Enhanced Calorie Estimation of Solid Foods using Federated Learning and YOLO Models: A Distributed Approach for Collaborative Caloric Data Analysis

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***Abstract*—In today's era of abundant data from diverse sources like social media, blogs, and newspapers, the quest for machines mirroring human capabilities is a reality. This study harnesses by using federated learning how YOLO (You Only Look Once) models to detect and differentiate various solid food items encountered daily, aiming to estimate their calorie content. The unique focus of this research lies in utilizing existing technologies, specifically the YOLO model with Federated Learning, to categorize manually countable solid food items and estimate their total calories. To achieve our objective, we curated a specialized dataset exclusively centered on solid food items, ensuring varied representations and ample data per category. This bespoke dataset formed the foundation for employing the YOLO model's object detection capabilities.Utilizing YOLO models, we rigorously evaluated their effectiveness in detecting and categorizing these food items, subsequently estimating their calorie content. Our emphasis was on leveraging existing technology rather than creating new models. Through meticulous experimentation with YOLO variants, encompassing different complexities and configurations, we gauged their accuracy in identifying diverse and intricate food images. Comparative analysis against existing works reaffirmed the efficacy of employing YOLO models for solid food detection and calorie estimation, showcasing the pragmatic application of established technology in this domain. In the training process, this federated learning will make an impact.In the training process, the integration of Federated Learning marks a significant stride towards collaborative and privacy-preserving machine learning. This approach empowers individual devices or nodes to perform local model training on their respective datasets while only sharing model updates or aggregated information with a central server. By employing Federated Learning in conjunction with YOLO models for solid food detection and calorie estimation, this research mitigates data privacy concerns. It ensures that sensitive user data remains decentralized and secure within the respective devices, thus aligning with evolving data privacy regulations and ethical considerations. the incorporation of Federated Learning fosters a collective learning paradigm, enabling the YOLO models to benefit from the diverse data representations across distributed devices without directly accessing raw data.**

***Index Terms*—Computer Vision (CV); You Look Only Once (YOLOv5); Food Detection; Federated Learning**

I. Introduction

In recent years, the realm of image analysis has witnessed exponential growth, propelled by advancements in Computer Vision and AI technologies. Food, as a vital component of human sustenance, embodies cultural diversity through myriad unique recipes found across the globe. The global awareness of unfamiliar foods, facilitated by social media, parallels an escalating consciousness regarding health concerns tied to dietary habits [1]. This confluence emphasizes an increasing need for precise food recognition and understanding amid

general consumption, dietary considerations, and fitness pursuits.The proliferation of smartphones with high-resolution cameras has transformed food photography into a popular social media trend, offering an avenue for implementing food recognition technologies [2]. Beyond mere identification, these technologies hold promise for evolving into tools offering calorie information, divulging food origins, and sharing recipes. The data shared across social platforms presents an opportunity for corporations to track eating trends, predict food popularity, estimate sales, and tailor marketing strategies for new food-related products.In this paper, we delve into the implementation of modern Convolutional Neural Networks (CNNs) specifically aimed at detecting various solid food items and estimating their calorie content. Object detection systems using machine learning have persistently addressed real-world problems. However, detecting and characterizing solid foods pose unique challenges owing to their varied shapes, sizes, textures, and varying quantities within datasets [3]. These complexities mandate significant data, memory, and computational resources for precise detection, especially when multiple food objects coexist within a dataset.Existing large datasets predominantly cover Western or Chinese foods, lacking specificity and diversity concerning solid food items [4]. To address this gap, our research focuses on curating a comprehensive dataset exclusively comprising images of various solid food items. Our endeavor aims to create a sizable and distinctive dataset encompassing a diverse array of solid foods from different cultural backgrounds, avoiding specificity to any one region.The deficiency in large, diverse datasets specific to South Asian cuisine is evident from existing repositories [4]. Notably, efforts like the TBFI dataset [5], comprising seven traditional Bangladeshi food classes, and the custom dataset [6] focused on a smaller scale with seven classes from Bangladesh have showcased accuracies of 86.0 percent and 95.2 percent respectively using transfer learning-based CNN models.Other attempts, such as the CAFD dataset [7], encompassing 42 classes from Asia, and the PFD dataset [9], consisting of 100 classes from Pakistani culture, highlighted challenges in balancing dataset diversity and achieving accuracy, achieving 88.7 percent and 69.38 percent accuracy, respectively.Various models like MobileNetV2[12], InceptionV3[13], DenseNet-201[14], and combinations of AlexNet[15], GoogleNet[16], and ResNet[17] have been employed on datasets like IndianFood10 and IndianFood20, showcasing accuracies ranging from 73.5 percent to 91.8 percent [11-17].The adoption of the YOLOv5 algorithm stems from its enhanced accuracy and training efficiency over previous models. Leveraging bounding box coordinates and labeling during annotation, this algorithm facilitates real-time object detection, augmenting neural network referencing and Multi-Object Tracking (MOT) capabilities [19-20].This paper meticulously documents the evolution of our dataset, models, and their comparative performance against existing research endeavors. Through this exploration, we aim to contribute to the advancement of solid food detection and calorie estimation technologies within the broader context of food recognition

