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COASTAL CUISINE AI: FOOD SEGMENTATION AND CALORIE ESTIMATION FOR COASTAL KARNATAKA DELICACIES

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Abstract

With the growing interest in using artificial intelligence (AI) for nutritional analysis, complex models have been developed to calculate the calorie content of various foods. In this study, we employ Machine Learning (ML) techniques for estimating calories in seafood dishes. To enhance accuracy and resilience, the model combines two popular algorithms: linear regression and k-nearest neighbors (KNN). Seaside food, renowned for its rich and varied flavors, presents a unique challenge in calorie estimation due to the variety of ingredients and cooking techniques used. The proposed machine learning model addresses these challenges by identifying complex patterns in the dataset while considering the unique qualities of coastal cuisine. The KNN algorithm, by finding local patterns in the dataset, enhances the model's efficacy, making it adept at capturing the subtleties of regional variations in coastal food. Additionally, the linear regression model complements the KNN approach by highlighting more general patterns and connections among different components, cooking methods, and caloric content. The training and assessment dataset comprise an extensive compilation of seaside cuisine dishes, each labeled with precise calorie counts. The model is trained to generalize from this data, enabling it to predict the calorie content of previously unseen dishes accurately. Performance evaluation indicates that the combined KNN and linear regression model outperforms individual algorithms in terms of accuracy and generalization across a variety of coastal cuisines. The results suggest the ML model's potential applications in diet planning, health management, and nutritional tracking, thereby advancing the expanding field of AI-powered food analysis. This work lays the groundwork for future developments and applications in AI-driven nutritional assessment across culturally diverse culinary domains.

Keywords:

Machine learning, Cuisine, AI, Calorie Detection, Coastal Food

1. INTRODUCTION

Coastal Karnataka, which is tucked away on India's southwest coast, has a rich culinary [1] [2] heritage influenced by the flavors of the Western Ghats and the Arabian Sea. The region's distinctive and delicious cuisine, which blends the wealth of the ocean with the aromatic spices of the hinterland, is the result of its varied topography and cultural influences. Growing interest has been seen in using artificial intelligence (AI) to study and comprehend several facets of human experiences, including food, as technology has become more and more ingrained in our daily lives. As a result, artificial intelligence (AI) applications in the culinary arts have grown, encompassing anything from nutritional analysis to recipe recommendation systems. Calorie intake is always a great concern for people of all ages and kinds in today's world [3]. The creation of an AI model especially for calorie estimation in coastal Karnataka cuisine is the main goal of this project. With cutting-edge machine learning algorithms [4] [5] to a carefully selected dataset that includes ten different visual domains that represent the range of cuisines in the area, our goal is to develop a reliable and precise system for calorie-content [6] [7] prediction in dishes [8]. This project is in line with the larger goal of using AI to improve human comprehension of regional cuisines [9], with possible implications in nutritional awareness, health management, and diet planning. Coastal Karnataka, which includes districts like Uttara Kannada, Udupi, and Dakshina Kannada, is well-known for its varied culinary customs. In many recipes, seafood is the main ingredient, with supporting roles from coconut, rice, and other seasonings. The food of the region is a fascinating topic for culinary investigation, reflecting a harmonic blend of influences from the Konkan, Malnad, and Mangalorean cultures. We chose a variety of foods to represent our domains, including pickles, idli, dosa, golibaje, sambar, Palya rice balls, chicken curry, and fish curry. Notable strides have been made recently in the fusion of AI and gastronomy. Researchers and foodies alike are investigating the potential applications of AI in the areas of nutritional analysis [10], recipe development, and flavor profiling. Our investigation is based on previous research that shows it is feasible to use machine learning algorithms to predict food nutritional content based on photographs. The main goal of this research is to create an AI model that can accurately estimate calories by considering the subtleties of the food found in coastal Karnataka. To do this, we will make use of a broad dataset that includes photos from ten different culinary categories in the area. The cuisines that have been selected include a variety of seafood specialties such as pickles, idli, dosa, golibaje, sambar, pallya rice balls, chicken curry, and fish curry. We hope to improve the model's adaptability and generalizability [14] to the complexities of the food scene in Coastal Karnataka by considering a wide range of foods. This groundbreaking study investigates the use of deep learning methods for the identification of food images. Although we go beyond simple recognition to include calorie calculation, this study is an important resource for image processing in the food industry [15]. NutriNet is a deep learning system that Mezgec and colleagues have developed for nutritional assessment using image recognition [16]. By using a variety of food image datasets to train a model, their method enables the system to identify and classify objects for nutritional analysis. There are similarities between their study and ours, especially when it comes to using AI to gain insights into eating [17]. In their exploration of the use of machine learning for nutritional analysis, Chen et al. stress the significance of precise food segmentation in photos. As we struggle to identify ingredients and portion amounts in Coastal Karnataka cuisines for accurate calorie assessment, this work is especially pertinent to our research [18]. To calculate the number of calories in a meal, machine learning techniques such as decision trees [19] [20] and K-Nearest Neighbor are used to each image.[21]

