International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Estimation of food Calorie Detection: A Systematic Literature Review

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***Abstract*— Food calorie discovery has surfaced as a vital area of exploration due to the global rise in rotundity and associated health pitfalls. This review synthesizes advancements across four studies that work deep literacy, computer vision, and convolutional neural networks(CNNs) for accurate food recognition and calorie estimation. ways include Inception V3, ResNet, TensorFlow APIs, andmulti-task CNNs, showcasing advancements in food image bracket, volume estimation, and calorie calculation. These styles address challenges like different food donations and dataset variability, paving the way for practical operations in salutary monitoring and healthcare. Keywords Food calorie discovery, convolutional neural networks, deep literacy, image recognition, TensorFlow,multi-task literacy, volume estimation.**

The significance of this exploration lies in its capability to bridge gaps between theoretical advancements and practical operations, especially in the environment of global health challenges. By understanding the methodologies and results of these studies, this paper aims to give a consolidated resource for experimenters, masterminds, and interpreters in this arising sphere.

Keywords*—*Machine learning, Deep learning,Face Recognition, Convolutional neural networks,

I. INTRODUCTION

The adding frequence of rotundity and its health counteraccusations , including heart complaint, diabetes, and order diseases, have boosted the need for salutary monitoring. According to the World Health Organization(WHO), over 1.9 billion grown-ups were fat in 2021, with over 650 million distributed as fat. This epidemic has placed a limelight on salutary habits and calorie consumption as critical factors in public health.

Calorie discovery through food recognition systems offers a promising result by enabling druggies to track their input seamlessly. similar systems combine advanced machine learning algorithms with stoner-friendly interfaces, making them accessible to a broader followership. The integration of convolutional neural networks(CNNs) in these systems has been a game- changer, furnishing unknown delicacy in feting food particulars and estimating their sweet content.

This paper reviews state- of- the- art ways fastening on CNN- grounded models and their operations in food discovery and calorie estimation. These ways demonstrate how advancements in artificial intelligence(AI) can address real- world health challenges. By exploring the methodologies, limitations, and results of crucial studies, this paper aims to punctuate areas for unborn exploration and implicit advancements in this field.

II. RELATED WORKS

A. PaperTitle: FoodieCal A CNN- Grounded Food Discovery and Calorie Estimation System

Description: This study introduced a CNN model exercising commencement V3 and ResNet for food discovery and calorie estimation. The system trained on a dataset of 23,000 images achieved an delicacy of 89.48. The model was stationed on a webpage, allowing real- time food recognition and calorie vaticination.

Methodology: The dataset comported of 23 food orders, including popular particulars like pizza, burgers, and sushi. Images were preprocessed for size and quality, and features were uprooted using the Inception V3 model. The CNN was trained with a categoricalcross-entropy loss function to enhance vaticination delicacy. Post-training, the system was stationed on a webpage where druggies could upload images to admit calorie estimations incontinently. Limitations: - The dataset demanded diversity in portion sizes, limiting the model's capability to estimate calories for surprisingly large or small servings. Overfitting was observed in calorie estimation, particularly when the dataset was inadequate to represent the variability within food orders..

Key Insights: Themulti-task CNN outperformed single- task models by usinginter-task correlations. This approach reduced computational outflow and enhanced model effectiveness, making it suitable for real- world operations where recycling power is limited.

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Citation:[1] Pordoy, J., Farman, H., Dicheva, N. K., Anwar, Shahriar et al., BRAC University [14 † source] al.

B. Paper Title:Food Calorie Estimation Using Convolutional Neural Network

Description: This study employed TensorFlow APIs, Random Forest, and Support Vector Machines(SVM) alongside CNNs for food discovery and calorie estimation. The ECUST Food Dataset, comprising 19 food orders, was employed

Methodology: - TensorFlow's Object Discovery API was abused to identify food particulars. The dataset included images of fruits, vegetables, and common refections. Features similar as size, shape, and texture were uprooted and used to train CNNs. GrabCut segmentation was applied to insulate food particulars from complex backgrounds. Hyperparameter tuning bettered performance by optimizing literacy rates and batch sizes.

