Deep Learning Driven Food Recognition For Accurate Dietary Assessment

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Abstract

Accurate food category classification plays a crucial role in dietary assessment and nutritional analysis. In this work, a transfer learning-based approach is implemented using the InceptionV3 deep learning model to classify food images into eleven categories: Bread, Dairy Product, Dessert, Egg, Fried Food, Meat, Noodles/Pasta, Rice, Seafood, Soup, and Vegetables/Fruit. The model was trained on the publicly available Food11 dataset from Kaggle, consisting of 16,600 well-labeled images. The trained model was integrated into a complete system with a Python-based backend for inference and a Streamlit-based frontend for user interaction. Users can upload a food image and receive top class predictions along with estimated nutritional information per 100 grams, covering metrics like calories, protein, carbs, fats, vitamins, and minerals. The system also provides a visual bar chart of prediction confidence using Plotly. The proposed model achieved strong results with an accuracy of 93.3%, precision of 100%, recall of 87.5%, and F1-score of 93.3%, demonstrating the potential of deep learning in real-time food recognition and dietary evaluation.

Key Words: Deep Learning, InceptionV3, Food Recognition, Dietary Assessment.

1. Introduction

In today's world, where convenience often outweighs mindful eating, there has been a significant rise in the consumption of energy-dense, nutrient-poor foods. This shift has led to a growing prevalence of diet-related health conditions across all age groups. Healthcare experts and public health institutions continuously advocate for increased nutritional awareness and better dietary habits as essential strategies for disease prevention and long-term wellness. However, accurately tracking one's diet remains a considerable challenge, largely due to the heavy reliance on self-reported dietary information, which is frequently incomplete or inaccurate. Many individuals lack awareness of the exact nutritional content of their meals, and manual food logging is often seen as time-consuming and inconsistent. These challenges result in poor adherence to dietary tracking, reducing the effectiveness of nutritional interventions. In response to this problem, the integration of artificial intelligence, machine learning, and computer vision offers a powerful alternative for enhancing dietary assessment. Recent advances in deep learning have made it possible to analyze visual data with high precision. These capabilities allow for the automated recognition of food items from images and the estimation of their nutritional composition eliminating the need for manual input. This approach reduces the burden on users and significantly improves the reliability and objectivity of dietary tracking. This project, titled "Deep Learning Driven Food Recognition for Accurate Dietary Assessment," aims to bridge the gap between technological innovation and nutritional science. It introduces an intelligent food classification system powered by deep learning techniques to assist users in evaluating their meals. By simply uploading or capturing a food image, users can instantly receive classification results and nutritional breakdowns. The core engine of the system is the InceptionV3 convolutional neural network, a high-performance architecture developed by Google. InceptionV3 is widely recognized for its strong classification accuracy and computational efficiency, making it an ideal choice for complex image-based tasks such as food recognition. The model employs several innovative design features, including inception modules, convolution factorization, asymmetric kernels, and auxiliary classifiers. These enhancements allow the model to learn deeper features and maintain efficiency even when dealing with visually complex food images that vary in lighting, angle, and composition. The training data consists of a diverse, well-labeled dataset containing multiple food categories representing different cuisines and preparation styles. To further enhance model generalization, data augmentation techniques such as rotation, scaling, and flipping are applied during training. Once trained, the system is capable of recognizing food items from images with strong accuracy. Upon identification, it retrieves corresponding nutritional data including caloric values, macronutrients (carbohydrates, proteins, and fats), fiber, and essential vitamins and minerals from a structured nutritional database. To ensure accessibility and ease of use, the model is integrated into a web-based application developed using Streamlit. This frontend enables users to upload food images and instantly view classification results along with detailed nutritional content in an intuitive format. Additional features include nutrient analytics over time, meal history logs, and personalized recommendations based on user preferences or dietary goals. The system has broad applications. It empowers individuals to better understand their dietary intake and supports those managing chronic conditions like diabetes or hypertension. In institutional environments such as hospitals, schools, and fitness centers, it can help monitor and guide nutritional adequacy. Furthermore, researchers can use this system to collect large-scale food consumption data, aiding epidemiological studies and public health initiatives. This project also addresses technical challenges associated with food image classification, such as high intra-class variation (different presentations of the same dish), inter-class similarity (visually similar but nutritionally distinct foods), and image obstructions. Through advanced preprocessing and model fine-tuning, these issues are systematically tackled. Performance evaluation is carried out using top-1 and top-5 accuracy scores, F1 metrics, and confusion matrix analysis to validate the model's reliability on unseen data. As digital health continues to evolve, this system stands as an example of how AI can be leveraged to solve practical, real-world challenges. It transforms dietary tracking from a manual and error-prone task into a seamless, data-driven process encouraging informed eating habits and contributing to the vision of a healthier, more aware society.

