental results show that SVM achieved the highest performance with an accuracy of 87.9%, outperforming MLP, which obtained 87.3%. The findings suggest that SVM with RBF kernel is more suitable for classifying Padang dishes on a limited dataset, while MLP holds potential with further optimization and larger datasets. This research contributes to the advancement of automated culinary recognition systems, supporting the preservation and promotion of Indonesian culinary heritage through artificial intelligence.

INTRODUCTION

Padang cuisine, originating from the Minangkabau ethnic group in West Sumatra, Indonesia, holds a prominent place in the nation's culinary heritage due to its rich, complex use of spices and a wide variety of distinctive dishes. This culinary tradition is recognized both nationally and internationally, playing a vital role in shaping the Nusantara (Indonesian archipelago) culinary identity through its unique flavor profiles and cultural significance (Faridah et al., 2024; Pugra et al., 2025). The robust spice blends and cooking techniques reflect deep cultural roots and regional biodiversity, making Padang food highly sought after by locals and tourists alike (Sekar Sari et al., 2023). However, the extensive diversity and visual similarity among Padang dishes present a significant challenge for precise identification, especially when integrating them into digital platforms and food recommendation systems (Prasetyo et al., 2023).

Recent developments in culinary digitization have explored the use of advanced digital image processing and machine learning techniques to improve food classification accuracy. Deep learning models, particularly convolutional neural networks (CNNs), have been employed to tackle the problem of visually similar dishes by learning subtle differences in texture, color, and presentation (Prajena et al., 2022; Wulandari, 2024). These technologies enable automated, scalable recognition systems that support culinary tourism, digital menus, and nutritional applications related to Padang cuisine. Such innovations not only facilitate accurate dish identification but also contribute to preserving and promoting Indonesia's rich gastronomic heritage in the digital era, thereby enhancing the accessibility of Padang cuisine to a global audience (Rangkuti et al., 2024).

In this study, ResNet was selected as the feature extraction method due to its ability to capture deep visual features through its residual architecture, which addresses the degradation problem encountered in very deep convolutional networks. On the ImageNet dataset, ResNet-152 demonstrated improved optimization ease and higher accuracy compared to earlier models, with an ensemble achieving a top-5 error rate of 3.57% (Shafiq & Gu, 2022). (Duta et al., 2020) eported that enhancements in residual architecture yielded approximately a 2% increase in top-1 accuracy on ImageNet without adding model complexity. Furthermore, (Albert et al., 2021) showed that a semi-supervised ResNet-50 trained on one billion unlabeled images achieved a top-1 accuracy of 81.2% on the ImageNet benchmark, underscoring ResNet’s robustness as a foundational architecture for transfer learning.

The features extracted by ResNet were subsequently used as inputs for two classification models: Support Vector Machine (SVM) and Multi-Layer Perceptron

(MLP). SVM with a Radial Basis Function (RBF) kernel was chosen for its proficiency in handling nonlinear classification tasks through mapping to a high-dimensional feature space, combined with a max-margin approach that enhances noise resistance and generalization (Andrianto et al., 2024). The parameter C was set to 1 to balance the trade-off between classification error and margin width, while gamma was fixed at 0.1 to define the influence radius of each support vector (Sharma et al., 2023). The SVM-RBF approach has proven effective across various image classification tasks, including hyperspectral image analysis, where it outperformed linear SVM, KNN, and LDA classifiers (Nhaila et al., 2019). (Mehta et al., 2023) even reported that SVM-RBF achieved accuracy, precision, and recall rates of 93.34%, 92.61%, and 92.35%, respectively, on a multi-class dataset.

The MLP utilized a 100-100-100 hidden layer architecture with ReLU activation functions and Adam optimization, selected for its flexibility in modeling complex nonlinear relationships within feature-extracted data. Thanks to multiple hidden layers and nonlinear activations such as ReLU, MLPs can capture patterns not representable by linear models (Al Bataineh et al., 2022). ReLU was chosen due to its computational simplicity, ability to mitigate the vanishing gradient problem, and sparse activation property that facilitates efficient training (Bai, 2022). The Adam optimizer was employed because of its adaptive learning rate, stability, and fast convergence, making it well-suited for deep layered architectures (Abdel-aziem & Soliman, 2023).

