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# Fruit Recognition and its Calorie Measurement Using Convolutional Neural Network (CNN)

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**ABSTRACT:**

Fruits play a vital role in our diet, offering energy, vitamins, fibre, and essential nutrients while being low in fat and calories. Recognizing the importance of fruit intake for health, this paper proposes a system utilizing image processing techniques for fruit recognition and calorie estimation. By analyzing shape, colour, and texture features alongside methods like Histogram of Oriented Gradients (HOG) and Gray Level Co-occurrence Matrix (GLCM) with Local Binary Pattern (LBP) algorithms, the system accurately identifies fruits and estimates their calorie content. Utilizing a multi-class support vector machine (SVM) classifier and nutritional lookup tables enhances classification accuracy. Evaluation using real and fake fruit databases in MATLAB demonstrates close alignment with actual calorie values. Furthermore, the paper discusses the development of an artificial intelligence system leveraging local features, colour space transformation, and machine classification to detect fruit calories from images captured via camera. This approach not only improves dietary assessment accuracy but also addresses privacy concerns and data processing burdens. Additionally, the paper presents a novel deep convolutional neural network (CNN) configuration for fruit image recognition, employing a Tensor Flow Lite model trained on Teachable Machine. CNN's architecture, inspired by biological processes, enables efficient image identification with minimal preprocessing. The proposed CNN framework outperforms conventional methods, achieving higher accuracy in fruit recognition and calorie measurement tasks.

**Keywords:** Convolutional Neural Networks, Fruit image recognition, Tensor Flow, Deep Learning, Teachable Machine, Calorie Measurement.

## Introduction

In recent times, the surge in health consciousness has led to the development of numerous mobile applications aimed at tracking daily meals. Some of these applications employ fruit image recognition technology to not only identify fruits but also estimate their calorie content. However, these apps often require users to input details such as fruit categories and sizes, making them cumbersome due to subjective evaluations. To address these challenges, this paper proposes automatic recognition of fruit photos on mobile devices. While existing applications typically estimate calories based on fruit categories or relative sizes compared to standard references, there's a lack of fully automated calorie estimation applications. Despite the effectiveness of CNN-based image recognition methods in various tasks, automatic fruit calorie estimation remains a challenge. This paper introduces a new image dataset named "fruits" and employs a deep neural network to enhance fruit image identification. The goal is to develop an application for estimating fruit calories and promoting healthier eating habits. High-fat fruits pose a challenge in calorie estimation, as fats contain double the calories of proteins or carbohydrates. It's difficult for individuals to ascertain the nutritional content of fresh fruits, emphasizing the need for accurate calorie measurement. This paper focuses on utilizing Convolutional Neural Networks (CNN) for fruit recognition and calorie measurement, leveraging deep learning's ability to extract complex features from images. The study aims to address the growing demand for accurate calorie tracking, particularly in the context of rising health consciousness. The project, known as the "Image Calories" app, utilizes smartphone cameras and Android Studio for development, aiming to provide a technical solution for improving dietary intake. By capturing sensor data at the time of photo capture, the application offers a unique methodology for calorie estimation. Additionally, the project emphasizes real-time fruit classification, enabling fast image capture and machine learning model control. Ultimately, the research aims to offer a user-friendly solution for monitoring fruit consumption and promoting healthier dietary habits

## Related Work

The fruit detection system begins with capturing images of fruits using mobile devices. These images undergo segmentation, where various segments of the fruit portion are abstracted using colour and texture segmentation tools. Feature extraction methods are then employed for each detected fruit portion, including size, shape, texture, and colour features. The research emphasizes the collection of datasets for dietary monitoring, with local features extracted using classifiers. Each image undergoes filtering operations, and surface area for the fruit portion is calculated by superimposing a grid of squares onto the image segment.

The paper introduces a measurement method to estimate calorie content from fruit images by measuring the volume of fruit portion and referencing nutrition facts tables. An artificial intelligence-based approach, particularly a convolutional neural networks (CNN) algorithm, is proposed for fruit image recognition. This framework incorporates user speech input to enhance fruit recognition. Additionally, machine-learned features are integrated with deep learning methods to achieve higher accuracy.

