Multisensory Culinary Image Classification based on SqueezeNet and Support Vector Machine

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***Abstract*— Food tourism can be a competitive advantage for Indonesian tourism. With diverse cultures and ethnicities, Indonesia certainly has local culinary characteristics not found in other regions. Although culinary tourism research has been conducted, not many have examined culinary tourism from multisensory experience analysis through a big data approach to obtain datasets that can be processed to visualize tourist experiences. This study aims to classify the multisensory experienced by tourists when doing culinary tours utilizing deep learning SqueezeNet for image extraction and Support Vector Machine with Linear Kernel for image classification. The primary dataset consisted of three image classes: Vibes, Place, and Food. This study succeeded in classifying multisensory culinary images with an accuracy rate of 98.6%.**

Keywords—multisensory, image classification, culinary tourism, support vector machine, squeezenet

I. Introduction

Culinary tourism can be a competitive advantage for the development of tourist destinations. Each region has local food with different tastes, raw materials, processing, and presentation methods. This can be a tourist attraction because it can provide a different sensation when eating local food. With enormous geographical and cultural diversity, Indonesian cuisine is rich in variety and taste. The assortment of traditional dishes is challenging for the government to promote to the international market [1]. Culinary connoisseurs have diverse inputs from their respective culinary tours. This results from what is recorded by the human senses, such as sight, hearing, food, taste, smell, and touch. The purpose of a picture can more or less represent or conjecture the initial value of some other Senses [2], [3]. The results of human vision that summarize several senses or multisensory can be compiled from several groups of culinary images ranging from photos of food to the atmosphere and location of culinary centers. Several studies around culinary tourism that collect tourist feelings and responses in the form of tweets and some food photos from online social media have been conducted [4]. Other studies only rely on various inputs from investors who first have culinary tourism experience from thematic locations [5]. The relationship between culinary tourism photos (food: food and beverage, vibes: atmosphere, and place: coziness) all represent the human senses (sight, taste, and touch) is closely related because culinary tourism not only includes the sensation of food, but also offers a rich multisensory experience [6].

A. Sighting and Photos of Culinary Tours

Multimedia technology is essential in developing, promoting, and presenting cultural tourism [7], [8] and especially culinary. The linkage between multimedia technology and cultural and culinary tourism involves using various multimedia elements to enhance the tourist experience and promote a region's cultural and culinary heritage. In a simple form, photo collection can represent places, activities, and various things about culinary tourism. Photos of culinary tourism play a crucial role in attracting human attention. Vision is the first sense when looking at pictures of food, atmosphere, or culinary attractions. Appetizing images, attractive food layouts, charming place décor, or beautiful natural scenery will influence interest and desire to taste food and visit the place [9].

B. Taste and Food

Taste is the primary sense involved when a person tastes food. When you see a stunning food photo, its taste immediately comes to mind. Taste is a critical element of the overall culinary experience, and food photos can stimulate one's taste buds and increase the desire to try the dish [10].

C. Atmosphere and Touch Experience

The atmosphere and tactile experience includes a variety of elements, including room décor, furniture, and food textures. Photos of the atmosphere in culinary attractions can present different nuances, such as relaxed, romantic, or adventurous. In addition, food photos can also show the texture of a dish, for example, food that is crispy, soft, or chewy. This tactile experience can affect a person's perception of the place and make them feel more connected to their surroundings [11].

This study intends to contribute to a culinary image classifier model with relatively high accuracy and represents several multisensory-related culinary tourism. The primary dataset consists of four classes: Vibes, Coziness, Place, and Food. One hundred nineteen images go through a VGG-16-assisted feature extraction process for further processing using the Support Vector Machine with a Linear kernel. We sourced the acquisition tools for this study from various types of gadgets owned by surveyors with an average image resolution of 4080 x 1780 pixels, density of 72 pixels, bit depth of 24, RGB color, exposure 1/100, ISO speed 179, maximum aperture 1.69. Processing using 1GHz CPU device, 4 GB RAM, without GPU.