2. Literature Review

2.1 Deep Learning-Based Image Classification

2.1.1 Convolutional Neural Networks (CNNs)

Lo et al. discuss the use of Convolutional Neural Networks (CNNs) for food classification, leveraging their ability to extract hierarchical features from images. CNNs automatically learn spatial hierarchies of features, making them highly effective for food recognition. Traditional image-processing techniques struggle with complex food items due to varying lighting conditions, occlusions, and diverse food appearances. CNNs address these challenges by utilizing convolutional layers that detect patterns such as edges, textures, and object parts, followed by pooling layers to reduce dimensionality and improve computational efficiency. The study highlights that deep CNN architectures, such as Inception V3 and ResNet, significantly enhance classification accuracy by learning deeper feature representations. Additionally, transfer learning using pre-trained models like Inception and MobileNet has proven effective in scenarios where limited labelled data is available, allowing for efficient adaptation to new datasets without extensive retraining [6].

2.1.2 Deep Neural Networks (DNNs) and Autoencoders

Deep Neural Networks (DNNs) and autoencoders have been explored for enhancing food recognition accuracy. Ahmadian et al. integrate deep sparse autoencoders with Particle Swarm Optimization (PSO) to refine feature extraction and reduce redundancy in learned representations. Autoencoders assist in unsupervised learning by capturing the most relevant features of food items, which improves classification performance, especially in scenarios with limited labeled data. The use of stacked autoencoders enables multi-layered feature learning, preserving key food characteristics while reducing noise. These networks improve upon traditional CNNs by enhancing the generalizability of the model and reducing dependency on large training datasets, making them well-suited for real-world dietary assessment applications [3].

2.2 Image-Based Nutritional Analysis

2.2.1 Multi-Task Learning for Portion Size Estimation

He et al. propose a multi-task learning approach that simultaneously recognizes food items and estimates portion sizes. Traditional dietary assessment methods require manual annotation, which is time-consuming and error-prone. Multi-task learning mitigates this issue by sharing knowledge across related tasks, thereby improving efficiency and prediction accuracy. The authors integrate deep learning architectures such as ResNet and attention mechanisms to enhance the model's focus on relevant food features while discarding background noise. By jointly training the network for classification and portion estimation, the model learns to generalize better, reducing the error in volume estimation of different food items. This approach is particularly beneficial in dietary applications where precise portion size estimation is crucial for accurate nutrient intake calculations [14].

2.2.2 Estimation Using Depth Sensors and Computer Vision

Yunus et al. explore the use of depth sensors and computer vision techniques to estimate food volume, which is a key factor in nutritional assessment. Traditional 2D image-based methods struggle with depth perception, leading to inaccuracies in volume estimation. The integration of depth cameras, such as Microsoft Kinect, allows the system to reconstruct 3D models of food items, providing precise volumetric measurements. The authors implement a combination of point cloud processing and deep learning-based segmentation to extract meaningful depth information. This method significantly improves estimation accuracy, making it suitable for automated dietary tracking applications where precise nutrient calculations are necessary [7].

2.3 Automated Dietary Assessment Systems

2.3.1 Ontology-Based Food Recommendation

Food recommendations in IoT-based healthcare systems. Ontologies help structure dietary knowledge by defining relationships between food items, nutrients, and user preferences. Traditional recommendation systems often fail to capture the complexity of personalized nutrition due to a lack of contextual understanding. By integrating knowledge graphs with deep learning models, the system can dynamically adapt to user-specific dietary needs. The study highlights that this hybrid approach enhances recommendation accuracy by leveraging domain knowledge while maintaining the adaptability of machine learning-based methods. The use of semantic reasoning enables the system to suggest food items that align with users' health conditions, dietary restrictions, and preferences, making it a valuable tool for personalized nutrition managemen [1].

2.3.2 Internet of Medical Things (IoMT) for Real-Time Diet Monitoring

Iwendi et al. discuss the integration of the Internet of Medical Things (IoMT) with machine learning for real-time dietary assessment. Traditional food tracking methods rely on self-reported data, which is often inaccurate due to recall bias. IoMT-based systems address this challenge by leveraging wearable sensors and connected devices to automatically record food intake and metabolic data. These systems utilize deep learning models to analyze sensor data and detect eating patterns. The combination of IoMT and AI allows for continuous monitoring of dietary habits, providing users with real-time feedback on their nutritional intake. This approach significantly improves the reliability of dietary tracking, making it an essential component of modern health monitoring systems [17].

