Research Article

Performance Comparison of the Support Vector Machine Algorithm with RBF Kernel and Random Forest in Classifying Tourism Images of Nusa Penida

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Abstract: Indonesia holds vast tourism potential, including Nusa Penida, Bali, renowned for its natural beauty. However, the adoption of modern technology to support tourism promotion and management remains limited. This study aims to compare the performance of Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel and Random Forest algorithms in classifying images of three main tourist attractions in Nusa Penida: *Angel's Billabong*, *Broken* Beach, and *Kelingking* Beach. The dataset consists of 450 images processed using the Histogram of Oriented Gradients (HOG) method for feature extraction. Two data split scenarios (80:20 and 70:30) were applied to evaluate the algorithms based on accuracy, precision, recall, and F1-score metrics. The experimental results revealed that SVM with RBF kernel outperformed Random Forest in all scenarios, achieving the best results in the 70% training and 30% testing data split with an accuracy of 0.967, precision of 0.969, recall of 0.967, and F1-score of 0.967. While Random Forest demonstrated stable performance, it remained inferior to SVM with RBF kernel. This study concludes that SVM with RBF kernel is superior for image classification tasks, offering opportunities for implementing artificial intelligence technologies to advance the tourism sector in Indonesia.

Keywords: Image Classification, Artificial Intelligence, Nusa Penida Tourism, Random Forest, SVM RBF Kernel

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1. Introduction

Indonesia, with its more than 17,000 islands stretching from Sabang to Merauke, possesses immense tourism potential[1]. The country's breathtaking natural beauty, combined with its rich cultural heritage, traditions, and diverse local wisdom, has established Indonesia as one of the world's premier tourist destinations[2]. Indonesia attracts not only domestic tourists but also serves as a magnet for international visitors, with annual visitor numbers showing consistent growth[3]. Among its premier tourist destinations internationally recognized is Nusa Penida on the island of Bali[4]. This small island offers natural beauty, rich marine life, and various tourist attractions, making it one of the regions with the highest tourist visits in Klungkung Regency[5]. Nusa Penida's tourism potential encompasses natural attractions, spiritual tourism, and marine cultivation activities, spread across two main destination routes: the eastern and western regions. The western region of Nusa Penida, in particular, serves as the main attraction with the beauty of *Broken* Beach, Angel's Billabong, *Kelingking* Beach, and Crystal Bay[6].

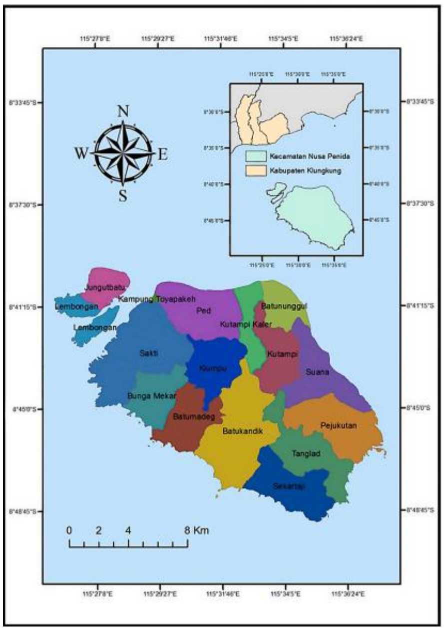

Figure 1. Map of Nusa Penida, Bali [7]

Broken Beach, or Pasih Uug, is renowned for its majestic cliff formation with a natural hole in its center, creating a unique panorama unmatched elsewhere[8]. *Angel's Billabong* presents a natural pool formed from coral formations with crystal-clear water, offering a stunning visual experience[9]. Meanwhile, *Kelingking* Beach, famous for its clean white sand and magnificent cliffs, has become one of the tourists' favorite destinations for enjoying serene and calming natural beauty[10]. However, despite Nusa Penida's growing popularity, the utilization of modern technology in supporting tourism promotion and management remains very limited. Digital image classification-based technology holds great potential for recognizing and distinguishing major tourist locations such as *Broken* Beach, *Angel's Billabong*, and *Kelingking* Beach. This system not only supports more effective promotional efforts but also provides practical solutions in modern technology-based tourism information management[11].