The systematics of reporting this research begins with a presentation describing the latest culinary tourism trends and how tourists interact with their culinary locations and attractions. Furthermore, various related studies were presented which became the basis for the contribution of this research. Then, it described how this research was carried out through a sequence of stages. A review of the results that have been achieved in this research is also presented and closed with conclusions and suggestions for further investigation.

II. Related Works

A study on the introduction and classification of food has been conducted using a deep-learning classifier. The research resulted in a food image recognition method called NutriNet. This deep learning architecture is used to recognize the image of real food as well as the image of fake food and drinks. This architecture is a modification of AlexNet by increasing the pixel size from 256x256 to 512x512 for each image processed. Modifications were also made to the AlexNet by adding a convolution layer. Six hundred thirty-one food images, which consist of 55 food classes, were used. In addition, processors other than NutriNet are used, classifiers using Fully Convolutional Network 8s [12]. However, the study only produced an accuracy of 92.18%.

Still, within food image recognition, research has been conducted to classify food into several groups: unprocessed, processed and ultra-processed, and other culinary. The study used secondary datasets, namely EgocentricFood and UECFOOD. A primary dataset containing food images was acquired using a makeshift gadget camera, and labeling was carried out on each group of images[13]. However, the study only succeeded in achieving an accuracy rate of 90% classification for mean Average Precision (mAP) metric and 86% for the NOVA food classifier.

Food classification using machine learning technology is also carried out for foods that are considered to have different nutritional values. The EfficientNetB0 algorithm is used in transfer learning mode. A total of 101 types of food in traditional and foreign food groups were classified. The experimental process goes through several stages: feature transfer, fine-tuning, pre-trained model, and result acquisition. Several comparison algorithms, namely CNN, Random Forest, InceptionV3, and GoogleNet, are also used as benchmarks [14]. However, the use of EfficientNetB0 used in this study was only able to produce a classifier accuracy rate of 80%, equivalent to its comparator GoogleNet, while other classifiers did not exceed 80%.

Similar research in culinary matters is devoted to sorting out foods for people who avoid obesity and how to choose healthy foods has been done. The dataset they used was an available secondary dataset under the name Food-101. Transfer learning and adjustment of several classification algorithms such as InceptionV3 and V4, are used to recognize food in the form of digital images. Several stages were carried out in the experimental process: augmentation, multi-crop and initial processing of other food images [15]. However, this study only succeeded in producing a classifier accuracy of the dataset used, which was 85%. The overall related research that has been done to make food image modeling is shown in n Table 1

Table 1 Related Research

Author	Method	Accuracy
Mezgec, 2019	NutriNet & Fully Convolutional Network 8s	92.18%
Elbassuoni, 2022	mAP & NOVA food Classifier	86% & 90%
Vutkur, 2022	EfficientNetB0	80%
Shen, 2020	Inception V3 & V4	85%

III. Method

Fig. 1 Experiment Flow

This research has several stages, from image acquisition to creating a dataset of culinary tourism visits to various places of interest. Followed by ground truth, feature extraction, separation of training and testing data, modeling, results, and obtaining evaluation, the entire process of this experiment is shown in Fig. 1

A. Dataset Compilation

The grouped images are split into three multisensory classes: those representing feelings are labeled "Vibes," the results of vision of culinary products are labeled "Food," and the consequences for hearing and touch sensors are labeled "Place." After all, images have been successfully acquired and grouped under predetermined labels. The next step is to do Ground Truth by selecting each image in more detail and removing photos between similar classes because it will decrease accuracy. It is essential to obtain a high-precision training model.

B. Feature extraction

The next stage is the feature extraction process using pre-trained Deep Learning, namely SqueezeNet [16]–[18]. All 119 Photos are converted into numeric data in Rows and Columns with 119 rows and 1000 columns. Each column contains vector features of each image as a result of extraction performed using the deep model SqueezeNet. The feature extraction process using SqueezeNet can be followed on pseudocode, as shown in Fig. 2. The extracted data is then divided in half by a 60:40 combination for training and testing. The purpose of dividing data into two groups, training, and testing, is to ensure that the model that has been created can be used to test data outside the model in the hope of producing identification that has a high level of accuracy.