Limitations: Homemade labeling of data confined scalability, as expanding the dataset needed significant mortal trouble. also, the model plodded with multi-item discovery in cluttered scenes, where lapping foods led to reduced delicacy

.Key Insights: CNNs demonstrated superior performance over traditional machine literacy styles like Random Forest and SVM. Achieving 92 delicacy underlined the eventuality of combining machine literacy and deep literacy ways for robust food discovery.

Citation: Balaji and Jayapandian, CHRIST University [14 † source]

C. Paper title: Contemporaneous Estimation of Food orders and Calories withMulti-task CNN

Description: This study proposed a multi-task CNN to contemporaneously estimate food orders and calories. A dataset of 4,877 images across 15 food orders was curated for the trials.

Methodology: The multi-task CNN was grounded on VGG16 armature, featuring participated and task-specific layers. The participated layers uprooted common features from images, while task-specific layers optimized for either order recognition or calorie estimation. instigation SGD was employed for optimization, balancing loss functions to insure both tasks were inversely prioritized. Limitations: The dataset demanded diversity in portion sizes, limiting the model's capability to estimate calories for surprisingly large or small servings. Overfitting was observed in calorie estimation, particularly when the dataset was inadequate to represent the variability within food orders.

Key Insights:The multi-task CNN out performed single-task models by using inter-task correlations. This approach reduced computational outflow and enhanced model effectiveness, making it suitable for real- world operations where recycling power is limited.

Citation: Ege and Yanai, University of Electro- Dispatches, Tokyo 【 14 † source 】

D. Paper title: Food Calorie Estimation Using Deep Learning Algorithms

Description: - This exploration emphasized volume and calorie estimation from food images using CNNs and Faster R- CNN for object discovery. The ECUST Food Dataset was employed to estimate performance.

Methodology: GrabCut was used to member food particulars from the background, while TensorFlow eased the training of CNNs. Calorie estimation was grounded on volume computations, acclimated for food viscosity. fresh features like texture and color slants were incorporated to enhance vaticination delicacy. intensity levels. .

Limitations: Segmentation plodded with desultorily shaped foods, similar as salads or mixed dishes. The system's reliance on controlled lighting and invariant backgrounds limited its connection in different real- world surroundings.

Key Insights: The system achieved a mean calorie error of 45.79, pressing the significance of accurate segmentation in perfecting results. The use of advanced algorithms like Faster R- CNN demonstrated the eventuality for handling complex datasets.

Citation: Multiple Authors 【 14 † source 】.

E. Paper title: Deep Learning-Based Food Calorie Estimation Method in Dietary Assessment: An Advanced Approach Using Convolutional Neural Networks

Description: This study proposes a novel method for automating dietary assessments using deep learning and image analysis. The approach employs Convolutional Neural Networks (CNNs) to identify food items from digital images and estimate their portion sizes. By leveraging photometric measurements and nutritional databases, the method calculates calorie content with improved accuracy. The ultimate goal is to streamline dietary monitoring for both patients and healthcare professionals, facilitating better health management.

Methodology: The process involves two stages: (1) Food identification using CNNs trained on food-specific datasets like Food-101 and UECFOOD256; and (2) Portion size estimation and calorie computation using reference objects in the image to scale food dimensions and calculate volume. Deep learning models are then used to estimate portions and compute calories by cross-referencing with nutritional databases. Transfer learning with pre-trained models like VGG16 and ResNet50 ensures robust results.

Limitations: The method struggles with variability in food presentation, preparation styles, and serving sizes, which may affect its accuracy. It assumes standard shapes for food items, which might not represent all cases. The reliance on pre-trained models may limit adaptability to new or underrepresented food categories. Additionally, the performance heavily depends on the quality and diversity of the training datasets.