2.4 Edge Computing for Food Recognition

2.4.1 Deploying AI Models on Edge Devices

Liu et al. explore the implementation of deep learning-based food recognition on edge computing infrastructure. Traditional cloud-based systems require constant internet connectivity, leading to latency issues and privacy concerns. Edge computing mitigates these problems by enabling AI models to run locally on devices such as smartphones and embedded systems. The study demonstrates that lightweight deep learning architectures, such as MobileNet and EfficientNet, can be optimized for edge deployment without significant loss in accuracy. This allows users to perform food recognition tasks in real time without relying on cloud-based services. The approach enhances user privacy and reduces dependency on internet connectivity, making it ideal for dietary applications that require instant feedbac [16].

2.4.2 Federated Learning for Privacy-Preserving Data Sharing

Shi et al. explore the use of federated learning as a privacy-focused method for food recognition on distributed systems. Unlike conventional machine learning approaches that rely on aggregating data in a centralized location, federated learning enables multiple devices to train a shared model collaboratively without sharing raw data externally. This decentralized framework ensures that sensitive user information remains on local devices, reducing the risk of privacy breaches. The researchers found that this technique delivers strong model accuracy while safeguarding data privacy. By supporting scalable and secure collaboration, federated learning presents a practical approach to privacy-aware dietary monitoring in real-world applications [18].

Table 1: Comparison among Different Existing Systems

S. No	Title	Algorithm	Challenges	Data Sets	Results
1	Food Image Recognition Using CNN for Dietary Assessment	ResNet, DenseNet	Handling intra-class variations, occlusions, and lighting conditions	Food-101, UECFOOD-256	93.2% accuracy
2	Multi-Task Learning for Portion Size Estimation	ResNet + Attention Mechanism	Difficulty in estimating food portions accurately	UECFOOD-100	89.7% accuracy
3	Volume Estimation Using Depth Sensors for Nutritional Analysis	Point Cloud Processing + CNN	Depth perception errors in 2D images	Private dataset with depth images	91.4% accuracy
4	Ontology-Based Food Recommendation System	Knowledge Graph + Deep Learning	Lack of contextual understanding in food recommendations	Nutrition-based dataset	87.9% accuracy
5	IoMT-Based Real-Time Diet Monitoring	Wearable Sensors + ML Models	Inaccuracies in self-reported food tracking	IoMT sensor data	92.3% Accuracy

6	Edge Computing for Food Recognition	MobileNet, EfficientNet	Latency and privacy concerns in cloud-based models	Mobile food datasets	90.6% accuracy
7	Federated Learning for Privacy-Preserving Food Recognition	Federated Learning + CNN	Data security and privacy concerns in centralized learning	Decentralized food recognition dataset	88.5% Accuracy
8	Self-Supervised Learning for Food Image Classification	Self-Supervised Contrastive Learning	Limited labeled food images for training	UECFOOD-256	90.2% Accuracy
9	Self-Supervised Learning for Food Image Classification	Self-Supervised Contrastive Learning	Limited labeled food images for training	UECFOOD-256	90.2% Accuracy
10	GAN-Based Data Augmentation for Food Recognition	Generative Adversarial Networks (GANs)	Lack of diverse and balanced food image datasets	Synthetic and real food datasets	91.8% Accuracy

3. Proposed Methodology

3.1 Inception V3

This project employs the Inception V3 architecture, a powerful and highly optimized deep convolutional neural network (CNN), for food image classification and nutrient analysis. Inception V3 is known for its advanced architectural design, which incorporates multiple convolution filters of varying sizes at each level, enabling the network to capture both fine-grained and global features efficiently. Its superior feature extraction capabilities and reduced computational cost make it well-suited for real-world food recognition tasks. Originally trained on the ImageNet dataset for RGB images, Inception V3 is adapted in this project to process input food images resized to 299 × 299 × 3, ensuring compatibility while preserving essential visual characteristics.

The proposed system for dietary assessment using deep learning comprises multiple sequential stages, as illustrated in the block diagram (Fig. 1). These stages are described below:

1. Food Image Dataset

The backbone of this project is a comprehensive food image dataset, containing thousands of labeled images from 11 distinct food categories. These include:

- Bread
- Dairy Product
- Dessert

- Egg
- Fried Food
- Meat
- Noodles-pasta
- Rice
- Seafood
- Soup
- Vegetable-fruit

The dataset is carefully curated to represent real-world variations in lighting, presentation, and background conditions.