C. Modeling

Some classifiers used as comparisons in experiments that have been carried out are Support Vector Machine (SVM) [19], Neural Network (NN), kNN, Random Forest (RF), Logistic Regression (LR), and Naïve Bayes (NB). The first modeling process or classification performed using is done using a Linear kernel and 3-fold Cross-Validation. 3-Fold is selected after going through iterations that show the highest accuracy results. Several other classifiers will also be tested against the dataset for comparison. Thus, SVM with a linear kernel will outperform traditional classifiers for this multisensory primary dataset.We choose SVM with a linear kernel as the most accurate. In general, SVM will use the train dataset in notation $(x_1, y_1), \dots, (x_n, y_n)$ where the class is represented by y_i which consists of x_i. Grouping using a linear hyperplane as shown in formula (1). Parameter w denotes a vector against a hyperplane, while b is offset.

$$wTx - b = 0 \tag{1}$$

$$\emptyset(z) = \frac{1}{1 + e^{-1}} \tag{2}$$

$$Q(w) = \frac{1}{n}\sum_{i=1}^{n} Q_i(w) \tag{3}$$

```
import numpy as np
from Orange.data import Domain, Table
from Orange.widgets.utils.signals import Output
data = Table("..\dataMultisensory")
def extract_squeezenet_embedding(image_path):
embedding = np.random.rand(512)
return embedding
num_channels = 512
attributes = [Orange.data.ContinuousVariable(f"channel_{i}") for i
in range(num_channels)]
embedding_domain = Domain(attributes)
embedded_data = []
for instance in data:
embedding=
extract_squeezenet_embedding(instance["image_path"])
embedded_data.append(embedding)
embedding_table = Table(embedding_domain, embedded_data)
output_data = embedding_table
Output(output_data)
```

Fig. 2 Feature Extraction process using Squeezenet

Next is the Neural Network, also known as the Multilayer Perceptron with backward propagation prepared as a classifier for performance comparison, assisted logistic activation function according to formula (2), and Stochastic Gradient Descent according to formula (3) in the form of stochastic estimates. NN works with a number of neurons in a number of hidden layers. $\emptyset$ Is logistic function notation, z is horizontal Asymptote Notation, Q_i is the sum result of each iteration i, while w is a parameter to minimize Q.

kNN as a guided non-parametric classifier, kNN produces an output, i.e., class membership. Each observation is classified by proximity between objects and represented in positive k values using a range of small numbers such as 1,3,5,10 and 20 [20], [21]. This algorithm can utilize a variety of distance metrics for the classification process, including Mahalanobis, Chebyshev, Manhattan, Minkowski, Hamming, and Euclidean. Furthermore, the proximity between objects in the observation is calculated using the Euclidean distance metric in the formula (4).

$$d(e, f) = \sum_{i=1}^{n} (e_i - f_i)^2 \tag{4}$$

d represents the distance between two objects represented by the notation e and f

Naïve Bayes uses a probability-based classifier, NB is also included and can be used for image processing. Data modeling in NB processes observations that have been grouped and arranged in classes [22], [23]. Usually, grouping is done through the stages of ground truth. Two NB models are available, namely simple bayes network and kernel density estimation. The simple bayes network used in this study can be seen in the formula (5).

$$p(C_k|x) = \frac{p(x|C_k)p(C_k)}{p(x)} \tag{5}$$

The following comparison classifier is Random Forest. Random forest or random decision forest is a classification method that utilizes ensemble learning, a prediction method that uses several stages of learning. One of the ensemble learning algorithms used in random forests is bootstrap aggregation, otherwise known as bagging [24], [25]. Random forest also uses regression methods and other tasks by prepare many decision trees with formulas, such as in (6).

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \quad (6)$$

The training data is denoted as $X = x_1, \dots, x_n$, while the responses notated with $Y = y_1, \dots, y_n$, and repetition bagging notated with B iteration. The amount of training data is denoted as n, samples with content replacement are notated with X_b, Y_b regression trees are denoted as f_b on X_b, Y_b, and after the training process, the prediction is notated as x'.