The dataset used in this study comprised five categories of Padang dishes: beef rendang (104 samples), dendeng batokok (109 samples), ayam pop (113 samples), gulai tambusu (103 samples), and gulai tunjang (119 samples), sourced from Kaggle. This dataset captures the visual and textural variability among these dishes. The research methodology involved extracting image features using ResNet, followed by classification using the SVM-RBF and MLP models. The performance of both models was evaluated using accuracy, precision, and recall metrics to identify the most optimal model for classifying types of Padang cuisine. This study aims to develop an accurate and reliable image-based classification model to support the preservation and promotion of Padang culinary culture through artificial intelligence technology.

RESEARCH METHODS

This study was designed to develop and evaluate the performance of digital image-based classification models for recognizing various types of Padang cuisine. The research methodology encompasses stages of data collection and preprocessing, the design of two classification model architectures—Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP)—and model performance testing using relevant evaluation metrics.

The initial phase involved selecting a dataset of Padang cuisine images obtained from online sources, followed by preprocessing steps to ensure data quality and uniformity. Next, image features were extracted using the ResNet architecture and employed as inputs for the two classification models designed. The SVM model was utilized to explore the capability of the maximal margin-based algorithm in separating data classes, while the MLP model tested the performance of an artificial neural network with a specified hidden layer structure. Both models were trained and tested on proportionally split data subsets to guarantee objective evaluation.

Model evaluation was conducted by measuring accuracy, precision, and recall for each model. This approach enables performance comparison between the two methods, allowing identification of the most effective model for classifying Padang cuisine images.

1. Data Source

This study used a digital image dataset of Padang cuisine consisting of five classes: beef rendang (104 images), dendeng batokok (109 images), ayam pop (113 images), gulai tambusu (103 images), and gulai tunjang (119 images). All images were sourced from the Kaggle platform via a search using the keyword "Masakan Padang" (Afrinanto, 2022). This dataset was selected for its representation of the variation in shape, color, and texture across the different dish types, making it relevant for training and testing digital image-based classification models.

Before use in model training, all images underwent the following preprocessing steps:

1. Resizing images to match the input resolution required by the ResNet architecture.
2. Normalizing pixel values to place color intensities within a consistent range, facilitating model learning.
3. Splitting the dataset into training and testing subsets according to a defined ratio to ensure objective model evaluation and prevent data leakage

These preprocessing steps aimed to enhance input data quality, minimize noise, and ensure compatibility with the feature extraction methods and classification algorithms applied in this research.

2. SVM Model Design

Support Vector Machine (SVM) was employed as one of the classification methods in this study. The SVM algorithm functions by constructing an optimal hyperplane that separates data into distinct classes with the maximum margin. To handle nonlinear data, this study used the Radial Basis Function (RBF) kernel, which projects data into a higher-dimensional feature space to enable linear separability. The RBF kernel function is defined as (Pardede et al., 2023):

$$K\left(x_i, x_j\right) = exp\left(-\gamma\left\|x_i - x_j\right\|^2\right) \tag{1}$$

where x_i and x_j are feature vectors, γ is the kernel parameter controlling the support vector's influence radius, and $\left\|x_i - x_j\right\|^2$ is the squared Euclidean distance between two data points.

Key SVM parameters—cost (C) and gamma (γ)—were set to balance model complexity and generalization capability. The value C=1 was chosen to control the trade-off between classification errors on training data and hyperplane margin width, while γ=0.1 defined the influence radius of each support vector, chosen to avoid both overfitting and underfitting.

SVM training was conducted using features extracted via the ResNet architecture, represented as high-dimensional numerical vectors. Training occurred on the training data subset, and testing on a separate subset ensured objective evaluation.

3. MLP Model Design

Multi-Layer Perceptron (MLP) served as the second classification method. MLP is an artificial neural network composed of multiple fully connected layers, including input, hidden, and output layers. The MLP architecture implemented in this study consists of three hidden layers, each containing 100 neurons. The model architecture is illustrated in Figure 1.