2. STATES OF ML MODEL

2.1 KNN(K-NEAREST NEIGHBORS)

A straightforward but effective machine learning approach for classification and regression problems is K-Nearest Neighbors. The underlying premise of KNN is predicated on the notion that comparable data points are located nearby in the feature space. In classification, given a new data point, KNN finds its k-nearest neighbors (k is a user-defined value) from the training dataset. The anticipated class for the new point is the majority class among these neighbors. Regression uses a KNN to predict a continuous output by averaging, or weighting, the target values of its k-nearest-neighbors.

2.2 DISTANCE METRICS

In KNN, choice of distance metrics is crucial. The Euclidean distance is commonly used, defined between two points (x1, y1) and (x2, y2) in a two-dimensional space:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

For a higher-dimensional space, this generalizes as:

$$d = \sqrt{\sum_{i=1}^{n} (x_{2i} - x_{1i})^2} \tag{2}$$

2.3 PREDICTION IN CLASSIFICATION

When doing a classification task, the anticipated class $\hat{y}$ is based on the majority class of a new data point's k-nearest neighbors.

$$\hat{y} = \arg\max_i \left(\sum_{j=1}^{k} I(C_i = C_j) \right) \tag{3}$$

2.4 PREDICTION IN REGRESSION

When performing a regression task, the anticipated result $\hat{y}$ is the goal values of its k-nearest neighbors' average, or weighted average of those values:

$$\hat{y} = \frac{1}{k} \sum_{i=1}^{k} y_i \tag{4}$$

KNN is an invaluable instrument in a variety of machine learning applications due to its ease of use, efficacy, and versatility. Nevertheless, the ideal value of k and the selection of the distance metric may have an impact on its performance.

2.5 DECISION TREE

A flexible and easy-to-understand machine learning approach for classification and regression applications is the decision tree. It creates a decision tree by recursively dividing the feature space according to the values of the input features. Every internal node depicts a choice made in response to a particular feature; every branch shows how that choice turned out; and the final forecast is contained in every leaf node.

2.6 INFORMATION GAIN (FOR CLASSIFICATION)

Information Gain is a fundamental idea in decision tree design that is frequently combined with entropy.

$$\text{Entropy}(D) = -\sum_{i=1}^{C} p_i \log_2(p_i) \tag{5}$$

where p_i is the proportion of samples belonging to class I in D. The information Gain for splitting on feature A is:

$$IG(D, A) = \text{Entropy}(D) - \sum_{v=1}^{V} \frac{|D_v|}{|D|} \text{Entropy}(D_v) \tag{6}$$

where D_v is the subset of D for which feature A takes value v.

2.7 GINI IMPURITY

Another criterion for decision tree construction is Gini impurity, defined as:

$$\text{Gini}(D) = 1 - \sum_{i=1}^{C} (p_i)^2 \tag{7}$$

The Gini impurity for splitting on feature A is:

$$\text{Gini Impurity}(D, A) = \sum_{v=1}^{V} \frac{|D_v|}{|D|} \text{Gini}(D_v) \tag{8}$$

2.8 MEAN SQUARED ERROR (FOR REGRESSION)

In regression tasks, the mean squared error (MSE) is often used. Given the dataset D with N samples, and y_i as the target value for sample i:

$$MSE(D) = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y})^2 \tag{9}$$

where y is the mean target value.