The literature review categorizes existing methods into fruit recognition and food calorie measurement. Bhanu Pratap et al. proposed an artificial neural network (ANN) based method for fruit recognition using image processing techniques. Their algorithm utilizes shape, color, and texture features, with MATLAB/SIMULINK software for implementation. Woo Chaw Seng and Seyed Hadi Mirisaee developed a fruit recognition system combining size, color, and shape features. They employed a nearest neighbors classification method to classify fruit images and provide fruit names and descriptions.

## Methodology

1. Data Collection:
Data acquisition involves gathering or adding to existing data assets. Methods for accumulating data include:
i) Creating a bespoke dataset
ii) Utilizing existing datasets.

2. Dataset Construction:
This study focuses on constructing Tensor Flow-based models, which has become more accessible through Google's AI experimentation platform, Teachable Machine. Teachable Machine allows for the generation of training datasets and training Machine Learning models directly from a web browser. Additionally, the trained model can be exported for use in native Tensor Flow, TensorFlow.js, and TensorFlow Lite. Datasets such as MNIST, CIFAR-10, Fruit-101, and Caltech-256 provide starting points for exploration and making initial predictions using simple Machine Learning algorithms.

3. Trained Model Export and Integration into Android Applications:
To make trained models applicable in real-world scenarios, it's essential to make them available for predictions on web or portable devices. TensorFlow Lite, a platform developed by Google, enables the training of Machine Learning models on mobile or portable devices. With TensorFlow Lite, the entire workflow is executed within the device, eliminating the need to upload or share data with servers. An Android application was created using Android Studio, integrating the TensorFlow Lite dataset model trained on Teachable Machine. This approach streamlines the training process using pre-trained models and transfer learning.

The proposed flow diagram illustrates the fruit recognition system, comprising two stages: fruit image classification and fruit image description. Designing and developing both stages involves thorough testing to ensure accurate recognition of fruit types from unknown images.

A. Android Studio:
For food detection and calorie measurement of fruits, an app developed using Android Studio, a Java-based software. Android Studio facilitates the building of Android apps for Android devices, leveraging Java programming language. It requires a recommended 8.4 GB RAM and supports Microsoft Windows 7/8/10 (32 or 64-bit). Features of Android Studio include:
1. Elegant UI design
2. Connectivity options
3. Storage capabilities
4. Media support
5. Multi-touch functionality
6. Multi-tasking capabilities
7. Resizable widgets

8. Integration with Google Cloud Messaging (GCM)
9. Wi-Fi Direct support
10. Android Beam functionality.

The project utilizes various classes, including:
1. Background class for implementing search optimization
2. Necessary permissions
3. Activity launching
4. Calorie finder and saving functionality
5. Image recognition
6. Image recognition with finder functionality.

While numerous mobile applications are available for measuring and recognizing the nutritional value of fruits, many require significant user interaction and internet connectivity as they rely on stored data. It's important to note that exact calorie estimation for fruits may not be achievable through electronic devices alone, as a high level of accuracy is often unattainable.