Dataset	Class	Images	Year	Country
FoodNet	50	5000	2017	India
Custom	7	700	2020	Bangladesh
PFD	100	4928	2020	Pakistan
TBFI	7	2835	2021	Bangladesh
IndianFood20	20	17817	2022	India
CAFD	42	16449	2023	Asia
Ours	9	6574	2023	Bangladesh

TABLE I
DATASET SPECIFICATIONS

Existing large datasets predominantly cover Western or Chinese foods, lacking specificity and diversity concerning solid food items [4]. To address this gap, our research focuses on curating a comprehensive dataset exclusively comprising images of various solid food items. Our endeavor aims to create a sizable and distinctive dataset encompassing a diverse array of solid foods from different cultural backgrounds, avoiding specificity to any one region.The deficiency in large, diverse datasets specific to South Asian cuisine is evident from existing repositories [4]. Notably, efforts like the TBFI dataset [5], comprising seven traditional Bangladeshi food classes, and the custom dataset [6] focused on a smaller scale with seven classes from Bangladesh have showcased accuracies of 86.0% and 95.2% respectively using transfer learning-based CNN models.Other attempts, such as the CAFD dataset [7], encompassing 42 classes from Asia, and the PFD dataset [9], consisting of 100 classes from Pakistani culture, highlighted challenges in balancing dataset diversity and achieving accuracy, achieving 88.7% and 69.38% accuracy, respectively.Various models like MobileNetV2[12], InceptionV3[13], DenseNet-201[14], and combinations of AlexNet[15], GoogleNet[16], and ResNet[17] have been employed on datasets like IndianFood10 and IndianFood20, showcasing accuracies ranging from 73.5% to 91.8% [11-17].The adoption of the YOLOv5 algorithm stems from its enhanced accuracy and training efficiency over previous models. Leveraging bounding box coordinates and labeling during annotation, this algorithm facilitates real-time object detection, augmenting neural network referencing and Multi-Object Tracking (MOT) capabilities [19-20].This paper meticulously documents the evolution of our dataset, models, and their comparative performance against existing research endeavors. In the larger framework of food recognition, we hope to further solid food detection and calorie estimation technologies through this investigation.

II. LITERATURE REVIEW

Rapid advancements in image recognition and classification technologies have ushered in a new era of refined applications, marked by notable improvements in accuracy. Despite these strides, the accurate identification of food items remains a persistent challenge within the realm of object recognition. The intricate nature of food recognition presents complexities that have hindered numerous proposed methods, resulting in suboptimal classification accuracies. However, the detection of food items holds immense significance across various in-

dustrial operations and boasts potential applications in health, fitness, and dietary domains.

Diving deeper into specific experiments, several studies have utilized YOLOv2 for food detection, primarily focusing on the categorization of Japanese cuisine [21]. These endeavors not only sought to identify food items but also gave rise to applications like Food Tracer. However, it's crucial to note that these applications were primarily designed for research purposes rather than practical real-world implementations. Subsequently, the development of YOLOv3 by J. Redmon & Farhadi [22] aimed to enhance accuracy by leveraging the Darknet 53 framework for improved feature extraction. Larger data batches caused performance problems, although significant progress was achieved in achieving optimal floating-point operations per second. When YOLOv3 was improved and compared to the previous version using the UECFOOD100 dataset for Asian food recognition, the improved version performed much better in terms of MAP (Mean Average Precision) scores.