The final stage is the evaluation process, which is displayed by the results of the classification of datasets using a confusion matrix. Confusion matrix plays a vital role in explaining classification and prediction results by presenting information about actual prediction results and prediction results made by the model [25], [26].

D. Measuring Classifier Performance

Advanced evaluation is to compare the performance of each classifier using several other quantities using information from the confusion matrix, and it can calculate several important evaluation metrics; some amounts used to determine classifier performance are Areas Under the Receiver Operating Characteristic Curve (AUC-ROC) or abbreviated AUC [26], Classification Accuracy(CA), F1, Precision and Recall. All of these variables work based on several actual prediction and observation results, namely, results where the model correctly predicts a positive class that is True Positive (TP), outcomes where the model predicts a negative class correctly that is True Negative (TN), results where the model incorrectly predicts a false positive class that is False Positive (FP), and results where the model incorrectly predicts a negative class, i.e., False Negative(FN) [27]. From these four quantities form several formulas, namely:

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$Recall(True\ Positive\ Rate) = \frac{TP}{TP + FN} \quad (8)$$

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$F1 = 2 * \frac{Recall * Precision}{Recall + Precision} \quad (10)$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN} \quad (11)$$

The AUC value is obtained by mapping the formulas (8) and (11) to form a Receiver Operator Characteristic Curve (ROC), where the highest or best value is close to 1.0, which means the best measurement is created.

IV. Results and Discussion

The overall image obtained from the data acquisition is divided into three classes: Vibes represent the atmosphere in the culinary center; the place represents information about the site, which can be in the form of restaurants, cafes, or street vendors; and food represents culinary diversity encountered by tourists. The illustration can be seen in Fig. 3. This research produces several outputs that can be used as a reference that a high-accuracy model under the objectives of this research is achieved. The result is a confusion matrix, accuracy between classifiers, and comparison of models based on ROC.

The first output, the confusion matrix table, displays the results of predictions that have been made using modeling of datasets with three classes, namely Food, Place, and Vibes. Based on 60:40 data separation, a total of 72 images trained were tested using 40% of the test data. The result was that 28 food labels were identified, while one image was incorrectly identified as the Place label. The other two labels, Vibes and Place, were all determined 100%. Everything is seen in Table 2

Fig. 3 Class Representation

Table 2 Confusion Matrix of SVM Linear tested **using 40% data.**

		Predicted Food	Predicted Place	Predicted Vibes	Σ
Actual	Food	28	1	0	29
Actual	Place	0	30	0	30
Actual	Vibes	0	0	13	13
	Σ	28	31	13	72

As seen in Table 3, by obtaining the prediction value displayed in the confusion matrix, the second output that becomes a benchmark for the success of experiments carried out is the accuracy table between classifications. In this table, some of the quantities used are Areas Under Curve, Classification Accuracy, F1, Precision, and Recall. sequentially from the classifier with the highest accuracy number, namely SVM, to the lowest classifier, namely Tree. There are three groups of classification accuracy quantities, namely the number group above 94% to 98%, the 80% group, and the 70% group. However, with a linear kernel for SVM classifiers, the extraction results in image datasets converted into numerical data can be selected on the support vector machine hyperplane to produce accurate models that are good enough to beat previous studies.

TABLE 3 ACCURACY BETWEEN CLASSIFIERS

Model	AUC	CA	F1	Precision	Recall
SVM	99%	98.6%	98.6%	98.7%	98.6%
LR	99.4%	97.2%	97.2%	97.4%	97.2%
kNN	96.2%	95.8%	95.8%	92.6%	95.8%
NN	98.8%	94.4%	94.4%	94.7%	95.8%
NB	97.6%	84.7%	85.3%	90.2%	94.4%
RF	95.1%	84.7%	83.8%	83.7%	84.7%
Tree	84.8%	73.6%	74.4%	76.7%	73.6%