This research aims to develop and compare the performance of two image classification algorithms: Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel and Random Forest, in recognizing major tourist imagery in Nusa Penida. The research employs the Histogram of Oriented Gradients (HOG) feature extraction method, with each tourist object category represented by 150 images. Two data-splitting scenarios (80:20 and 70:30) are used to evaluate algorithm performance based on metrics such as accuracy, precision, recall, and F1 score. This scientific article makes significant contributions in several aspects. First, this research extends the application of pattern recognition and image classification technology to support the tourism sector, particularly in regions with natural beauty like Nusa Penida. Second, the research results can serve as a reference for developing artificial intelligence-based applications capable of automatically recognizing tourist locations, thus facilitating smarter and more integrated tourism information systems. Third, by comparing the performance of two machine learning-based algorithms, this article offers practical guidance for technology developers in selecting the most suitable algorithm for image processing in specific contexts.

Previous research has applied image classification techniques in diverse contexts. For instance, the study published in the International Journal for Research in Applied Science & Engineering Technology (IJRASET), titled Monument Tracker: Deep Learning Approach for Indian Heritage, explores monument recognition using advanced Deep Learning models, specifically focusing on cultural heritage preservation in India[12]. Meanwhile, the paper from the Journal of Environmental

& Earth Sciences, titled Comparison of Machine Learning Methods for Satellite Image Classification: A Case Study of Casablanca Using Landsat Imagery and Google Earth Engine, employs various supervised and unsupervised machine learning methods to classify urban land cover in Casablanca using multispectral satellite images[13]. Compared to these studies, this research uniquely addresses the use of artificial intelligence to promote tourism by classifying images of iconic attractions in Nusa Penida, Indonesia. By utilizing Histogram of Oriented Gradients (HOG) and relatively lightweight algorithms like Support Vector Machine (SVM) and Random Forest, this study demonstrates the potential of simpler approaches in achieving high accuracy, especially in resource-constrained environments. The following table summarizes the key differences between these studies.

Table 1. Comparison Table

Aspect	Performance Comparison of the Support Vector Machine Algorithm with RBF Kernel and Random Forest in Classifying Tourism Images of Nusa Penida	Monument Tracker: Deep Learning Approach for Indian Heritage	Comparison of Machine Learning Methods for Satellite Image Classification: A Case Study of Casablanca Using Landsat Imagery and Google Earth Engine
Focus	Classifying tourism images of Nusa Penida's key attractions (*Angel's Billabong*, *Broken* Beach, and *Kelingking* Beach).	Recognizing Indian monuments for cultural heritage preservation.	Classifying land cover in the urban area of Casablanca.
Algorithm Used	Support Vector Machine (SVM) with RBF kernel and Random Forest.	Deep Learning models (VGG16, Inception, ResNet50) with Transfer Learning.	Supervised and unsupervised algorithms (Random Forest, SVM, CART, Gradient Tree Boost).
Data Type	RGB images resized to 128×128 pixels.	Pre-trained image datasets from public sources.	Multispectral images (Landsat 8).
Preprocessing Methods	Histogram of Oriented Gradients (HOG) for feature extraction.	Data augmentation and fine-tuning of pre-trained models.	Atmospheric correction and radiometric calibration.
Unique Contribution	Focuses on applying AI for tourism promotion and the recognition of iconic locations in Nusa Penida. Highlights the efficiency of HOG and SVM in resource-limited settings.	Emphasizes cultural heritage preservation through advanced deep learning techniques.	Targets urban land management using large-scale satellite imagery and multiple classification methods.

2. Methodology

This research aims to compare the performance of two classification algorithms - Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel and Random Forest - in classifying three categories of tourist imagery from Nusa Penida: *Angel's Billabong*, *Broken* Beach, and *Kelingking* Beach. The image dataset was obtained through the Pinterest platform, with each category containing 150 images, resulting in a total dataset of 450 images. These digital images were downloaded with varying resolutions and underwent further processing. The initial research phase involved data preprocessing to ensure data quality and consistency before model training. All images were resized to 128×128 pixels for uniformity and converted to grayscale to simplify data complexity without sacrificing relevant visual features. Subsequently, feature extraction was performed using the Histogram of Oriented Gradients (HOG) method[14].