Further studies focused on algorithmic comparisons, pitting various versions of YOLO against RCNN, emphasizing the importance of speed without compromising accuracy [24]. Researchers dedicated efforts to enhance the accuracy of identifying specific cuisines, such as Thai Food, by augmenting neural network layer counts [25]. Despite these efforts, the Inception network [26] stood out for its pivotal role in advancing CNN classifiers, achieving a noteworthy accuracy rate of 68.7% despite modifications using NU Inception modules. Additionally, studies underscored the efficacy of functions like Categorization and Segmentation when deployed in conjunction with Deep CNNs [27].

Efforts to gauge meal size detection deployed a revised U-Net rooted in CNN, segmenting specific food regions for accurate labeling [28]. However, challenges persisted due to dataset limitations, including image capture orientation and sensitivity. Introducing Support Vector Machine (SVM) techniques to resolve multi-class issues [29], coupled with CNN features, facilitated the successful classification of unique fast-food datasets into ten distinctive categories [30]. Further comparative analyses showcased the effectiveness of techniques such as combining classifiers K-NN and SVM and CNN4096, with the latter yielding optimal results through posterior probability techniques [31].The evaluation of GoogleNet, Res-Net, and MobileNet on the Food101 dataset unveiled GoogleNet's superior accuracy of 87.2% [32]. Extending its application to identify diverse food classes from archive images, system tweaks pushed the accuracy to an impressive 95.97%. However, refashioned versions of Inceptions for food recognition encountered limitations in handling specific types of foods, particularly liquids [33]. Pre-trained InceptionV3 models, augmented using shear and flip techniques, achieved an accuracy of 91.5% for 20 food classes [34].Moreover, studies incorporated methodologies such as the bag-of-features theory, Extreme Learning Committee strategy, and multi-scale multi-view fusion to bolster food recognition [35-37]. Advocacy for computer vision in automating food detection gained traction [38], proving its efficacy compared to alternative methods [39]. Instance segmentation and pixel segmentation techniques showcased improvements in prediction quality [40-42].Successful execution of neural network models necessitates significant computational resources and parameter tuning to enhance factors like training time and precision. Despite efforts to curate a sizable dataset encompassing 9 unique food classes i, challenges persist due to the intricate and diverse nature of the cuisine.

Previously YOLO had been used with Federated Learning to enable Autonomous Vehicles (AVs) to achieve reliable safe driving in snow weather [47] . For IoT applications, FL can provide several significant advantages such as data privacy enhancement, low-latency network communication, enhanced learning quality, etc [48]. FL had also been used for training a recurrent neural network language model for next-word prediction in virtual keyboards for smartphones [49]. Some of the challenges from these researches include increased communication overhead and improper distribution of data of clients.

III. Food Detection & Tracking

Object detection involves the identification of objects within an image and precisely defining their spatial boundaries using bounding boxes. On the other hand, image classification revolves around determining the presence of an object in an image based on calculated probabilities. Images possess distinctive features, such as edges, crucial for extraction within an object recognition model. Automating this process is feasible through the integration of Convolutional Neural Networks (CNNs) in tandem with Auto Encoder algorithms and various other methodologies [44]. The optimal object detection technique strikes a balance between accurately identifying diverse objects with varying sizes and shapes while demonstrating robust computing capabilities for swift processing. Techniques like YOLO and SSD offer promising results, albeit with a trade-off between speed and accuracy. Therefore, the selection of the algorithm heavily relies on the specific application's requirements and constraints.

IV. Federated learning

Federated learning within the scope of this project fundamentally redefines how machine learning models are trained and improved in a privacy-centric paradigm. Operating as a distributed learning framework, it facilitates training across diverse devices or servers without consolidating raw data, crucially safeguarding individual data privacy. This innovative technique allows disparate sources to independently train models on their localized data while periodically amalgamating only anonymized model updates, ensuring that sensitive information remains decentralized and secure. This collaborative approach refines a global model without compromising the confidentiality of the original data. In the context of food detection and calorie estimation, this method ensures that food-related image datasets collected from various sources retain their privacy while allowing for collective model refinement,