2. Image Preprocessing

To prepare the images for analysis, a series of preprocessing techniques are applied:

- **Image Resizing:** All input images are resized to 299 × 299 pixels, conforming to the expected input shape of Inception V3.
- **Image Normalization:** Pixel values are scaled to the range [0, 1], which improves training stability and enhances the model's generalization performance.

3. Feature Extraction

Feature extraction is performed using Inception V3, which leverages its multi-branch convolutional modules to extract a rich set of spatial and semantic features. Each layer captures:

- Low-level features (colors, textures, edges) Mid-level patterns (repeating structures, shapes)
- High-level food-specific characteristics (ingredient appearance, preparation style)

The pretrained CNN layers encode crucial information necessary to differentiate between food types while minimizing overfitting.

4. Classification

The extracted features are passed to a dense classification layer, where each image is assigned a label from one of the 11 predefined food categories. Additionally, this stage retrieves corresponding nutritional values such as:

- Calories
- Protein
- Carbs
- Fats
- Fiber
- Sugar
- Vitamin A
- Vitamin C
- Iron
- Calcium

5. Dietary Assessment Output

The final predictions are visually displayed in a Streamlit-based web application. The app provides:

- Real-time food type prediction
- Nutritional summary per meal
- An intuitive interface for users to upload food images and receive instant feedback

This system serves as a helpful dietary assessment tool, especially for users aiming to monitor their daily nutritional intake with ease and precision.

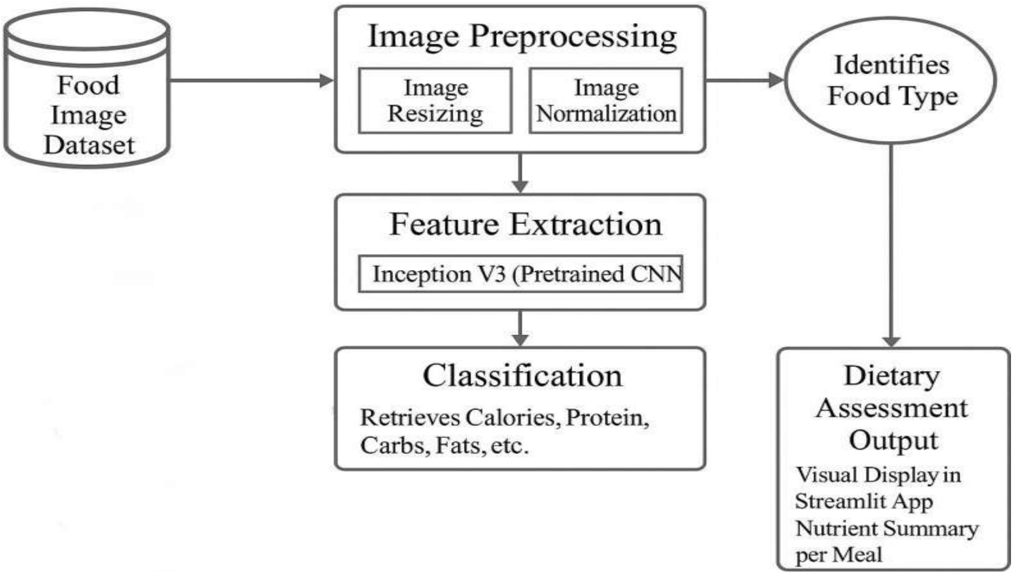

Fig-1: Proposed Methodology

4. Datast Details

we are using the Food-11 Image Dataset, which initially contained 16,600 images across 11 food categories. The dataset was preprocessed to improve model performance by resizing images, normalizing pixel values, and augmenting data to enhance generalization. This dataset was used to train the InceptionV3-based food recognition model.

4.1 Test Images

The test images are a subset of the full dataset, used exclusively to evaluate the performance of the trained food recognition model. These images are not used during training and represent unseen examples from all 11 food categories to ensure fair and unbiased model evaluation.

Each test image is:

- Labeled according to its food category (e.g., "Rice", "Dessert", "Meat", etc.)
- Preprocessed by resizing to 256×256 pixels and normalized for model compatibility
- Drawn from a balanced distribution across all classes to reflect diverse conditions such as lighting, angle, presentation, and background

