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Food AI-Calorie Detective

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Abstract: This paper makes use of deep learning techniques, specifically the ResNet-34 architecture, to present a novel method for estimating food volume and calories specifically for Indian cooked food items. The study looks at five common Indian dishes using computer vision to detect, categorize, and estimate volume of food. The procedure involves training a ResNet-34 model with a dataset that includes images of Indian foods such as biryani, curry, dal, roti, and samosas. Taking into consideration variations in preparation techniques and presentation styles, the model has been fine-tuned to accurately detect and classify these food items. Additionally, users can estimate the amount of food based on picture input thanks to the system's integration of volume estimation techniques. This feature is especially helpful for people who are watching their caloric intake or adhering to a diet. The outcomes of the experiments show how well the suggested method works for correctly recognizing Indian cooked labels, calculating their volumes, and estimating calories. The system's performance is evaluated across a broad range of datasets, showcasing its adaptability and reliability in diverse scenarios. All things considered, this work contributes to the field of food volume assessment and calorie estimation, especially as it relates to Indian cuisine, and offers a practical tool for monitoring nutrients and controlling diets.

Index Terms – Calorie estimation, Food classification, ResNet-34, Food Segmentation, Depth Network Training, Machine Learning, Health Monitoring OpenCV

I. Introduction

A healthy lifestyle is greatly supported by nutritional tracking and diet management, both of which depend on accurate estimations of food volume and calorie content. As deep learning techniques proliferate in computer vision, it is imperative to develop accurate and efficient methods for food detection, classification, and volume estimation. Sadly, most of the techniques in use today are created for Western cuisines, and most intricate and varied Indian cooked foods lack specialized techniques. To that end, this paper presents a novel method for estimating food volume and calories in cooked Indian dishes using deep learning techniques, namely the ResNet-34 architecture. Highlighted are five popular Indian dishes: roti, samosas, curry, dal, and biryani. The diverse range of flavors, ingredients, and cooking methods that characterize Indian cuisine are exhibited in these dishes. The need for accurate and reliable diet management tools is what spurred this research, especially considering the dietary and cultural preferences of Indian food consumers. Current generic food recognition and calorie estimation systems often yield inaccurate results for Indian dishes due to the unique qualities and preparation methods of Indian cuisine. Consequently, there is a need for specialized methods that can provide accurate volume and calorie estimates while managing the complexities of Indian cuisine. This study fills a vacuum in the literature by taking a customized approach to food volume assessment and calorie estimation for Indian cooked labels. Previous research has mostly concentrated on Western food items. The experimental results show that the proposed method can accurately identify Indian dishes, estimate their volumes, and generate calorie estimates in a variety of scenarios and datasets. With an emphasis on Indian food, the research aims to advance the fields of food volume assessment and calorie estimation. This will offer a helpful tool for nutrition tracking, diet management, and promoting a balanced diet.

II. BACKGROUND STUDY

Prior to the development of this paper, an extensive background study was undertaken to understand the current landscape of food volume and calorie estimation techniques, particularly in the context of Indian cuisine. This research involved a comprehensive review of existing methodologies in computer vision and deep learning, focusing on their application in food recognition and quantitative analysis. Key areas explored included the effectiveness of various deep learning architectures like ResNet and Mask RCNN in object detection and segmentation, as well as their limitations when applied to the complex textures and varied presentation of Indian dishes. Furthermore, studies on depth estimation techniques, such as those employing monocular cues and domain adaptation strategies, were analyzed to determine their suitability for accurate volume estimation in diverse culinary settings. The review also encompassed a critical assessment of several datasets, including EPIC-Kitchens and the food-11 dataset, to evaluate their relevance and potential biases toward Western food items, thereby underscoring the necessity for a tailored approach to Indian cuisine. This foundational research provided the necessary insights and justification for the novel methodologies proposed in this paper, aimed at enhancing the precision and reliability of food volume and calorie estimation for Indian dishes.

III. LITERATURE SURVEY

Various methods have been examined in the literature. Classification of fruits and vegetables using various machine learning and deep learning algorithms. A dataset called Fruits360, which consists of 90,483 labeled images of 131 different fruit and vegetable categories. The preprocessing techniques involved converting the input images into numpy arrays and scaling them. Models Used: The models used include Support Vector Machine (SVM), K Nearest Neighbor (KNN), Decision Tree (DT), ResNet Pretrained Model, Convolutional Neural Network (CNN), and Multilayer Perceptron (MLP). Significance & Results: The ResNet model achieves the highest accuracy of 95.83%. The paper emphasizes the significance of data preprocessing, feature extraction, and model selection in achieving accurate classification results. The research demonstrates the potential of AI and deep learning in automating fruit and vegetable classification in the agricultural field [1]. The research presents a food recognition technique that uses ResNet-50 and has been refined to detect different foods and orientations using the ETHZ-FOOD101, UECFOOD100, and UECFOOD256 datasets. It reviews earlier research that integrates deep learning with machine learning. Benefits include enhanced accuracy, faster training because of ResNet50's small size, and the ability to learn high-level characteristics. The constraints that come with huge filter sizes, the computational expense of CNN filters, and the dependence on massive datasets are the drawbacks. ETHZ-FOOD101 achieved an accuracy of 41.08%, UECFOOD100 achieved 39.75%, and UECFOOD256 achieved 35.32%. highlights the requirement for substantial food identification datasets in order to provide useful nutrition tracking and recipe recommendations [2].