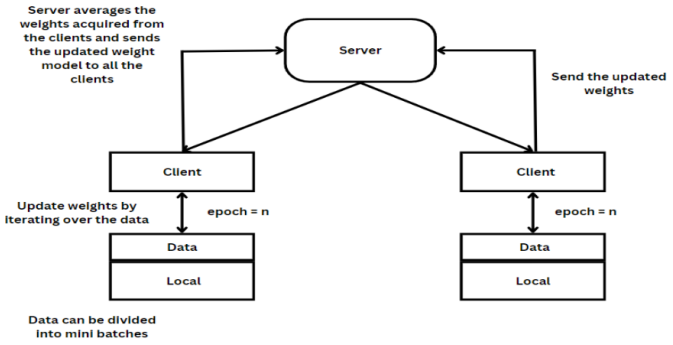

Fig. 1. Federated Learning Workflow

ultimately culminating in highly accurate recognition and estimation capabilities while preserving strict data privacy across all contributing entities.

V. Proposed Methodology

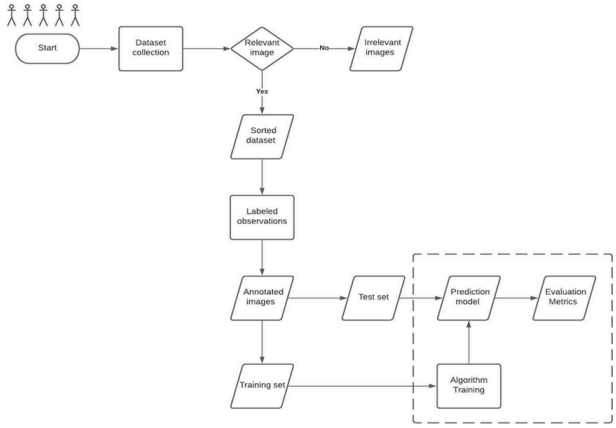

Fig. 2. Food Detection Methodology Flowchart

Our methodology, depicted in (Fig. 2), commenced with the collection of diverse images portraying a wide array of multiple sources.

Upon completion of the image collection phase, the gathered images underwent a meticulous curation process involving categorization into a comprehensive dataset. Irrelevant images were systematically eliminated from consideration. Each image was meticulously sorted and manually labeled to ensure its suitability for integration into the deep learning model.Upon completion of the image collection phase, the gathered images underwent a meticulous curation process involving categorization into a comprehensive dataset. Irrelevant images were systematically eliminated from consideration. Each image was meticulously sorted and manually labeled to ensure its suitability for integration into the deep learning model.Following this categorization, the dataset underwent a random split adhering to the conventional method. Eighty percent of the data constituted the training set, while the remaining 20% formed the validation set. This partitioning strategy aimed to facilitate accurate model evaluation while mitigating the risk of overfitting. The training set provided the learning algorithm, and the validation set allowed for the evaluation of the model's predictive performance. Upon completion of the training phase, the resulting outcomes furnished a comprehensive array of metrics and statistics for each variation, facilitating a thorough evaluation and comparison of the models.After the detection process, we initiated the calculation phase. In this stage, a CSV file containing food item names and quantities was processed using Node.js. Utilizing the 'fs' module, the script read and parsed the file, subsequently calculating the total calories by correlating items with predefined calorie values. The output was a comprehensive report outlining both individual and cumulative caloric content. This approach prioritized accuracy by harnessing JavaScript and file operations to estimate calorie counts using provided quantities and predefined values for each food item.

After completing all the training, we will initiate the calorie estimation process. Initially, the system will count the images. Subsequently, the counting results will be sent to the main system, which possesses the calorie estimation counting capacity. In this project, we will train our model with only nine classes, each representing a solid food item. Additionally, we will assign a specific calorie number to each solid food. Consequently, when the system tallies the total count, it will calculate the total calorie count and display the result.

A. Design & Implementation

In the architecture of our system, federated learning was implemented to train three distinct models from the YOLOv5 family – encompassing small, medium, and large variants – using our meticulously curated custom food dataset. This comprehensive dataset comprised a total of 6,574 diverse images, meticulously categorized into 9 distinct classes representing various food types. The meticulous preprocessing and augmentation procedures were integral components of the preparation process, enhancing the dataset's quality and diversity.