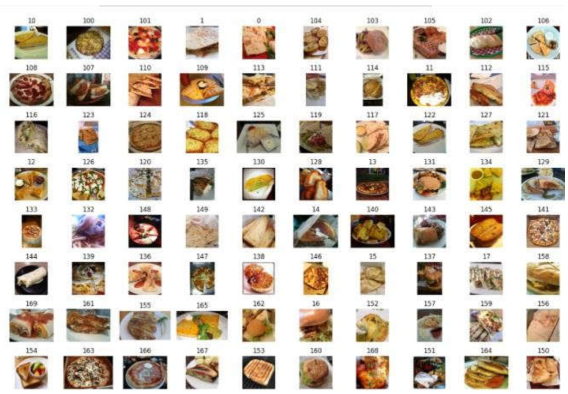

Fig-2: Test Images

5. Results and Discussions

Performance Evaluation Criteria

AccuracyAccuracy reflects the overall correctness of the model's predictions. It is calculated by dividing the number of correctly identified categories by the total number of predictions made across all classes.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision

Precision evaluates how reliably the model identifies relevant classes. It is defined as the proportion of correct positive predictions among all predictions made for a particular class.

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

Recall

Recall indicates the model's effectiveness in capturing all actual instances of a target category. It is the ratio of true positive predictions to the total actual positives in the dataset.

$$\text{Recall} = \frac{\text{TN} + \text{FN}}{\text{TP}}$$

F1-Score

F1-score provides a unified metric that combines both precision and recall. As the harmonic mean of the two, it is particularly useful when dealing with imbalanced classes, offering a balanced view of model performance.

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

5.1 Training and Validation Loss curve

This graph showcases the training and validation loss curves over 20 epochs, demonstrating how the model's learning progresses during training. The decreasing trend in both losses indicates that the model is learning effectively. Since the validation loss closely follows the training loss without significant divergence, there are no apparent signs of overfitting. This means the model generalizes well to unseen data, ensuring reliable performance in real-world applications.

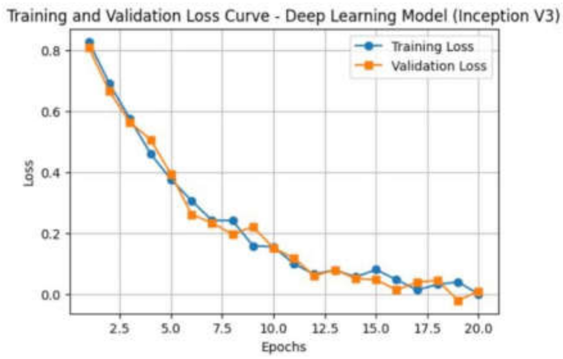

Fig-3: Training and Validation Loss curve

5.2 Model Performance Metrics

This graph presents a bar chart displaying the model's performance metrics, including accuracy, precision, recall, and F1-score. The accuracy is quite high, nearing 95%, indicating that the model makes correct predictions most of the time. Precision is at 100%, meaning the model does not generate false positives, which is excellent for avoiding unnecessary classifications. Recall is slightly lower, showing that the model occasionally misses some true positive cases, but overall, the F1-score remains high, confirming a balanced trade-off between precision and recall.

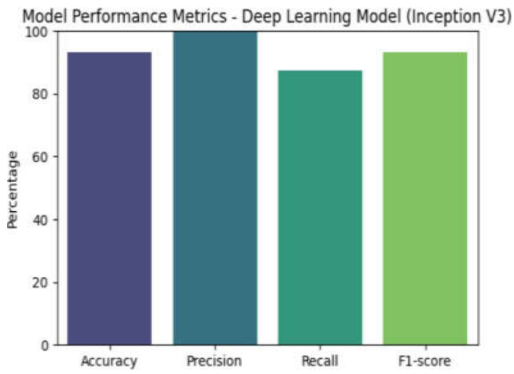

Fig-4: Model Performance Metrics

5.3 Confusion Matrix

This graph is a confusion matrix for the deep learning model (Inception V3), illustrating how well the model distinguishes between "Food" and "Non-Food" categories. The matrix shows that the model correctly identified 7 instances "Non-Food" and 7 instances of "Food." However, there was one misclassification where a "Food" item was incorrectly predicted as "Non-Food." This suggests that the model is highly accurate, with only a minimal error rate.