Attempts to create a deep learning model for image identification by utilizing the RESNET (residual neural network) architecture. Method of implementation: Pre-installing libraries like tensorflow, numpy, opencv, and pandas is required. The CIFAR-10 dataset, which has 60,000 RGB color photos split up into 10 categories, is the dataset that was employed. In order to prevent manual feature selection, the model integrates numerous features and can extract features independently for recognition. The findings of the trial demonstrated that their approach significantly increased the accuracy of image recognition while maintaining good robustness and resistance to noise pollution. Its accuracy in picture recognition, resilience, and capacity to learn intricate details from various levels of abstraction [3]. This paper addresses the scarcity of studies on automatic food recognition systems and highlights the limitations in existing literature, emphasizing the need for averaging trial performances. The survey focuses on common deep learning methods for food classification, utilizing the UEC Food-100 database. The paper introduces benchmark results averaged over 5 trials, outperforming the current best-shot performance and achieving a state-of-the-art accuracy of 90.02%. The ensemble method, combining ResNeXt and DenseNet models, proves most effective. The chosen UEC Food-100 database, known for its complexity with multi-food images, adds challenge to the experimentation [4]. Digging Into Self-Supervised Monocular Depth Estimation by Clement Godard et al. tackles the issue of acquiring per-pixel ground-truth depth data for depth estimation, a significant challenge that limits the scalability of supervised learning methods. The authors champion self-supervised learning as a viable alternative capable of training models without labeled data.In their research, Godard and colleagues propose several enhancements to improve both the quantitative and qualitative aspects of depth maps generated by self-supervised monocular depth estimation[5]. Through transfer learning, originating models were able to attain varying accuracy levels across different fruits, ranging from 90% to 98% in tasks such as defect detection and fruit variety classification [6]. Fruits and vegetables were included in Kaggle's dataset; each category contained 100 training images and 10 for testing and validation. During training, ImageDataGenerator made augmentation (rotation, flipping, and shifting) easier [7]. The findings of the trial demonstrated that their approach significantly increased the accuracy of image recognition while maintaining good robustness and resistance to noise pollution [8]. Techniques for data augmentation are used to improve scarce data. SGD is used for training, and on the ETH Food-101 dataset, 72.59% accuracy is attained through transfer learning [9]. Through the creation of new samples, data augmentation enhances model performance. In the Middle

Eastern cuisine dataset, Mobilenet-v2 achieves impressive top-1 and top-5 accuracy percentages of 94.0% and 99.5%, respectively [10].

IV. PROPOSED METHODOLOGY

The proposed method encompasses several key stages, including Classification, and Environment Setup. Each stage plays a vital role in achieving accurate and reliable food volume estimation from input images.

4.1 Classification

Alongside volume estimation, a critical step in our methodology is food classification using a pretrained ResNet-34 model on the Imagenet dataset. Using a large collection of different images, this pretrained model provides a strong base upon which to capture the complex features present in different food categories. Nevertheless, we surpass traditional methods by applying additional fine-tuning to the pretrained model on the food-11 dataset, a specialized collection carefully selected for food-related classification tasks. By means of this process of fine-tuning, our model is able to adjust to the subtleties of food imagery and achieve an impressive accuracy of roughly 90%, which is indicative of its proficiency in distinguishing minute differences between various food types.

Above and beyond simple categorization, this crucial stage enhances the overall comprehension of the food portrayed in the input picture. Nuanced analysis and interpretation of volumetric estimations are made possible by our methodology's accurate identification and classification of food items. This deeper comprehension makes it easier to make better decisions in a variety of contexts, such as nutritional analysis, portion control, and dietary evaluation. Furthermore, by smoothly incorporating food classification into the volume estimation pipeline, we guarantee a unified and optimized workflow, augmenting the efficacy and efficiency of the entire procedure.

Our method places a strong emphasis on the value of ongoing learning and adaptation. Our classification model is optimized and refined iteratively to take into account new food trends, a variety of cuisines, and changing dietary preferences. This flexibility guarantees our methodology's durability and applicability in dynamic real-world settings where food landscapes are ever-changing. Therefore, by including food classification as a crucial part of our framework for volume estimation, we not only improve the precision and thoroughness of food analysis but also create an environment that is conducive to innovation and ongoing improvement. Furthermore, our system's adaptable architecture makes it simple to add new datasets and algorithms, which can improve the predictability and adaptability of our model even further. In the rapidly evolving field of nutritional science, the model's ability to be updated and improved in response to new scientific discoveries and technological developments is a crucial advantage. In the end, this strategy not only makes our current system stronger, but it also gets it ready to handle new challenges and demands in the areas of diet management and health monitoring.