Despite the meticulous curation, the dataset's composition exhibited a non-uniform distribution due to the randomness in the image collection. This resulted in certain classes displaying a notably higher number of instances than others. For instance, the 'shingara' class stood out with a staggering 10,680 instances, while classes such as 'jalebi' and 'samosa' were represented by fewer instances.

The utilization of federated learning played a pivotal role in optimizing these models' training process, allowing for collaborative learning while respecting data privacy across multiple decentralized devices. This innovative approach not only facilitated robust model development but also ensured the security and confidentiality of the individual contributors' data.

To offer a glimpse into the dataset's diversity, the figure below showcases a handpicked selection of images representing var-

ious food classes. This representation highlights the dataset's richness and variety, essential for training robust and accurate models for food classification and detection.

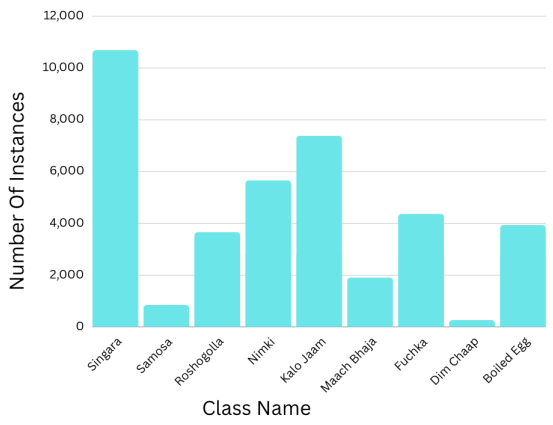

Fig. 3. Dataset Classification

B. Model Training YOLO

We trained three different YOLOv5 architectures (YOLOv5l, YOLOv5m, and YOLOv5s) using the dataset. An average of around 10 hours were needed to train each model for 100 epochs. The flowchart shown in Fig. 8 provides a visual representation of the model training procedure. The network is first trained on a predetermined set of training data and is trained to predict target values that correspond to the training set. A Train-Test split based on available data is necessary for the proper dataset, which is necessary for the training of a deep learning network. Validation losses are continuously monitored during the training phase, which causes values to fluctuate after few epochs. The model with the lowest validation score was chosen for further testing, and hyperparameters were changed to reduce the validation loss. When a model performs well after training on an enhanced dataset or exhibits high recall and precision rates with new datasets, it is considered effective.

C. Federated Learning Framework

The FLOWER (Federated Learning Over Encrypted Data) framework represents an open-source federated learning library designed to enable secure and privacy-preserving collaborative machine learning across distributed devices. FLOWER facilitates federated learning by allowing multiple clients or edge devices to train machine learning models collectively without sharing raw data. It employs encryption techniques and secure aggregation protocols, ensuring data privacy by performing computations on encrypted data. With FLOWER, participants can train models locally on their data, sharing only model updates or gradients, which are aggregated securely at a central server to create a global model. This framework serves as a foundational tool for researchers and developers seeking to implement federated learning techniques securely across decentralized networks while prioritizing data privacy and confidentiality.

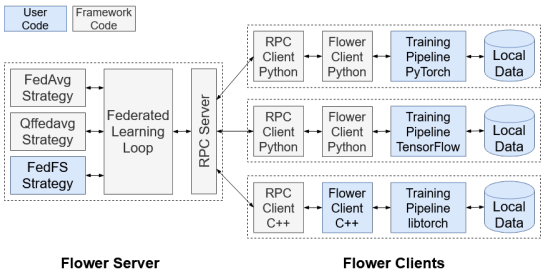

Fig. 4. FLOWER Architecture

D. Model Training With Federated Learning

In the federated learning framework described by the dataset specifications, the training process unfolds iteratively across multiple clients, each possessing unique subsets of data crucial for model refinement. Initially, a global model, serving as the foundation, is disseminated to all participating clients. Each client autonomously trains its model locally using its distinct dataset—Client-1 with 300 images, Client-2 with 250 images, and Client-3 with 200 images—ensuring individualized learning experiences while preserving data privacy. Post-local training, model updates or enhancements, encapsulating learned insights, are securely transmitted to a central server. This central aggregator merges and refines these updates, iteratively enhancing the global model by incorporating diverse knowledge gleaned from the various client datasets. Subsequently, the improved global model is redistributed to individual clients, initiating a new round of localized training, update transmission, aggregation, and model refinement. This cyclical process continues, fostering collaborative model improvement across all clients while upholding stringent data privacy measures and culminating in a refined, collectively informed global model.