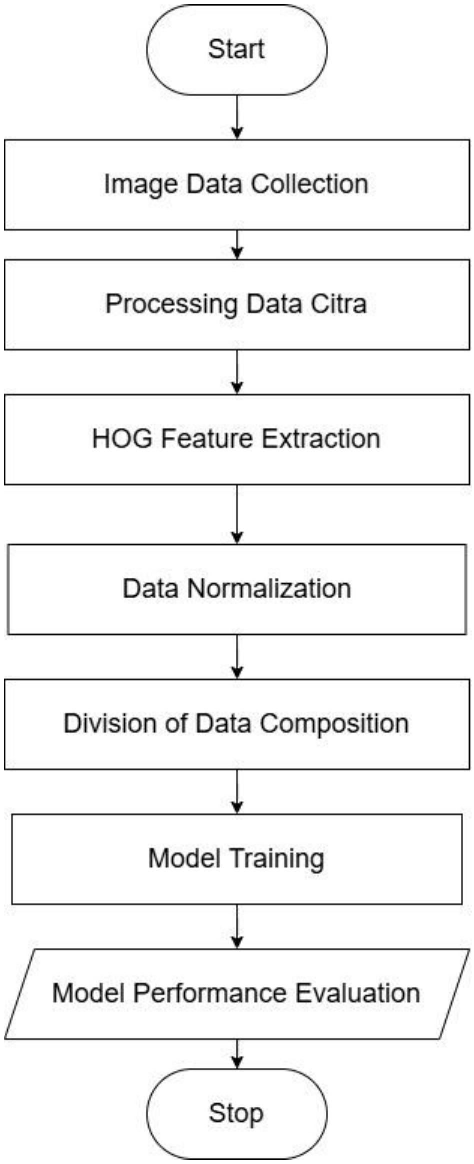

Figure 2. Flowchart System

HOG is a feature description technique designed to capture visual patterns based on gradient orientation distribution within an image[15]. It works by calculating gradient orientation frequencies in specific image areas[16]. This approach enables HOG to effectively represent object texture patterns and shapes, making it particularly valuable for object recognition and classification tasks[17]. In this research, HOG was implemented with parameters of 9 orientations, 8×8 pixels per cell, and 2×2 cells per block, producing numerical feature vectors as image representations. After feature extraction, the data was normalized using the StandardScaler method to ensure each feature had a mean of 0 and a standard deviation of 1.

Following preprocessing, the dataset was divided into two data-splitting scenarios to evaluate algorithm performance under different conditions. The first scenario utilized 80% of the data for training and 20% for testing, while the second scenario employed a 70-30 split[18]. The division was performed using stratified random sampling to maintain data distribution across all categories, ensuring a balanced representation of all image categories in the model. Classification models were trained using two algorithms: SVM and Random Forest. Support Vector Machine (SVM), introduced by Vapnik, is a kernel-based machine learning model used for classification and regression tasks[19]. This model supports various kernel functions that satisfy Mercer's conditions, including Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid[20]. Among these functions, Polynomial and RBF kernels are frequently employed in image analysis, including remote sensing applications, due to their effectiveness in capturing complex and non-linear patterns[21]. Random Forest is a machine-learning algorithm built on the combination of decision trees and bagging techniques[22]. In this algorithm, multiple decision trees are constructed based on training data subsamples. Predictions from each tree are then combined by calculating averages (for regression) or performing majority voting (for classification)[23]. Random Forest is an ensemble learning method that operates by constructing multiple decision trees during the training phase and outputting the class that represents the mode of the classes (classification) or mean prediction (regression) of the individual trees. In this research implementation, the Random Forest classifier was configured with 100 decision trees (n_estimators=100), where each tree is built using a bootstrap sample of the training data. The algorithm employs a technique called bagging (Bootstrap Aggregating), which creates different training subsets by randomly sampling the original dataset with replacement.

For each decision tree, at each node split, only a random subset of features is considered, specifically using the square root of the total number of features as recommended for classification tasks. This feature randomization helps prevent individual trees from becoming too correlated with each other, thereby reducing overfitting and improving generalization. Each decision tree in the forest grows to its maximum depth, splitting nodes based on the Gini impurity criterion to determine the best feature and threshold for splitting. The final classification decision for each image is made through majority voting across all trees, where each tree casts a vote for the predicted class, and the class with the most votes becomes the final prediction. This democratic voting system, combined with the random sampling of both observations and features, makes Random Forest particularly robust against noise in the dataset and capable of capturing complex patterns in the HOG feature space of tourist location images.