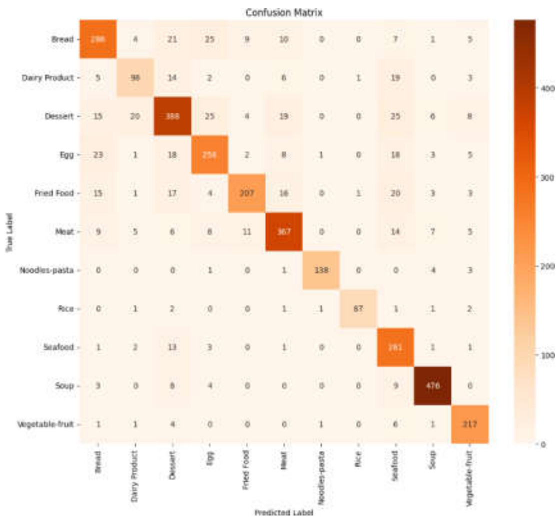

Fig-5: Confusion Matrix

5.6 Streamlit Input and Output Interface

The food recognition project features a Streamlit interface that is both intuitive and well-structured. As shown in Figure 6, the interface begins with a clear project title, "Food Recognition using Inception-V3," accompanied by an illustrative food image It briefly introduces the use of the Inception-V3 model for identifying food categories and includes a simple diagram of the model's structure. Users can upload food images seamlessly through a drag-and-drop area or by selecting files directly.