Dataset	Class	Images
Global Dataset	9	2000
client-1 dataset	9	300
client-2 dataset	9	250
client-3 dataset	9	200

TABLE II
DATASET SPECIFICATIONS FOR FEDERATED LEARNING

Run the training command with the following parameters to start training:

- img: Indicates the input image's dimensions.
- batch: Establishes the size of the batch.
- epochs: Indicates how many training epochs there are.
- data: Indicates where our YAML file is located.
- weights: Specifies the route for determining the starting weights.
- cfg: Shows our model's configuration.
- name: Indicates the unique number for the outcomes.
- no save: Just the last checkpoint is saved.
- cache: Holds onto photos to speed up learning."

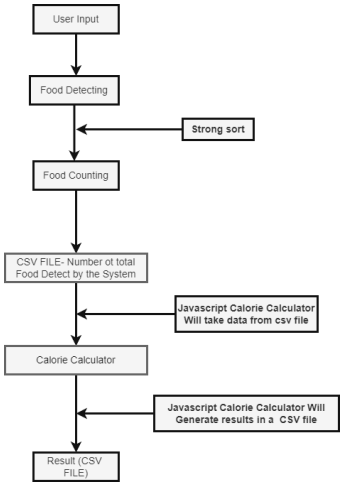

Fig. 5. Calorie Estimation

E. Calorie Estimation Calculator

The caloric estimation process was initiated by importing a CSV file containing food item names and respective quantities. The data was processed using Node.js with the 'fs' module to read the file, parse its contents, and conduct the computations.Data Reading and Parsing: The script used the 'fs' module to read the 'input.csv' file, which contained food item names and their corresponding quantities. The data was parsed by splitting it into rows and columns for further computation.Caloric Mapping and Computation: A predefined mapping ('CALORIE_MAPPING') associating food item names with their respective calorie values was utilized. The script calculated the total caloric content by multiplying the quantity of each food item with its assigned calorie value and summing these values.Result Generation: After computation, the script generated a report presenting the total calories alongside individual calorie counts for each food item quantity. This data was then written to an 'output.txt' file using the 'fs' module.The methodology outlined a straightforward approach leveraging JavaScript and file system operations to process food quantity data, apply calorie mappings, and compute the overall caloric content of the listed food items from the CSV file. The approach focused on accuracy in estimating calorie content based on the provided quantities and predefined calorie values for each food item.

VI. Result & Analysis

Our efforts led us to gather a significant collection of data customized from more than 9 distinct categories, comprising roughly 6574 images. This extensive dataset was utilized to train our models and derive pertinent findings for analysis and comparison.

A. Performance Metrics

To comprehend the outcomes derived from training on the YOLOv5 model, we utilize various metrics to gauge its performance. These metrics, detailed below, assist in assessing its effectiveness. Confusion Matrix provides a thorough analysis of the model's output, emphasizing its errors. With reference to Table 2, the collected data allows us to carry out various performance evaluations.

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

TABLE III
Confusion Matrix

Attributes	**Features**
Image Type	RGB
Image Extension	JPG, PNG
Image Dimension	1920 * 1920

TABLE IV
Dataset Specifications

True Positive (TP): When the expected value and the actual positive value line up. True Negative (TN): A situation in which the expected value and the real negative value coincide. False Positive (FP): A situation in which a positive value is mistakenly identified when a negative value actually exists. False Negative (FN): A situation in which a positive value is actually recorded but the predicted value is mistakenly classified as negative.

Accuracy: Since accuracy gives all errors the same weight, it is invalid as a stand-alone metric. It is determined by the following formula and is only appropriate for balanced datasets:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{1}$$

Precision: Precision measures the accuracy of the positive predictions made by a model and aids in assessing the reliability of each model. It is calculated using the formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Recall: Measures how well the model can reliably distinguish positive cases from all real positive instances. It is computed using the following formula, which quantifies the percentage of true positives the model successfully captures:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

The mean average precision (mAP), an essential statistic in object detection, is very important. It is used to assess object detection models such as Mask R-CNN, YOLO, and Fast R-CNN. This statistic addresses both false positives (FP) and false negatives (FN), accounting for the trade-off between precision and recall.