For SVM, the parameters included the RBF kernel with hyperparameter C=1 and automatically scaled gamma (scale). For Random Forest, the model was trained with 100 estimators and a fixed random state to ensure consistent results. This training process aimed to develop models capable of recognizing unique patterns in image data based on extracted features. Model performance evaluation was conducted using accuracy, precision, recall, F1-score metrics, and Confusion Matrix[24]. The Confusion Matrix provides insights into correct and incorrect predictions for each image category, encompassing True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values[25]. Accuracy was calculated as the ratio of correct predictions to total predictions, while precision and recall measured the proportion of correct positive predictions and the model's success rate in detecting positive categories, respectively. The F1-score, as the harmonic mean between precision and recall, was used to assess model performance balance[26]. Experiments were conducted on both algorithms with 10 different random states to ensure consistent and valid results. For each experiment, model performance results were recorded through classification reports and Confusion Matrix visualizations for each data-splitting scenario. The assessment of experimental results provided insights into the effectiveness of SVM and Random Forest in classifying images based on HOG features, with in-depth analysis comparing the performance of both algorithms under various conditions.

3. Result and Discussion

The dataset encompasses images representing these three tourist locations. The research consists of three main phases: data collection, data preprocessing, and model training, testing, and evaluation. An evaluation was conducted by dividing the dataset into two scenarios: 80% for training 20% for testing, 70% for training, and 30% for testing. Each scenario was repeated 10 times using different random states to ensure consistent and valid results. This research aims to evaluate the advantages of both algorithms based on performance metrics such as accuracy, precision, recall, F1-score, and Confusion Matrix analysis, providing deep insights into algorithm performance in tourist site image classification.

3.1 Dataset

The dataset consists of 450 images collected from the Pinterest platform, with each category (*Angel's Billabong*, *Broken* Beach, and *Kelingking* Beach) containing 150 images. These images were downloaded with varying resolutions and subsequently processed to ensure uniform data quality. The dataset was designed to capture visual features representative of each tourist location category.

Table 2. Number of Image Data

No	Image Data	Number of Images
1	*Kelingking* Beach	150
2	*Broken* Beach	150
3	*Angel's Billabong*	150

While the current study utilized 150 images per category (450 total images), increasing the dataset size could potentially enhance model performance and generalization capabilities. A larger dataset of 500+ images per category would allow the models to learn more diverse visual features and variations in lighting conditions, angles, and seasonal changes at each location. This expansion would be particularly valuable given that tourist attractions are photographed under varying conditions throughout the year. The current dataset size was chosen based on available high-quality images that met our strict criteria for a clear representation of each location, though future work could benefit from a more extensive collection process incorporating multiple seasons and weather conditions.

Figure 3. *Kelingking* Beach

3.2 Data Preprocessing

Data preprocessing was performed to ensure input quality consistency and optimally prepare data for model training. The first preprocessing step involved resizing each image to a uniform dimension of 128x128 pixels. This dimension was chosen to simplify data complexity while preserving relevant visual features. Subsequently, the resized images were converted to grayscale. This conversion aims to reduce data dimensionality, thereby decreasing computational requirements while maintaining essential visual elements for pattern recognition. After image transformation and simplification, features were extracted using the Histogram of Oriented Gradients (HOG) method. The HOG technique is designed to capture texture and shape information from images by analyzing gradient orientation distribution in specific image areas. This process generates a numerical representation in the form of comprehensive feature vectors useful for distinguishing unique patterns between image categories.

The final preprocessing step involved data normalization using the StandardScaler method. Normalization was performed to ensure all features had uniform scaling, with a mean of 0 and a standard deviation of 1. This is crucial for avoiding feature dominance due to different scales and for improving the stability and performance of the machine learning algorithms used.

3.3 Training, Testing, and Evaluation of the Classification Model

The training and testing process was conducted with two data training: testing compositions - 80%:20% and 70%:30%. Each composition was experimented with using ten different random state values (57, 127, 257, 357, 457, 497, 515, 535, 575, and 635) to enhance result validity, with each model tested separately to identify the best performance from both algorithms. Model evaluation was performed using several matrices including Precision, Recall, F1-Score, and Accuracy.

The following table presents the evaluation results of the Support Vector Machine (SVM) algorithm with an RBF kernel, using a data composition of 80% for training and 20% for testing. In this experiment, ten variations of the random state (57, 127, 257, 357, 457, 497, 515, 535, 575, and 635) were applied to assess the consistency and performance of the model. The table provides the values for Precision, Recall, F1-Score, and Accuracy for each configuration.