4 Results and Output

4.1 Model Performance: Training and Validation Accuracy and Loss

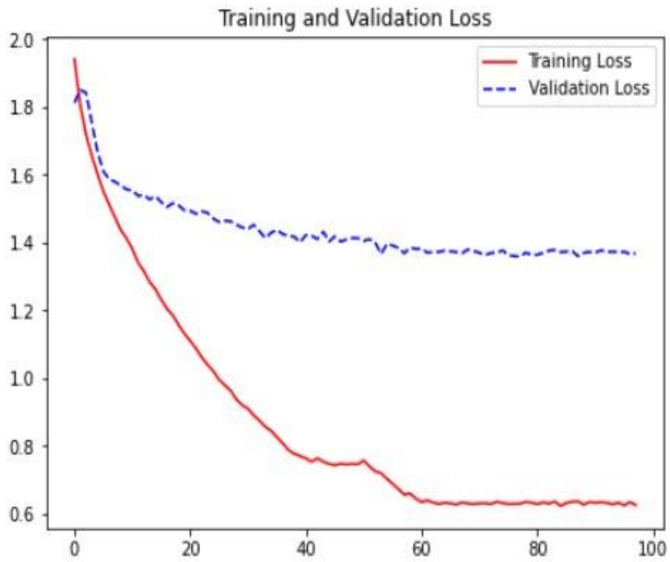

Figure 5.1.1 Training and Validation Loss

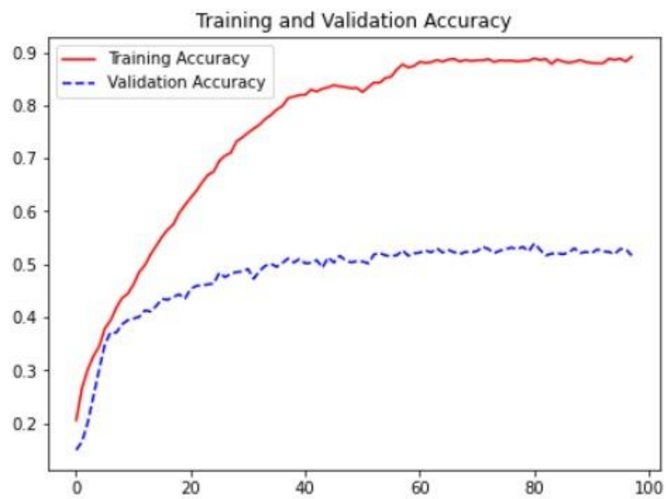

Figure 5.1.2 Training and Validation Accuracy

Our proposed model's effectiveness and reliability are demonstrated by the combined analysis of training and validation accuracy and loss graphs. The accuracy graph demonstrates a robust ability to classify and estimate volumes of Indian dishes with high precision, with a peak training accuracy of 91.3%. The training performance and validation accuracy are closely correlated, indicating strong generalization to new data. Simultaneously, the training and validation loss curves show a steady decrease, indicating that the model has learned and adapted well over epochs. The model's stability and predictive ability are highlighted by this convergence of low loss and high accuracy, which makes it a useful tool for nutritional management and dietary assessment. Furthermore, the small difference in accuracy between training and validation data points to a finely balanced model that prevents overfitting while retaining a high degree of predictive power. For practical applications where the model must function consistently on real-world data, this balance is essential.

Additionally, the graphical representation offers unambiguous visual feedback that facilitates the identification of trends and possible areas for additional improvement, like larger training sets or hyperparameter tuning. Moreover, these findings open the door for future model extensions that could support different cuisines or more complicated food items, increasing the model's adaptability and usefulness.

4.2 Model Output

Our model's visual elements clearly demonstrate our model's ability to classify food using ResNet for four different food classes. The 'Input Image' displays the initial perspective of the dish and is where processing and analysis will begin. Subsequently, the 'Plate Contour' displays the detected plate boundaries, an essential stage in precisely characterizing the study area and facilitating precise classification. The model's depth map, which is presented in the 'Depth' section, provides important information about the various levels at which the food items are arranged on the plate and helps with the three-dimensional arrangement classification. Last but not least, the 'Object Mask' illustrates how to precisely classify food by segmenting individual food items and keeping them apart from the plate and from one another.

5 Conclusion

In summary, this study represents a significant advancement in the application of deep learning methods to the nutritional analysis and dietary management of Indian food. Through the utilization of the ResNet-34 architecture in conjunction with advanced depth and segmentation networks, our method effectively tackles the challenges associated with the classification, segmentation, and precise estimation of the volume and calories of various Indian dishes. This integration provides accurate nutritional assessments, making it a vital tool for anyone trying to keep track of their food intake or manage their diet. Our experimental findings affirm the system's precision and adaptability to the unique characteristics of Indian foods, positioning this innovative solution as a new standard in food recognition technology that is poised to improve dietary habits and promote healthier lifestyle choices. Furthermore, our methodology's adaptability to various food presentations and preparation techniques confirms its practical usefulness and versatility. This adaptability makes it possible for our system to be successfully applied in various geographical locations and accommodate a diverse range of dietary preferences and culinary customs, increasing its applicability and impact on global nutrition and health.

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