The mAP is calculated by averaging the Average Precision (AP) of each class over a number of classes.

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{4}$$

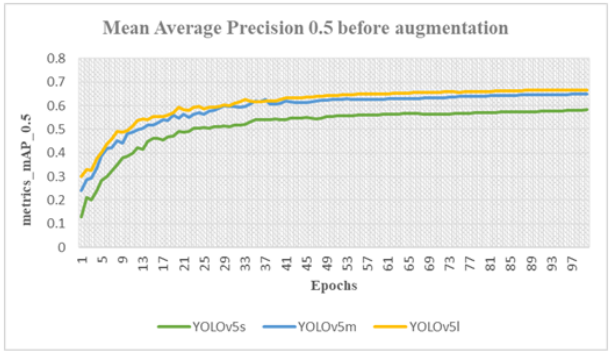

Fig. 11: mAP graph of models before augmentation

Fig. 6. mAP of models

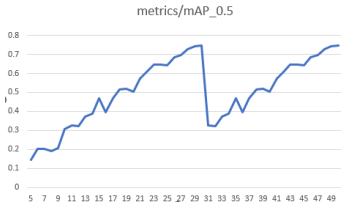

Fig. 7. mAP graph of Global Model (Federated Learning

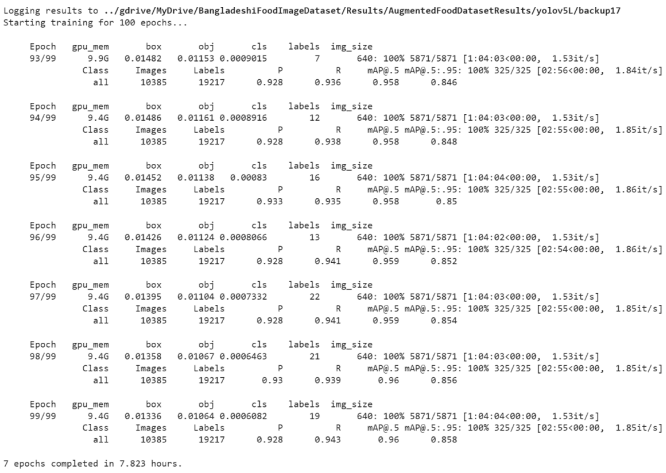

Fig. 8. Epoch Results

Attributes	Small	Medium	Large	Comment
mAP_0.5	0.583	0.650	0.667	Higher is better
mAP_0.5:0.95	0.425	0.482	0.501	Higher is better
train/box loss	0.027	0.024	0.023	Lower is better
train/class loss	0.009	0.004	0.004	Lower is better
val/box loss	0.022	0.022	0.021	Lower is better
val/class loss	0.009	0.009	0.008	Lower is better
F1 Score	0.604	0.600	0.651	Higher is better

TABLE V
MODEL RESULTS WITHOUT AUGMENTATION

The F1 Score aims to maximize the Precision and Recall values together into a single metric that will improve our model. But it can be difficult to understand the F1 score, which hides the precise metric that the model is trying to optimize. It is computed with the following formula: The box_loss, obj_loss, and cls_loss components make up the YOLO loss function.

Three different architectures—small, medium, and large—from the YOLOv5 family were used in this study. The dataset was preprocessed and augmented prior to training. These YOLOv5 architectures differ in terms of depth and complexity. The best model for food recognition was found by comparing the results of each model that was run on our dataset.

B. Dataset Epoch Results

Subsequently, we trained our augmented dataset for another 100 epochs. The best of which was the large model whose precision was 0.943, recall was 0.943 and mAP was 0.96. The results for the YOLOv5l model can be seen in Fig. 13.

C. Overall Performance Analysis

We have documented the performance results before and after the application of augmented data in order to examine the performances of YOLOv5 based on its three distinct designs.