Table 1. Experiment on Support Vector Machine Algorithm with RBF Kernel Using 80% Training Data and 20% Testing Data

Experiment to-	Precision	Recall	F1-Score	Accuracy	Random State
1	0.95	0.94	0.94	0.94	57
2	0.97	0.97	0.97	0.97	127
3	1	1	1	1	257
4	0.98	0.98	0.98	0.98	357
5	0.95	0.94	0.94	0.94	457
6	0.99	0.99	0.99	0.99	497
7	0.96	0.96	0.96	0.96	515
8	0.94	0.94	0.94	0.94	535
9	0.94	0.93	0.93	0.93	575
10	0.96	0.96	0.96	0.96	635
Average	**0.964**	**0.961**	**0.961**	**0.961**	

The following table presents the evaluation results of the Random Forest algorithm with a data composition of 80% for training and 20% for testing. In this experiment, ten variations of the random state (57, 127, 257, 357, 457, 497, 515, 535, 575, and 635) were applied to evaluate the model's consistency and performance. The table provides the metrics for Precision, Recall, F1-Score, and Accuracy for each configuration.

Table 2. Experiment on Random Forest Algorithm with 80% Training Data and 20% Testing Data

Eksperimen to-	Precision	Recall	F1-Score	Accuracy	Random State
1	0.92	0.91	0.91	0.91	57
2	0.91	0.91	0.91	0.91	127
3	0.96	0.96	0.96	0.96	257
4	0.97	0.97	0.97	0.97	357
5	0.93	0.93	0.93	0.93	457
6	0.90	0.90	0.90	0.90	497
7	0.88	0.88	0.88	0.88	515
8	0.87	0.84	0.85	0.84	535
9	0.94	0.93	0.93	0.93	575
10	0.93	0.92	0.92	0.92	635
Average	**0.921**	**0.915**	**0.916**	**0.915**	

The following table presents the evaluation results of the Support Vector Machine (SVM) algorithm with an RBF kernel, using a data composition of 70% for training and 30% for testing. In this experiment, ten variations of the random state (57, 127, 257, 357, 457, 497, 515, 535, 575, and 635) were applied to assess the model's consistency and performance. The table provides the metrics for Precision, Recall, F1-Score, and Accuracy for each configuration.

Table 3. Experiment on Support Vector Machine Algorithm with RBF Kernel Using 70% Training Data and 30% Testing Data

Experiment to-	Precision	Recall	F1-Score	Accuracy	Random State
1	0.96	0.96	0.96	0.96	57
2	0.97	0.97	0.97	0.97	127
3	1	1	1	1	257
4	0.99	0.99	0.99	0.99	357
5	0.97	0.97	0.97	0.97	457
6	0.99	0.99	0.99	0.99	497
7	0.96	0.96	0.96	0.96	515
8	0.94	0.94	0.94	0.94	535
9	0.94	0.93	0.93	0.93	575
10	0.97	0.96	0.96	0.96	635
Average	**0.969**	**0.967**	**0.967**	**0.967**	

The following table presents the evaluation results of the Random Forest algorithm, using a data composition of 70% for training and 30% for testing. In this experiment, ten variations of the random state (57, 127, 257, 357, 457, 497, 515, 535, 575, and 635) were applied to evaluate the model's consistency and performance. The table provides the metrics for Precision, Recall, F1-Score, and Accuracy for each configuration.

Table 4. Experiment on Random Forest Algorithm with 70% Training Data and 30% Testing Data

Experiment to-	Precision	Recall	F1-Score	Accuracy	Random State
1	0.96	0.96	0.96	0.96	57
2	0.94	0.94	0.94	0.94	127
3	0.95	0.95	0.95	0.95	257
4	0.93	0.93	0.94	0.93	357
5	0.96	0.96	0.96	0.96	457
6	0.94	0.93	0.93	0.93	497
7	0.92	0.92	0.92	0.92	515
8	0.91	0.90	0.90	0.90	535
9	0.88	0.88	0.88	0.88	575
10	0.93	0.92	0.92	0.92	635
Average	**0.932**	**0.929**	**0.930**	**0.929**	

The following table summarizes the average values of Precision, Recall, F1-Score, and Accuracy from the experiments conducted on the Random Forest algorithm and the Support Vector Machine (SVM) algorithm with an RBF kernel. The experiments were performed using two data split compositions: 80% training data with 20% testing data, and 70% training data with 30% testing data, along with ten variations of the random state (57, 127, 257, 357, 457, 497, 515, 535, 575, and 635).