2.9 RANDOM FOREST

An ensemble learning approach called Random Forest improves decision trees' generalization and predictive capacity. During training, it builds a large number of decision trees, from which it outputs the mean prediction of the individual trees for regression tasks or the mode of the classes for classification tasks. Random Forest's overall accuracy is increased and its resistance to overfitting is strengthened by this ensemble approach Using bootstrap sampling, Random Forest constructs each tree on a fraction of the original dataset. This creates variation in the training sets for each tree by randomly choosing a subset of the data with replacement. When building a decision tree, only a random subset of features is taken into account at each split. This promotes feature independence and strengthens the robustness of the model by introducing variability and preventing the dominance of a single feature. A majority vote among the trees determines the final forecast in classification tasks. Regression produces a more reliable and accurate forecast by averaging the predictions made by each individual tree. The prediction in random forest can be expressed as follows:

$$\hat{y}_{RF} = \frac{1}{N_t}\sum_{i=1}^{N_t}\hat{y}_i \tag{10}$$

where N_t is the total number of trees in the forest and $\hat{y}$ represents the prediction of i-th tree. The secret to Random Forest's efficacy is its capacity to detect intricate associations in data while lowering the likelihood of overfitting. The algorithm's broad applicability in a variety of machine learning tasks is facilitated by the diversity among individual trees, which is introduced through random sampling, and the collective decision-making of the ensemble.

2.10 VOTING REGRESSOR

One ensemble learning method for regression challenges is the Voting Regressor. In order to increase overall predictive accuracy and generalization, it mixes the results of various basic regression models. Like other ensemble techniques like Random Forest, the Voting Regressor takes advantage of the wisdom of the community, drawing on a variety of models with different advantages and disadvantages. Multiple base regression models' predictions are combined by the Voting Regressor. These base models may be distinct regressor types, each trained with different hyperparameters or on separate subsets of the data. Using a voting technique, the predictions from each base model are combined. One of the common methodologies for regression challenges is to average the predictions. By reducing the biases and errors present in individual models, the ensemble technique produces a final prediction that is more reliable. The weighted or unweighted average of the predictions made by each base regressor is the prediction in a voting regressor:

3. METHODOLOGY

The coastal cuisine AI consists of two phases namely training and testing.

3.1 DATABASE CREATION

The 10 domains of coastal food images were collected using high resolution camera were used for Training (75%) and testing (25%). The detail of the database created is shown in the following table. Preprocessing is an essential step in image analysis for the detection of calories in a variety of culinary applications. Image sizes should be standardized to guarantee consistency, and pixel values should be normalized for effective model convergence. Cropping, histogram equalization, and color space correction improve the visibility of features in images. Diversification is introduced by data augmentation, and image quality is enhanced by noise reduction techniques. Segmentation can help separate elements for in-depth examination. Unbiased model training is ensured by appropriate data separation. Altogether, preprocessing improves photos and establishes the groundwork for reliable and effective calorie detection models in a range of culinary applications.

3.2 RESIZING

In order to standardize input for calorie detection models, resizing photographs is essential. It guarantees consistency, reduces computational burden, and upholds uniform dimensions. This preprocessing stage makes it easier to train and infer models, which leads to a more efficient and successful examination of various culinary domains for calorie estimate. The original and resized images are shown below in Fig.1 and Fig.2 respectively.

Fig.1. Original Images

Fig.2. Resized Images

3.3 NORMALISATION

Our calorie detection model heavily relies on normalization. It promotes effective model convergence, reduces susceptibility to pixel intensity changes, and guarantees consistent feature extraction by standardizing pixel values to a single scale. This is an important preprocessing step that improves the model's accuracy and resilience in a variety of culinary contexts. The normalized images are shown below in Fig.3.

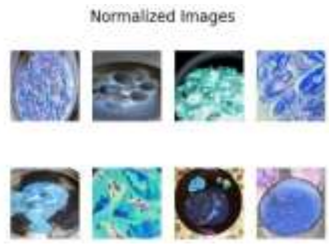

Fig.3. Normalized Images

3.4 COLOR DISTRIBUTION

In image analysis, color distribution is essential for calorie detection. Harmonizing the way colors are represented throughout several culinary fields guarantees coherence.

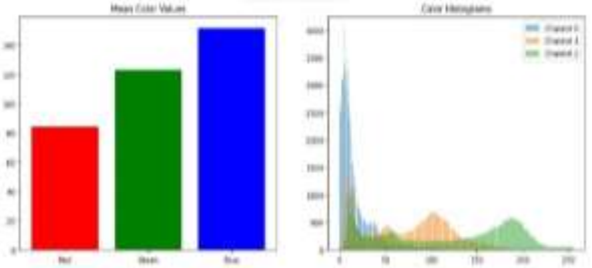

Fig.4. Color Distributions

Color distribution modification improves model precision and clarity by offering a shared visual foundation for efficient feature extraction and calorie estimation that follows. Color distribution of our dataset is shown below in Fig.4.