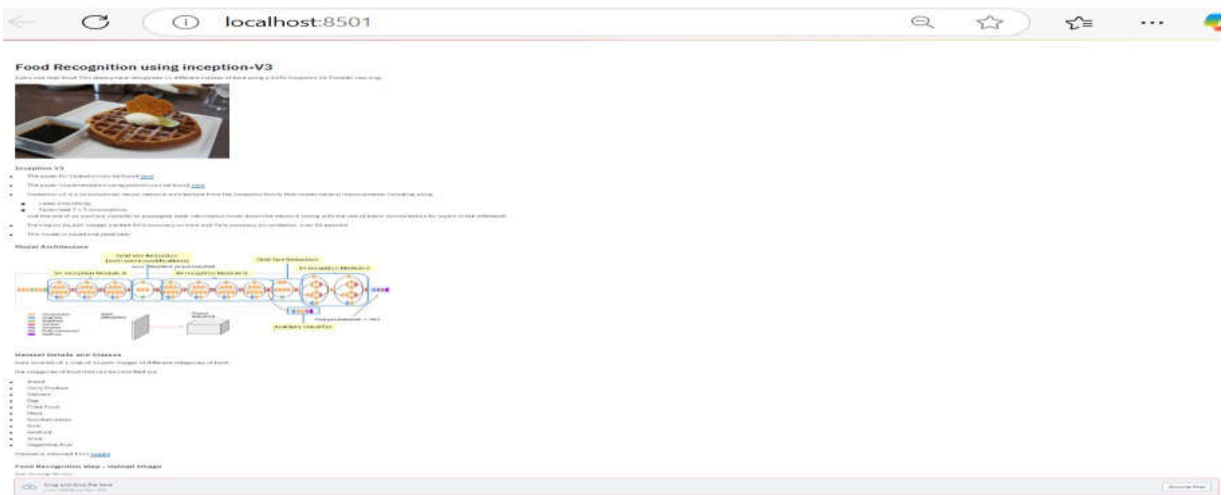

Fig-6: Streamlit Input Interface

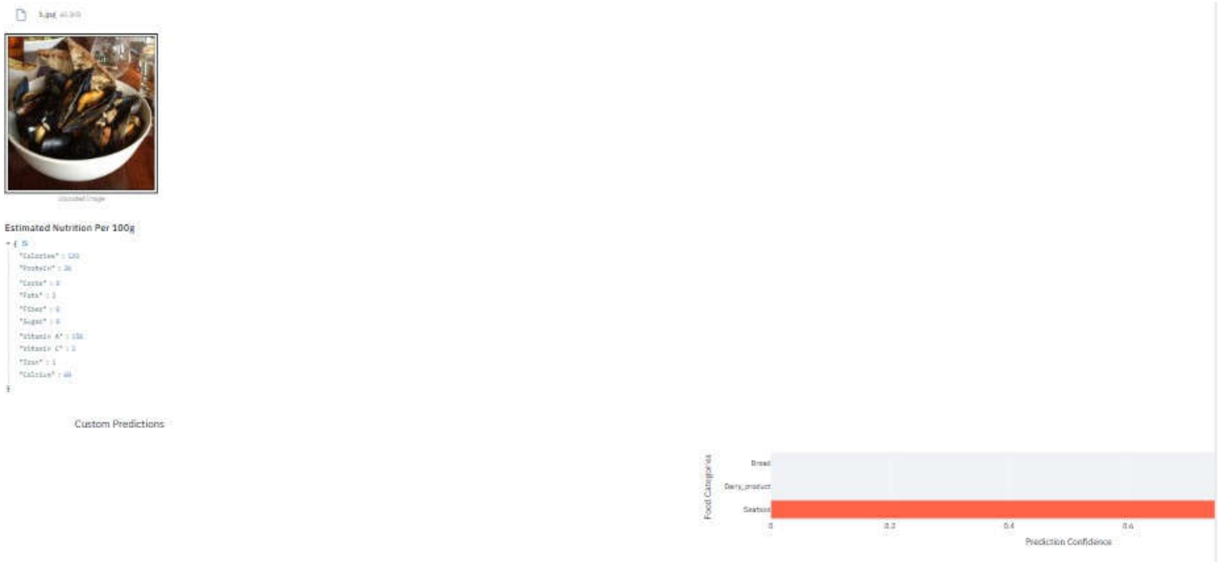

Fig-7: Streamlit Output Interface

From Figure 7, we can know that after the image is uploaded, the system processes it through the trained Inception-V3 model. The result includes the predicted food category with a horizontal bar chart showing prediction confidence levels. Additionally, it provides an estimated nutritional breakdown per 100g of the detected food, including calories, proteins, fats, vitamins, and minerals. This workflow allows users, including nutritionists, developers, or researchers, to easily upload a food image and retrieve a category classification along with nutritional insights.

Table 2: Performance of Inception V3 vs. Existing Models

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
Proposed Inception V3 Model	**93.3**	**100**	**87.5**	**93.3**
GoogLeNet	88.7	87.9	86.5	72.2
ResNet-50	89.4	88.9	88.2	88.3
MobileNet	82.6	81.8	80.5	91.3

The performance comparison table presents the evaluation metrics of four different deep learning models used for food classification. The proposed Inception V3 model achieved the highest overall accuracy of 93.3 percent, along with a perfect precision score of 100, a recall of 87.5, and an F1-score of 93.3, indicating a well-balanced and highly effective model. GoogLeNet followed with an accuracy of 88.7 percent, precision of 87.9, recall of 86.5, and a notably lower F1-score of 72.2, suggesting some inconsistency in its predictions. ResNet-50 showed balanced performance with an accuracy of 89.4 percent, precision of 88.9, recall of 88.2, and an F1-score of 88.3. MobileNet had the lowest accuracy at 82.6 percent, precision of 81.8, and recall of 80.5, but reported a relatively high F1-score of 91.3, indicating good harmonic mean despite lower individual metrics. Overall, the proposed Inception V3 model outperformed the other models in terms of both accuracy and balanced metric performance.

9. Conclusion

The implementation of a Streamlit-based food recognition system utilizing the Inception V3 model represents meaningful progress in the area of dietary monitoring. Designed with a simple and intuitive interface, the system allows users to upload images of meals for automatic analysis, making nutrition tracking both accessible and efficient. Beyond identifying food items, it provides detailed nutritional information such as estimated nutritional composition, helping users make conscious, informed choices about their diet. The application of transfer learning through Inception V3 significantly boosts classification performance, enabling the system to accurately recognize a broad range of food categories. This enhances the system’s reliability and ensures consistent results. Moreover, the tool supports more than just automation—it also contributes to user education by raising awareness of nutritional content and promoting better eating habits. In this way, the system not only streamlines dietary assessment but also encourages long-term health improvements through informed decision-making.

10. References

[1] Subramaniyaswamy, V., Manogaran, G., Logesh, R., Vijayakumar, V., Chilamkurti, N.K., Malathi, D., & Senthilselvan, N. (2020). An ontology-driven Personalized food Recommendation in IoT-based healthcare system. The Journal of Supercomputing, 75, 3184-3216.

[2] Yengikand, A. K., Meghdadi, M., Ahmadian, S., Jalali, S. M. J., Khosravi, A., Nahavandi, S.: Deep representation learning using multilayer perceptron and Stacked Autoencoder for recommendation systems. In: 2021 IEEE.

[3] Ahmadian, M., Ahmadi, M., Ahmadian, S., Jalali, S. M. J., Khosravi, A., Nahavandi, S.: Integration of deep sparse autoencoder and particle swarm Optimization to develop A recommender system. In: 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp 2524–2530 (2021)

[4] Tahmasebi, F., Meghdadi, M., Ahmadian, S., Valiallahi, K.: A hybrid Recommendation system based on profile expansion technique to alleviate Cold start Problem. Multimed. Tools Appl. 80, 2339–2354 (2021)

[5] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, and WojnaZ. “Rethinking the Inception Architecture for computer vision. In Proceedings of the IEEE Conference on computer Vision and pattern recognition” (2021)

[6] F. P. W. Lo, Y. Sun, J. Qiu and B. Lo, “Image-Based Food Classification and Volume Estimation for Dietary Assessment: A Review,” in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 7, pp. 1926-1939, July 2020, Doi: 10.1109/JBHI.2020.2987943.