D. Limitation

Communication Overheads: Since the model training occurs locally on individual devices or nodes, there is a need for frequent communication between the central server and these

Attributes	Small	Medium	Comment
mAP_0.5	0.413	0.49	Higher is better
mAP_0.5:0.95	0.39	0.37	Higher is better
train/box loss	0.022	0.02	Lower is better
train/class loss	0.013	0.008	Lower is better
val/box loss	0.029	0.027	Lower is better
val/class loss	0.014	0.019	Lower is better
F1 Score	0.504	0.500	Higher is better

TABLE VI
MODEL RESULTS WITH FEDERATED LEARNING GLOBAL MODEL

Attributes	Small	Medium	Comment
mAP_0.5	0.213	0.29	Higher is better
mAP_0.5:0.95	0.27	0.29	Higher is better
train/box loss	0.019	0.08	Lower is better
train/class loss	0.023	0.01	Lower is better
val/box loss	0.041	0.037	Lower is better
val/class loss	0.024	0.023	Lower is better
F1 Score	0.314	0.303	Higher is better

TABLE VII
MODEL RESULTS WITH FEDERATED LEARNING CLIENT 1

Attributes	Small	Medium	Comment
mAP_0.5	0.224	0.23	Higher is better
mAP_0.5:0.95	0.212	0.26	Higher is better
train/box loss	0.018	0.013	Lower is better
train/class loss	0.022	0.04	Lower is better
val/box loss	0.037	0.04	Lower is better
val/class loss	0.034	0.045	Lower is better
F1 Score	0.29	0.41	Higher is better

TABLE VIII
MODEL RESULTS WITH FEDERATED LEARNING CLIENT 2

Attributes	Small	Medium	Comment
mAP_0.5	0.2	0.3	Higher is better
mAP_0.5:0.95	0.19	0.25	Higher is better
train/box loss	0.02	0.18	Lower is better
train/class loss	0.027	0.11	Lower is better
val/box loss	0.039	0.44	Lower is better
val/class loss	0.03	0.024	Lower is better
F1 Score	0.34	0.29	Higher is better

TABLE IX
MODEL RESULTS WITH FEDERATED LEARNING CLIENT 3

distributed devices. This exchange of model updates introduces communication overheads, especially when dealing with a large number of participants or devices.

Privacy Concerns: While Federated Learning aims to preserve user privacy by keeping the data local, there is still a risk of privacy breaches. Models trained through Federated Learning could potentially reveal sensitive information about individual datasets, especially when aggregating updates.

Heterogeneous Data Distribution: Federated Learning assumes that the data across devices or nodes are distributed similarly or follow the same statistical characteristics. However, in practical scenarios, the data might be highly imbalanced, have different distributions, or be inconsistent across devices, impacting the model's performance and generalization.

Limited Access to Global Knowledge: Since each device trains a model locally and shares only model updates, the central server might not have access to a comprehensive global view of the dataset. This limited view might hinder the learning process, affecting convergence and model accuracy.

Security Risks: Federated Learning introduces security risks associated with sharing and aggregating model updates. Adversarial attacks, such as poisoning attacks or model inversion attacks, might exploit vulnerabilities in the communication process, leading to compromised model integrity or privacy breaches.

Resource Limitations: Devices participating in Federated Learning might have limited computational capabilities, memory, or power resources. This limitation can affect the quality of local model training and the ability to participate effectively in the learning process.

Algorithmic Challenges: Developing efficient algorithms that can handle asynchronous updates, varying data distributions, and maintaining model convergence in Federated Learning settings poses significant challenges. Ensuring fairness and unbiased model aggregation across diverse participants is also a challenge.

Network Bandwidth: Devices participating in federated learning might have varying network conditions, leading to differences in latency. High latency can significantly affect the overall training process, especially when waiting for slow devices to send or receive updates, resulting in increased communication

E. Conclusion

The exploration and assessment of various modules within YOLOv5 enabled a closer examination of their impact on food item detection. Our meticulously assembled dataset provided ample rich data for thorough testing, aiming for favorable outcomes across each model. To compare their effectiveness, models were chosen based on distinct differences in nodes, complexity, and speed. Following intensive training sessions, it became evident that among the three, YOLOv5l stood out as superior. Due to its higher complexity—it had a lot more convolutional layers than the others—it was the most effective in terms of processing speed, but at the cost of longer processing times. YOLOv5l's exceptional performance and efficiency when compared to YOLOv5s and YOLOv5m have potential for practical uses in food detection and calorie estimate in a variety of commercial areas.

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