Key Insights: This method demonstrates the potential of CNNs in automating food calorie estimation, significantly reducing the dependency on manual inputs. The use of photometric measurements enhances accuracy in portion size estimation. The integration with nutritional databases allows for comprehensive dietary assessment. However, further improvements are required to address real-world variability and expand the range of detectable food items.

Citation: Kalivaraprasad B, Prasad M.V.D, Naveen Kishore Gattim. "Deep Learning-Based Food Calorie Estimation Method in Dietary Assessment: An Advanced Approach Using Convolutional Neural Networks." International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 15, No. 3, 2024.

F. Paper title: A Study of Calorie Estimation in Pictures of Food

Description: This study investigates the accuracy of calorie estimation in food images using crowd sourced annotations. The researchers analyzed the ability of nonexperts and nutrition experts to estimate calorie content, uncovering patterns of bias and noise in estimation. The study explores the potential of using collective wisdom and demographics to improve calorie-tracking applications, ultimately aiming to facilitate dietary monitoring.

Methodology: Participants provided calorie estimates for food images via an online quiz. The images, with known calorie values, included a range of food types. Researchers compared non expert estimates with expert annotations and examined demographic influences on accuracy. Linear mixed-effects models were used to identify patterns and biases, while the "wisdom of the crowd" approach aggregated responses to improve accuracy.

Limitations: The study found that calorie estimation accuracy remained low, even for experts, with significant variability across food types. Reference objects in images, like credit cards for scale, failed to improve accuracy and occasionally introduced confusion. The participant sample skewed younger and more female, limiting the generalizability of the findings. Additionally, biases in estimating calorie content for energy-dense and energy-sparse foods were noted.

Key Insights: Crowd sourcing outperforms individual experts in estimating food calorie content, with demographic factors influencing accuracy. Reference objects like credit cards do not improve estimates and may cause confusion. Biases in estimating "healthy" versus "unhealthy" foods highlight opportunities for app improvements.

Citation: Zhou, J., Bell, D., Nusrat, S., Hingle, M., Surdeanu, M., & Kobourov, S. G. (2017). A Study of Calorie Estimation in Pictures of Food. The Bell DOI: [10.2196/ijmr.9359](https://doi.org/10.2196/ijmr.9359)

III. METHODOLOGY

The methodology integrates image processing and machine learning to estimate calories from food images. A Convolutional Neural Network (CNN) is utilized for food classification, trained on annotated datasets containing food categories, calorie values, and volume information. The system begins by acquiring images using cameras or hardware like Raspberry Pi modules. These images undergo segmentation using techniques such as Graph Cut to isolate food regions. Ultrasonic sensors measure depth, and pixel-to-real distance conversion calculates the surface area.

The estimated volume is derived by multiplying area and depth, and the weight is determined by applying food density values. Calorie content is calculated using these weights and nutritional databases, ensuring accuracy. The CNN architecture includes convolutional layers, pooling layers, and fully connected layers, optimized through hyperparameter tuning. Loss functions such as cross-entropy for classification and mean square error for regression are employed to enhance performance.

The model is trained using datasets like ECUST Food Dataset, which includes labeled images with real volume and mass information. Features such as color, texture, and shape are extracted during training. Random Forest and Support Vector Machines (SVMs) are also evaluated for comparative performance. Post-training, the system uses TensorFlow's Object Detection API for real-time image recognition and calorie estimation.

To improve accuracy, hyperparameter tuning adjusts learning rates, activation functions, and the number of neurons in hidden layers. Statistical analyses, including mean error and confusion matrix evaluations, validate the

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model. Tests show high recognition accuracy (over 90%) and a mean calorie estimation accuracy of approximately 88%. Errors are analyzed, with improvements recommended for complex food shapes and irregular servings. The methodology demonstrates scalability and precision, making it applicable for dietary tracking and health monitoring applications..

IV. ALGORITHMS USED

A. GrabCut

GrabCut is asemi-automatic segmentation algorithm used to insulate objects in an image. By iteratively enriching object boundaries grounded on stoner inputs and energy minimization ways, GrabCut excels in separating food particulars from cluttered backgrounds. This makes it necessary for calorie estimation tasks that calculate on precise volume measures.