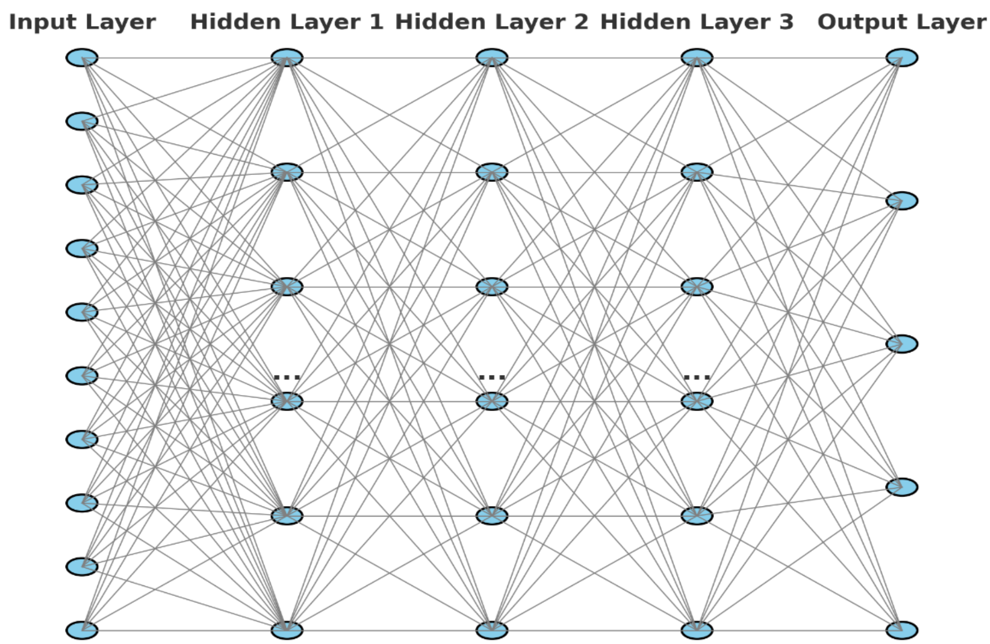

Figure 1. MLP Model Architecture

The activation function applied at each hidden layer was the Rectified Linear Unit (ReLU), defined as (Pardede et al., 2024):

$$f(x) = max(0, x) \tag{2}$$

ReLU was selected for its advantages in mitigating the vanishing gradient problem, producing sparse activations, and having low computational complexity.

Model training employed the Adam optimization algorithm, which combines the strengths of Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). Adam adaptively adjusts learning rates for each parameter, accelerating convergence and improving training stability.

The input data for MLP consisted of feature vectors extracted using ResNet. Training was performed on the training subset, with testing conducted on a separate subset to prevent data leakage.

4. Model Evaluation

Model performance was assessed based on the algorithms' ability to recognize Padang cuisine types from digital images. Three main evaluation metrics were employed: accuracy, precision, and recall.

a. Accuracy measures the proportion of correct predictions over the total number of test samples and is defined as:

$$Accuracy = \frac{TP+TN}{TP=FP+FN+TN} \tag{3}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives..

b. Precision quantifies the accuracy of positive predictions and is expressed as:

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

High precision indicates few false positive predictions.

c. Recall evaluates the model's ability to identify all relevant positive samples, defined as:

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

High recall reflects successful detection of most positive samples.

The use of these three metrics provides a comprehensive understanding of model performance, especially for multi-class classification tasks. Evaluation was conducted separately for the SVM-RBF and MLP-ReLU models on the test dataset to compare and determine the best-performing classification model.

RESULTS AND DISCUSSION

1. Presentation of Results

he evaluation results of the MLP and SVM classification models on the Padang cuisine dataset are presented in Table 1. The evaluation was conducted using three main metrics: accuracy, precision, and recall.

Table 1. Evaluation Results of MLP and SVM Models

Model	Akurasi	Presisi	Recall
MLP	0.873	0.873	0.873
SVM	0.879	0.881	0.879

Figure 2 illustrates a comparison of the performance of both models based on these three metrics. Overall, the SVM model demonstrated slightly superior performance compared to the MLP across all evaluation metrics.

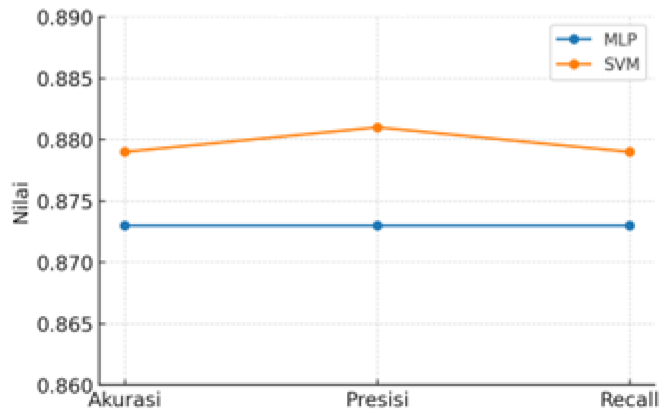

Figure 2. Performance Comparison Graph of MLP and SVM Models

2. Performance Comparison Analysis

Based on the results in Table 1, the SVM model with the RBF kernel showed marginally better performance than the MLP model in all evaluation metrics. For accuracy, SVM achieved 87.9%, which is 0.6% higher than the MLP's accuracy of 87.3%. A similar pattern was observed in precision, where SVM recorded 88.1% compared to MLP's 87.3%. Recall also favored SVM (87.9%) over MLP (87.3%).