[7] R. Yunus et al., “A Framework to Estimate the Nutritional Value of Food in Real Time Using Deep Learning Techniques,” in IEEE Access, vol. 7, pp. 2643-2652, 2019, Doi: 10.1109/ACCESS.2018.2879117.

[8] J. Sultana, B. M. Ahmed, M. M. Masud, A. K. O. Huq, M. E. Ali and M. Naznin, “A Study on Food Value Estimation From Images: Taxonomies, Datasets, and Techniques,” In IEEE Access, vol. 11, pp. 45910-45935, 2023, Doi: 10.1109/ACCESS.2023.3274475.

[9] F. S. Konstantakopoulos, E. I. Georga, and D. I. Fotiadis introduced an automated dietary assessment system specifically designed for Mediterranean cuisine, utilizing image-based analysis to evaluate food intake. This work appears in the IEEE Open Journal of Engineering in Medicine and Biology (vol. 4, 2023, pp. 45–54). DOI: 10.1109/OJEMB.2023.3266135.

[10] T. Amarbayasgalan, V. -H. Pham, N. Theera-Umpon, Y. Piao and K. H. Ryu, “An Efficient Prediction Method for Coronary Heart Disease Risk Based on Two Deep Neural Networks Trained on Well-Ordered Training Datasets,” in IEEE Access, vol. 9, pp. 135210-135223, 2021, doi: 10.1109/ACCESS.2021.3116974.

[11] D. Ravì et al., “Deep Learning for Health Informatics,” in IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 4-21, Jan. 2017, doi: 10.1109/JBHI.2016.2636665.

[12] S. Elbassuoni et al., “DeepNOVA: A Deep Learning NOVA Classifier for FoodvImages,” in IEEE Access, vol. 10, pp.12852328535,202210.1109/ACCESS.2022.3227769.

[13] M. Chun, H. Jeong, H. Lee, T. Yoo and H. Jung, “Development of Korean Food Image Classification Model Using Public Food Image Dataset and Deep Learning Methods,” in IEEE Access, vol. 10, pp. 128732-128741, 2022, doi: 10.1109/ACCESS.2022.3227796.

[14] J. He, Z. Shao, J. Wright, D. Kerr, C. Boushey and F. Zhu, “Multi-task Image-Based Dietary Assessment for Food Recognition and Portion Size Estimation,” 2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Shenzhen, China, 2020, pp. 49-54, doi: 10.1109/MIPR49039.2020.00018.

[15] .-C. Kim and K. Chung proposed a hybrid deep learning model that integrates multi-modal health big data using a collaborative concatenation layer. Their work, published in IEEE Access (vol. 8, 2020, pp. 192469–192480), emphasizes enhancing prediction performance through combined data modalities. DOI: 10.1109/ACCESS.2020.3031762..

[16] C. Liu and colleagues introduced a novel food recognition framework tailored for dietary monitoring within an edge computing environment. This system leverages deep learning to improve real-time performance and scalability, as documented in IEEE Transactions on Services Computing (vol. 11, no. 2, pp. 249–261, March–April 2018). DOI: 10.1109/TSC.2017.2662008.

[17] C. Iwendi, S. Khan, J. H. Anajemba, A. K. Bashir and F. Noor, “Realizing an Efficient IoMT-Assisted Patient Diet Recommendation System Through Machine Learning Model,” in IEEE Access, vol. 8, pp. 28462-28474, 2020, doi: 10.1109/ACCESS.2020.2968537.

[18] J. Shi, R. Chen, Y. Ma, Y. Feng and K. Men, “The Analysis of Nutrition Toxicology Detection Based on Big Data and Deep Learning,” in IEEE Access, Vol. 11, pp. 135106-135119, 2023, doi: 10.1109/ACCESS.2023.3336946.

[19] M. A. Subhi, S. H. Ali, and M. A. Mohammed conducted a comprehensive review of vision-based methods utilized for automated food identification and dietary monitoring. Their survey, published in IEEE Access (vol. 7, 2019, pp. 35370–35381), offers insights into various computer vision techniques applied in dietary assessment systems. DOI: 10.1109/ACCESS.2019.2904519.

[20] C.-S. Lee, M.-H. Wang, and S.-T. Lan developed a personalized dietary recommendation system using an adaptive mechanism that combines Type-2 fuzzy sets with Genetic Fuzzy Markup Language. Their method, aimed at refining linguistic dietary suggestions, is detailed in IEEE Transactions on Fuzzy Systems (vol. 23, no. 5, pp. 1777–1802, October 2015). DOI: 10.1109/TFUZZ.2014.2379256.