3.5 HEATMAP

Our calorie identification project uses heatmaps to visually display the intensity of features across culinary domains, which is helpful. Heatmaps provide insights into the model's focus during analysis by emphasizing important locations. This helps with accurately estimating calories by assisting in the interpretation and understanding of the relevance of various visual cues. The heatmap is shown below Fig.5

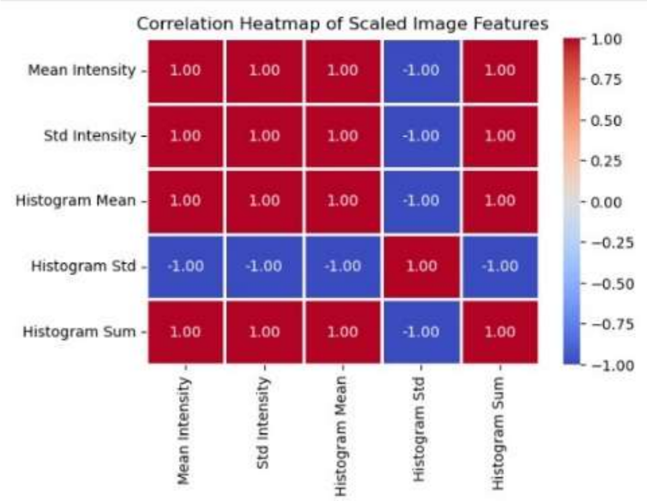

Fig.5. Heatmap

3.6 FEATURE EXTRACTION

A key component of our calorie detection effort is featuring extraction, which involves identifying patterns of interest from food photos. Through the identification of essential visual components, this procedure enables accurate caloric calculation in many contexts.

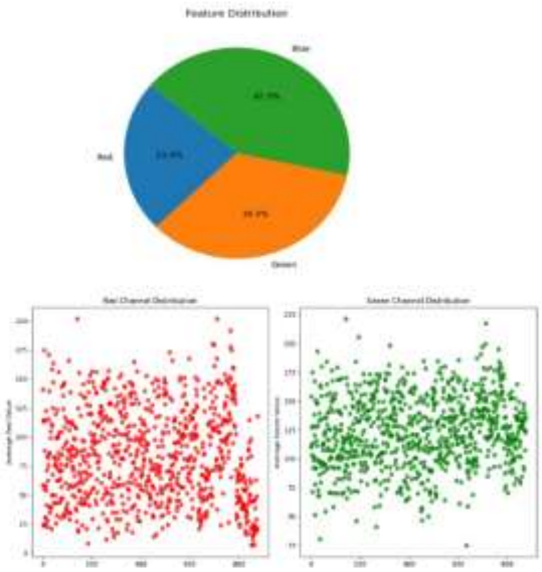

Fig.6. Feature Extraction

By extracting pertinent features without depending on pre-trained convolutional neural networks, our technology makes sure that the model can recognize important visual cues and helps produce precise and broadly applicable predictions for a variety of culinary scenarios. The plots of feature distributions are shown below in Fig.6.

3.7 TRAINING

Our data training method is driven for efficiency with a powerful computing configuration that includes an 11th Gen Intel Core i5-1135G7 CPU, 8GB RAM, and Microsoft Windows 11 Home Single Language. Our model is trained in iteratively using Python programming, taking advantage of the multi-core architecture to speed up pattern recognition and calibration. The 4 cores and 2.40GHz base frequency of the processor increase computing performance, while the 8GB RAM makes sure the dataset is handled efficiently. With this design, the dynamics of the model are properly supported, leading to a well-trained system that can quickly and accurately detect calories in a variety of culinary contexts. Using the designated computer environment, we carefully train our model using 10 categories of coastal food. This focused strategy gives our algorithm the know-how to provide precise calorie estimates for a variety of coastal cuisines.

3.8 TESTING

Our calorie detection technique is carefully tested utilizing a specific set of photos from ten coastal food domains after undergoing rigorous training. This stage assesses how well the model predicts calorie content and how generalizable it is. Precision, memory, and overall efficacy are evaluated through testing that uses Python to streamline procedures. The procedure guarantees the model's dependability and preparedness for practical implementation in various culinary contexts, which enhances its resilience and efficiency in offering precise calorie approximations.