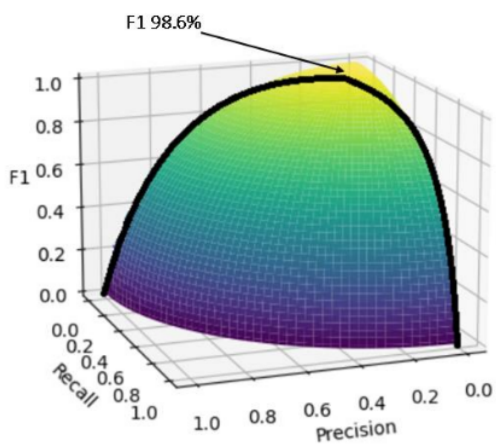

Fig. 4 Visualization of the Highest F1 score

Referring to the accuracy between each classifier, the comparative evaluation that can be used as a measure for accuracy is the value of F1. The following is a visualization of the F1 position of the SVM classifier with a Linear Kernel that managed to reach 98.6% depicted on the back of the spherical quarter graph, as shown in Fig. 4

TABLE 4 MODEL COMPARISON BASED ON ROC

	SVM	LR	kNN	NN	NB	RF	Tree
SVM		0.296	0.819	0.737	0.973	0.765	0.997
LR	0.704		0.817	0.733	0.966	0.722	0.997
kNN	0.181	0.183		0.186	0.337	0.569	0.979
NN	0.263	0.267	0.814		0.848	0.715	1.000
NB	0.027	0.034	0.663	0.152		0.685	0.998
RF	0.235	0.288	0.431	0.285	0.315		0.879
Tree	0.003	0.003	0.021	0.000	0.002	0.121	

Based on the previous two outputs then the last one output to ensure classifier performance is displayed in the comparison table of each model based on the ROC: TABLE 4 shows the probability that the score for the models in the row is higher than the model in the column, a small number indicates the likelihood that the difference is negligible. A comparative analysis of classifiers based on ROC can be read in TABLE 4 represented by reading the first line, i.e., the probability of SVM to Logistic Regression is more significant by numbers 0.296, notated with p(SVM>LR)=0.296, further against k-Nearest Neighbor denoted as p(SVM>kNN)=0.819, then against Neural Network as p(SVM>NN)=0.737, and the probability against Naïve Bayes as p(SVM>NB)=0.973, followed change against Random Fores as p(SVM>RF)=0.765 and finally is the probability of the Decision Tree as p(SVM>Tree)=0.997.

Why use SqueezeNet and not others? it is based on fewer parameters than other feature extraction algorithms. In comparison, InceptionV3 produces 2048 vector features, VGG16 makes 4096 vector features, while SqueezeNet only generates 1000 vector features containing information from the image. Thus, this quantity cuts down the iteration process in the training and testing stages of the data. Of the several classifiers used, namely SVM, NN, kNN, RF, LR, Tree, and NB, the highest classifier accuracy is obtained when using SVM. The combination of SqueezeNet and SVM for the feature extraction and classification process in this study is the choice that produces the model with the highest accuracy based on the dataset used. Then, all the classification results using various algorithms can be seen in TABLE 3. Furthermore, all of these results are seen in probability using TABLE 4, namely ROC; the relationship between TABLE 3 and TABLE 4 is complementary, although it is easier to read the results in TABLE 3. However, ROC is completeness to justify results in machine learning.

V. CONCLUSION

Some of the human senses represented by the three photo classes, such as Vibes, Food, and Place, include sight, taste, and atmosphere, and touch, interact, and influence each other in a culinary tourism experience. For example, a tasty image of food can trigger hunger and a desire to taste the dish. Likewise, a comfortable atmosphere and attractive views can increase satisfaction when eating. The holistic experience creates lasting and enjoyable memories for visitors. Accordingly, culinary tourism photos influence human perception and experience of food, atmosphere, and places. Sight provides the initial understanding of what is on offer, taste is the final judgment on food, and atmosphere and touch contribute to an overall experience that engages all the human senses. The paper studied a classification system for the culinary multisensory problem. The study targeted to classify the multisensory experienced by tourists when doing culinary tours by considering SqueezeNet deep learning for image extraction and Support Vector Machine with Linear Kernel for image classification. The proposed image extractor and classifier resulted in remarkably high accuracy for the multisensory culinary image classification problem.

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Multisensory Culinary Image Classification based on SqueezeNet and Support Vector Machine

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