Table 5. Summary of Experiment Results on SVM with RBF Kernel and Random Forest Algorithms

Algorithm	Training Data	Test Data	Precision	Recall	F1-Score	Accuracy
SVM kernel RBF	80%	20%	0.964	0.961	0.961	0.961
Random Forest	80%	20%	0.921	0.915	0.916	0.915
SVM kernel RBF	70%	30%	0.969	0.967	0.967	0.967
Random Forest	70%	30%	0.932	0.929	0.930	0.929

Based on the summarized results of the experiments on the Random Forest and Support Vector Machine (SVM) algorithms, it is evident that the SVM with an RBF kernel outperformed the Random Forest algorithm in both experimental compositions: 80% training data with 20% testing data and 70% training data with 30% testing data. In the experiment with 80% training data and 20% testing data, the SVM with an RBF kernel achieved an accuracy of 0.961, precision of 0.964, recall of 0.961, and an F1-Score of 0.961. These metrics were superior to those of the Random Forest algorithm under the same composition, which recorded an accuracy of 0.915, precision of 0.921, recall of 0.915, and an F1-Score of 0.916. Similarly, in the experiment with 70% training data and 30% testing data, the SVM with an RBF kernel again outperformed the Random Forest algorithm. It achieved an accuracy of 0.967, precision of 0.969, recall of 0.967, and an F1-Score of 0.967, compared to the Random Forest algorithm, which recorded an accuracy of 0.929, precision of 0.932, recall of 0.929, and an F1-Score of 0.930. The experiment with 70% training data and 30% testing data using the SVM with an RBF kernel yielded the best evaluation results across all metrics Precision, Recall, F1-Score, and Accuracy compared to other experimental scenarios.

The experimental results demonstrate strong performance from both algorithms, particularly the SVM with RBF kernel. However, several factors could be analyzed more deeply to maximize performance. First, the impact of HOG parameters on classification accuracy could be investigated through systematic parameter tuning. The current configuration of 9 orientations, 8×8 pixels per cell, and 2×2 cells per block was chosen based on common practices, but optimal parameters might vary for this specific application. Second, the effect of different kernel functions for SVM could be explored, by comparing RBF with polynomial and linear kernels across different parameter settings. The Random Forest performance might also be improved through more extensive hyperparameter tuning, particularly regarding the number of trees and maximum depth settings. Additionally, analyzing the misclassified images could provide insights into challenging cases and guide future improvements. A detailed confusion matrix analysis for each experiment would highlight specific strengths and weaknesses in distinguishing between different tourist locations.

4. Conclusion

Based on experiments conducted using two data split scenarios 80% training data with 20% testing data, and 70% training data with 30% testing data with ten variations of random states, it was found that the SVM with an RBF kernel consistently outperformed the Random Forest algorithm. The evaluation results indicated that in the best scenario, with a data composition of 70% for training and 30% for testing, the SVM with an RBF kernel achieved an accuracy of 0.967, precision of 0.969, recall of 0.967, and an F1-Score of 0.967. These scores were higher compared to the Random Forest algorithm in the same scenario, which recorded an accuracy of 0.929, precision of 0.932, recall of 0.929, and an F1-Score of 0.930.

The superiority of the SVM with an RBF kernel lies in its ability to capture complex non-linear patterns in the image dataset, making it more effective for image classification applications in this context. Meanwhile, although Random Forest demonstrated stable performance, its results were consistently lower than those of the SVM with an RBF kernel across all evaluation metrics. Based on these findings, the SVM with an RBF kernel is recommended for implementation in the Nusa Penida tourism image classification system, particularly for applications requiring high accuracy and strong generalization capabilities. This research provides a significant contribution to the application of machine learning technology in the tourism sector while also paving the way for future studies. Potential directions include testing on larger datasets, applying data augmentation techniques, and developing models that are more adaptive to variations in image data.

5. Future Research

This research opens several promising avenues for future development and enhancement. First, expanding the dataset significantly beyond the current 150 images per category could improve model robustness and generalization capabilities. Future studies could incorporate seasonal variations, different weather conditions, and various photography angles to create a more comprehensive training dataset. Second, implementing data augmentation techniques such as rotation, flipping, and brightness adjustment could artificially expand the dataset and improve model resilience to different image conditions. Third, exploring deep learning approaches, particularly convolutional neural networks (CNNs), could potentially capture more complex visual features than traditional machine learning methods. Additionally, developing a mobile application interface for real-time tourist location recognition would make this technology more accessible to tourists and tourism operators. Future research could also expand to include more tourist locations across Nusa Penida and integrate this classification system with location-based services and tourist information systems. Finally, investigating transfer learning approaches using pre-trained models could potentially improve classification performance while requiring less training data.

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