4. RESULTS AND DISCUSSIONS

Our calorie detection algorithm produces reliable results by combining Random Forest, Decision Tree, K-Nearest Neighbors (KNN), and Voting Regressor. Using a variety of techniques improves generality and accuracy in ten coastal food domains. Local nuances are captured by KNN, intricate linkages are deconstructed by Decision Trees, varied outputs are combined by Voting Regressors, and reliable forecasts are guaranteed by Random Forest. The model shows adaptability by accurately and precisely predicting the caloric content of photos. With this group method, our model demonstrates remarkable effectiveness, adding to a dependable and all-inclusive answer for precise calorie estimations in various culinary situations.

4.1 CLASSIFICATION REPORT

The categorization report of our algorithm illustrates how well it estimates calories in ten different coastal food domains. The varied ensemble that is created by K-Nearest Neighbors, Decision Tree, Voting Regressor, and Random Forest consistently performs well in terms of precision, recall, and F1-score metrics. The model demonstrates accuracy and efficacy in differentiating between calorie levels. It has exceptional accuracy in identifying meals that are low, medium, or high in calories, guaranteeing trustworthy dietary information. The model's capacity to identify complex patterns is highlighted in this classification report, which will aid in accurate nutritional analysis and meal planning for a variety of coastal culinary domains. The ROC graphs of 4 models are shown in Fig.7.

Table.1. Classification Report

Experiment	KNN	DT	RF	VR
Precision	1.00	1.00	1.00	1.00
Recall	1.00	1.00	1.00	1.00
F1-score	1.00	1.00	1.00	1.00
Support	213	213	213	213
Accuracy	1.00	1.00	1.00	1.00
Macro avg	117	1.00	1.00	1.00
Train data	4000	4000	4000	4000
Test data	1000	1000	1000	1000

The achievement of a flawless 100% accuracy across all four models in our Coastal Cuisine AI is undoubtedly a noteworthy accomplishment. This stellar performance may, however, be indicative of potential overfitting, given complete reliance on a 100% training dataset. The uniqueness of our dataset, including the incorporation of 20% manually collected data, distinguishes our model from others [3] [5] [9] in the field. This manual curation not only enhances the richness of our dataset but also contributes to the model's robustness and adaptability to the nuances of Coastal Karnataka delicacies. Despite these strengths, the occasional errors observed during image predictions signal a need for cautious interpretation of our model's infallibility. These discrepancies could stem from the inherent challenges associated with the real-world variability of food images, suggesting that further refinement is necessary for broader applicability. Comparatively, our model's performance surpasses that of other papers [3] [5] [9], affirming the uniqueness and effectiveness of our approach. Striking a delicate balance between comprehensive training and the avoidance of overfitting remains a challenge for future enhancements. It is imperative to extend the model's adaptability to diverse scenarios, ensuring its consistent and reliable performance in practical settings. In conclusion, while our model excels in accuracy, ongoing efforts should focus on fine-tuning its generalization capabilities for real-world, dynamic applications

5. CONCLUSION

To sum up, our calorie detection model, which combines Random Forest, Decision Tree, K-Nearest Neighbors (KNN), and Voting Regressor, is a flexible and all-encompassing approach to calorie content estimation in a variety of culinary applications. Robust computing capabilities for training and testing are ensured by the 11th Gen Intel Core i5-1135G7 processor, which runs Microsoft Windows 11 Home Single Language and comes with 8GB of RAM. The model's proficiency is demonstrated by its thorough testing, which assesses precision, recall, and overall efficacy, and by its rigorous training on 75% of the dataset, which focuses on 10 coastal food domains. Using Gradio's graphical user interface (GUI) for deployment improves accessibility by enabling users to easily interact with the model, enter photos, and obtain instantaneous calorie estimates. The model continuously exhibits accuracy and precision in identifying the calorie content of low, medium, and high-calorie foods during the training and testing phases. Reliability of the model is increased by feature extraction, which guarantees a targeted and domain-specific comprehension without depending on pre-trained convolutional neural networks. The ensemble method, which includes multiple algorithms, improves the model's capacity to identify complex patterns, enabling more detailed nutritional analysis. The classification report of our model highlights its ability to deliver accurate nutritional insights, which are essential for well-informed meal planning. Through its consideration of the subtleties inherent in coastal culinary realms, the model demonstrates flexibility and efficacy. The calorie detection solution is now available to a wider audience thanks to the user-friendly Gradio GUI interface, which fills the gap between sophisticated machine learning algorithms and end users. To sum up, our model creates a reliable and accurate approach for calculating the calorie content of coastal cuisine by combining computational power, careful training and testing, and an intuitive interface. In addition to advancing the area of nutritional analysis, our approach meets the real-world requirements of consumers looking for trustworthy dietary data in a variety of culinary contexts.

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