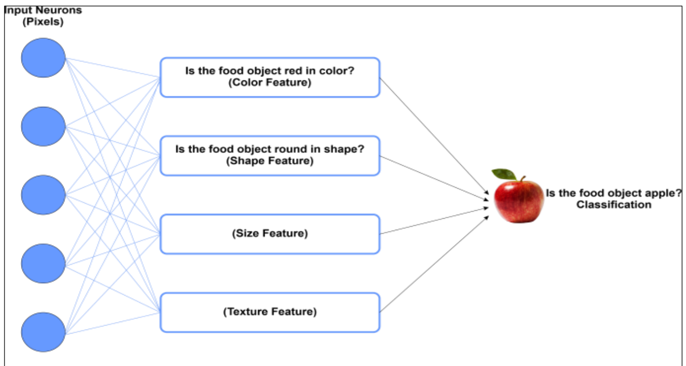



**Fig.2 Concept of CNN in the Food Recognition Model**

## Modeling and Analysis

### *1. Convolutional Neural Network (CNN):*

CNNs offer a robust model architecture for image classification and recognition, as depicted in figure 2. Comprising multiple layers, CNN neurons handle small shifts and rotations within images. The architecture typically includes three layer types: Convolutional layer, which applies convolution filters (kernels) with specific weights to input image data, generating single output values through mathematical operations across image sections. Each layer incorporates multiple filters, generating multiple outputs. The second layer type is the pooling layer, which downsamples the resulting image from the convolution layer to reduce feature map size for faster processing, commonly using algorithms like maximum pooling. This enhances CNN output invariance with respect to position. Lastly, the fully connected layer performs classification on downsampled feature maps generated by the pooling layer, with each unit representing class probability.

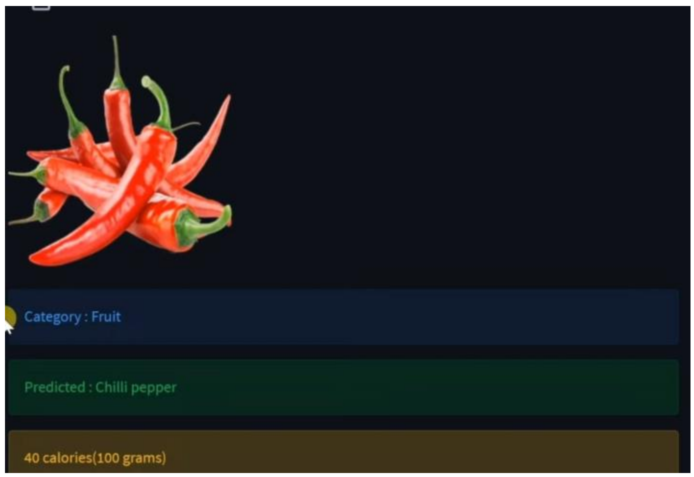
### *2. Dataset Model Training Analysis:*

Machine Learning algorithms rely on training data for learning. Neural networks and other AI programs require an initial training dataset, accurately labeled, to establish a foundational understanding for further processing. The training dataset serves as the cornerstone for the program's information repository. Before processing and learning, the dataset must undergo upgrading, enrichment, or labeling. The amount of training data required depends on factors such as desired accuracy. For instance, achieving around 85% accuracy in sentiment analysis requires a well-labeled dataset. To a system, an image comprises pixels, and accurate labeling is essential for recognition. Adequate labeled images enable machines to interpret unlabeled images accurately. Human-in-the-loop labeling ensures accurate and efficient data enrichment, enhancing model performance and yielding more precise results.

## Results and Analysis

***Dataset Model Training Analysis:***

Machine Learning algorithms rely on data to learn. Neural networks and other AI programs require an initial dataset, termed a training dataset, to establish a foundational understanding for further processing and utilization. This dataset serves as the bedrock for the program's expanding repository of information. Before processing and learning, the training dataset must undergo labeling accurately. Typically, the dataset intended for training necessitates enhancement, enrichment, or labeling. Determining the requisite volume of training data involves considering various factors. Paramount among these factors is the importance of accuracy. For instance, in creating a sentiment analysis algorithm, achieving 80 or 90% accuracy is often deemed sufficient for most applications. To a system or machine, an image merely comprises a series of pixels. The system lacks the capacity to discern that an image represents a fruit until it is labeled accordingly. With appropriate labeling of images depicting fruits, machines can discern similar pixel arrangements in unlabeled images as constituting fruits. The most effective approach to preparing training data is to involve human input for accurate and efficient labeling and enhancement. The model's performance hinges on the accuracy of labels associated with the training data.




## Conclusion

After this study, we can conclude that we have built an easy and effective approach to build CNN based application to recognize the fruit and measuring calories. The dataset were collected from web and trained on web browser application Teachable.

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