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Nutrivision: A CNN-based Mobile Application for Food Classification and Analysis

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Abstract: *With the increasing awareness of health and nutrition, demand for intelligent systems that provide the appropriate dietary advice is growing. NutriVision is a mobile application on the basis of Convolutional Neural Networks (CNN) for real-time fruit, vegetable, packaged food classification. It employs a deep learning-based computer vision model trained from a representative dataset to achieve high classification accuracy. With the inclusion of a large nutritional database, NutriVision provides the user with rich nutrition information, which can be utilized for appropriate dietary choice and monitoring of individual nutrition. This paper presents an analysis of CNN architecture efficiency for food categorization, comparison of the accuracy of the system via performance metrics, and exploration of real-world deployment challenges implications. Experimental results validate the efficiency and stability of the model, placing NutriVision as a worthy AI-based system for automated food recognition and nutritional control.*

Keywords: Convolutional Neural Network (CNN), Mobile Application, Food Classification, Nutritional Analysis, Dietary Management, Deep Learning, Computer Vision etc.

I. INTRODUCTION

In the busy life of today, it is tougher than ever before to consume a healthy diet. Individuals find it hard to consume healthy food as they lack appropriate nutritional knowledge. Nutrivision was designed to fill this knowledge gap by utilizing Artificial Intelligence and Computer Vision technology to assist consumers in making the right healthy food choices easily. With a simple snap using their smartphone camera, consumers can immediately access detailed nutritional information, calorie levels, and macronutrient breakdowns, eliminating the time consumed searching manually. Convolutional Neural Networks (CNNs) in the app accurately recognize fruits, vegetables, and processed foods to give real-time insights into the nutritional composition of each. As health issues like obesity, diabetes, and starvation increase, there is an urgent need for technology that makes nutritional monitoring easier. NutriVision not only alerts consumers to the health impacts of their food but also encourages wholesome eating by suggesting alternatives based on facts. Through the combination of AI-powered food identification and a user-friendly mobile application, the app guarantees users the ability to embrace a healthy lifestyle without the need for expertise in nutrition.

BACKGROUND

In the last decade, public anxiety about diet-linked health problems such as obesity, diabetes, and malnutrition highlighted the importance of healthy food habits. Yet, the majority of people lack

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necessary information to compare the nutritional values of foods routinely consumed. Taking time to read the food label or consulting web-based databases is inconvenient. With advancements in Computer Vision and Artificial Intelligence, particularly CNN, exhibiting impressive image classification and recognition capabilities. Such technology is capable of transforming human interaction with food by providing real-time accurate nutritional analysis based on image-based food recognition.

MOTIVATION

The increasing prevalence of diet-related health problems such as obesity, diabetes, and malnutrition further emphasizes the importance of readily accessible and reliable nutritional guidance. It is difficult for most individuals to assess the nutritional value of their food, and consequently make poor food choices that could potentially harm their health. Depending on traditional methods, such as reading nutrition labels by hand or searching for food data on the internet, is often cumbersome and time-consuming. This creates the necessity for a simple-to-use AI solution that can provide instant and accurate food analysis with reduced user effort. Emerging trends in Artificial Intelligence (AI) and Computer Vision have yielded promising results for food identification and analysis.
Convolutional Neural Networks (CNNs), in particular, have achieved high accuracy rates in image-based classification tasks, thus making them an ideal choice for food identification. With the widespread availability of food datasets and improved deep learning techniques, a real-time AI-based food recognition system is now possible to enable people to make healthier food choices. Using these technological advancements, NutriVision aims to bridge the gap between nutrition knowledge and food recognition so that users can make informed decisions and adopt healthier eating habits easily.

OBJECTIVES

The objective of this research is to create NutriVision, a smartphone application based on Convolutional Neural Networks (CNNs) for real-time food recognition and nutritional analysis. The goal is to provide consumers with a simple and intuitive tool to find the nutritional value of food in real-time. This research aims to create a CNN based food classification platform that can recognize fruits, vegetables, and packaged food products with high accuracy through the techniques of image processing. By making it simple and assessing the efficacy of the Deep learning model on diverse datasets, the research aims to enhance accessibility and dependability. The ideal goal for NutriVision is to inform people about the food they have eaten, with the hope of welcoming them towards healthier eating and overall health.