B. Commencement V3

Inception V3 is a sophisticated CNN armature designed for optimal point birth. By employing ways like factorized complications and supplementary it can be classifiers, commencement V3 reduces computational complexity while maintaining high delicacy. Its layered are is mature allows it to capture different patterns in food images, making it particularly useful for datasets with intricate details.

C. ResNet

Residual Networks(ResNet) attack the evaporating grade problem, enabling the training of veritably deep networks. ResNet introduces" skip connections," which bypass certain layers to insure that slants flow effectively during backpropagation. This armature is pivotal for feting subtle differences in analogous- looking foods, as it enables deeper analysis of image features. address this problem.

D. Random Forest Algorithm

Random Forest is an ensemble learning technique that combines several decision trees to increase prediction accuracy. In order to classify or regress the data, it constructs a set of decision trees during training and averages their predictions. This approach improves generality and decreases overfitting. Large, highly dimensional datasets can be handled with Random Forest's adaptability and efficiency. Its capacity to efficiently handle noisy features, outliers, and missing data makes it popular in a variety of industries, including banking, healthcare, and remote sensing.

```
To generate c classifiers:
for i = 1 to c do
   Randomly sample the training data D with replacement to produce D_i
   Create a root node, N_i containing D_i
  Call BuildTree( N_i )
end for

BuildTree(N):
if N contains instances of only one class then
   return
else
   Randomly select x% of the possible splitting features in N
   Select the feature F with the highest information gain to split on
   Create f child nodes of N , N_1 ,..., N_f , where F has f possible values ( F_1 , ... , F_f )
   for i = 1 to f do
      Set the contents of N_i to D_i , where D_i is all instances in N that match
      F_i
      Call BuildTree( N_i )
   end for
end if
```

Fig. 5. Random Forest Algorithm

E. Convolutional Neural Networks (CNN)

CNNs, or convolutional neural networks With a particular focus on image and video processing, Convolutional Neural Networks (CNNs) are sophisticated deep learning models designed for structured data analysis. By using fully connected layers for decision-making, pooling layers to lower computational complexity, and convolutional layers to extract features, they mimic the human visual system by spotting hierarchical patterns. CNNs thrive in a variety of applications, including object detection, medical diagnostics, autonomous cars, and facial recognition, because of their ability to recognize edges, textures, forms, and objects. Their capacity to automatically extract features from unprocessed data, eliminating the need for feature engineering, has transformed computer vision and is propelling advancements in artificial intelligence.

V. RESULTS

The studies collectively demonstrated the effectiveness of CNN-based approaches in food calorie discovery, achieving accuracy levels between 89% and 92%. Techniques like Inception V3 and ResNet excelled in feature extraction, handling complex datasets, and recognizing intricate patterns in food images. Multi-task learning further improved efficiency by combining calorie estimation with food classification, reducing computational overhead. TensorFlow APIs and GrabCut segmentation proved vital in streamlining object detection and isolating food items from complex backgrounds. However, challenges remain, including limited dataset diversity, difficulty handling overlapping or occluded food items, and reliance on controlled environments. Models often struggled with misclassification in similar-looking foods, such as soups and stews, and faced issues with varying portion sizes. Overfitting was observed in some cases, particularly when datasets lacked variability. Despite these limitations, the integration of advanced architectures and algorithms highlighted the potential for scalable, real-world applications in healthcare and dietary monitoring.

VI. CONCLUSION

The integration of deep literacy ways has revolutionized food calorie discovery, making it doable for real- world operations in healthcare and salutary monitoring. By perfecting the scalability and robustness of these models, unborn exploration can address limitations similar as dataset diversity, complex food as a donations, and segmentation crimes. Expanding the compass to include different cookeries, portion sizes, and real- world conditions will insure broader connection. These advancements hold pledge for accessible and accurate tools that empower individualities to lead healthier lives while supporting broader public health pretensions.

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