Although the performance differences are relatively small, these results indicate that SVM provides more consistent classification of Padang cuisine types based on digital images in this dataset. This advantage may be attributed to the RBF kernel's ability to map data into a higher-dimensional feature space, allowing for more optimal class separation in non-linear data distributions.

Conversely, the MLP model, despite its high flexibility in modeling non-linear relationships, showed slightly lower performance in this study. This could be due to the limited dataset size, which constrained the MLP network with three hidden layers (each with 100 neurons) from reaching its full potential. MLPs generally require larger datasets or more extensive augmentation techniques to avoid overfitting and improve generalization.

Considering the metric values and model characteristics, SVM can be regarded as the more suitable choice for limited-size datasets with features extracted via ResNet. However, MLP's near-equivalent performance suggests its potential, especially if further hyperparameter tuning or additional training data are applied in future work.

3. Interpretation of Results

The evaluation results indicate that both SVM and MLP models can achieve relatively high performance in classifying Padang cuisine types from digital images, with accuracy values above 87% for both models. This suggests that the feature extraction process using ResNet successfully generated informative and relevant visual representations for the classification task.

The slight edge of SVM over MLP can be interpreted as evidence of the RBF kernel's effectiveness in handling data distributions that are not linearly separable. By projecting data into a higher-dimensional space, the kernel enhances the clarity of the margin separating classes. Meanwhile, the MLP, as a neural network-based model, demonstrated performance close to SVM despite the limited data, reflecting its ability to adapt to non-linear patterns present in ResNet-extracted features.

These findings also highlight the importance of considering dataset size and characteristics when selecting classification models. For smaller datasets, SVM tends to be a safer option due to its relative stability against overfitting compared to MLP. However, for larger datasets or with adequate data augmentation, MLP has the potential to match or surpass SVM performance.

Thus, this study contributes to the understanding of model selection for image-based classification, particularly in the context of recognizing traditional Indonesian cuisine. Furthermore, the findings provide a foundation for the development of broader digital culinary recognition systems that support the digitization and preservation of Indonesia's culinary heritage.

4. Limitations

This study has several limitations that should be addressed in future research. First, the dataset size is relatively small, with each class containing between 100 and 120 images. This limits the model's ability—especially the MLP—to learn optimally and may cause overfitting in deeper neural network architectures.

Second, although the SVM and MLP parameters were set according to literature references, the study did not perform extensive hyperparameter optimization techniques such as grid search or random search. More precise tuning could significantly improve both models' performance.

Third, the dataset has limited visual variation and originates from a single source (Kaggle), which may not fully represent the real-world variability of Padang cuisine. Collecting more diverse and representative data would enhance the model's generalization capability.

CONCLUSION

This study successfully developed a digital image-based classification system for Padang cuisine types by utilizing features extracted through ResNet, subsequently classified using two models: Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel and Multi-Layer Perceptron (MLP) with three hidden layers and ReLU activation. Based on evaluations using accuracy, precision, and recall metrics, the SVM model demonstrated slightly superior performance, achieving accuracy of 87.9%, precision of 88.1%, and recall of 87.9%, compared to the MLP model which obtained 87.3% across all three metrics. This advantage of SVM highlights its effectiveness in handling nonlinear data classification on limited-size datasets. Meanwhile, the MLP model also showed competitive results, indicating its potential in modeling nonlinear patterns, albeit requiring larger datasets and further optimization to reach its full performance capacity. The study confirms that feature extraction using ResNet is highly effective in providing rich and informative image representations for the classification of traditional culinary dishes. For future research, it is recommended to expand the dataset size and diversity by incorporating images from various sources and lighting conditions to enable the model to learn from more representative data. Data augmentation techniques should be applied to enhance model performance, particularly for the MLP. More in-depth hyperparameter optimization for both models, especially MLP, using methods such as grid search or random search, is necessary to find the best configurations that improve accuracy and generalization. Furthermore, exploring more complex deep learning architectures and integrating the classification system into mobile or web-based applications could serve as practical steps to support the broader digitalization and preservation of Padang cuisine.

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