CONTRIBUTION

Nutrivision provides automated food recognition with CNN and real-time nutritional analysis with AI. The major contributions of Nutrivision are as follows:

1. Designing a CNN based food classification model with high accuracy in recognizing the fruits and vegetables.
2. Building feature in mobile app by which user can get complete nutritional analysis regarding packaged food by scanning the barcode.

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3. Launch of mobile app through which user can scan food product using phone's camera functionality and obtain real-time nutritional breakdown.
4. Integration of an easy-to-use interface to improve usability and accessibility so that nutritional assessment can be readily accessible to people with different technical competency level.

II. LITERATURE REVIEW

Some researchers have suggested research with different approaches to construct classification models. [1] Conventional fruit classification methods are based on visual capabilities or traditional image processing techniques. But it has limitations in detecting a large volume of dataset. To overcome this issue, a classification model was employed using the CNN approach to classify fruit types. According to the classification test table, the model can achieve an accuracy rate of 66.0%. Thus, the new model can prove to be a good solution in handling enormous fruit classification problems.

In [2] three models were evaluated to classify date fruit where model 1 was MobileNetV2 architecture which was modified by modifying the classification layer and having merely eight nodes in order to classify the said date fruits. Model 2 was the MobileNetV2 model where the classification layer was substituted with five alternative layers (identical to the proposed model) and the final layer was tailored to match the dataset employed. Model 3 was identical to Model 2 but in Model 3 the existing layers of the model were frozen for the initial 20 iterations and the tailored head was trained separately for these iterations. Upon completion of the 20th iteration, the entire model was trained.

In [3] a model is proposed to identify fruits from images. While doing such work, machine learning techniques have been formulated to build the model. In the current research work, a 4-class dataset of fruits was proposed for introduction. To implement the model work, Convolutional Neural Networks (CNNs) were applied, which were formulated to accomplish a machine learning technique. This model can achieve an accuracy of 99.89%, which confirms that the performance of this model to identify fruit from images is more sophisticated.

The designed framework in [4] applies multi-modal deep learning on fruit identification. Fruit images are identified with a multi-model classifier. A multi-model classifier is used for training fine and coarse labels. The Convolution Neural Network is used to train discriminative features, and the recurrent Neural Network (RNN) is used to train sequential labels, and LSTM is used in classifying fruits by best-extracted and labeled features.

The primary goal of the proposed technique in [5] is to extract the best features, label the best features and ultimately categorize the fruits depending on optimal features by deep learning applications. Here in this research work, CNN, RNN, and LSTM deep learning architectures are integrated in order to classify the fruits. In feature extraction with CNN, segment obtained features into various strategies, we have the features partitioned into coarse and fine types. CNN generator is engaged for extracting fine and coarse label classes.

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An intelligent module designed in [6] for an automatic identification of food items in specific fruits and vegetables for realizing the task of computer vision in smart refrigerators are suggested. The algorithm and module designed has been significantly tested for accuracy by employing pre-trained InceptionV3 and MobileNetV3 CNN models on standard fruits and vegetables dataset. Between the two CNN models under consideration, it is clear from the results that MobileNetV3 CNN performed much better than the InceptionV3 model in terms of training time as well as accuracy achieved using test images. Additionally an accuracy of 99.9% is achieved on a large dataset like FRUIT360.

Designed a smartphone-based food recognition app [7] for visually impaired children. The suggested application employs a deep CNN model that has been trained to identify the food items. In addition, we suggest an ensemble model combining several deep CNN models with the soft voting technique for better food recognition. The food classification performance of the proposed ensemble model on various food datasets demonstrates its performance for food classification tasks.

A good model was suggested in [8] for hazelnut variety classification. The suggested model was trained with a data set that comprised images of 17 hazelnut types. This model was then compared to four pre-trained models, whose last layer only were modified. The model was fine-tuned for enhancing the performance of classification by each model. The models were optimized and cross-validated in order to raise the rate of accuracy and reduce the rate of error. The correctness of the model presented was obtained as 98.63%. The outcomes revealed that pre-trained models were not able to satisfy the condition for the classification of hazelnuts. Hence, a new architecture of CNN was introduced and employed in this research.

In [10] the paper initially, overview the recent work on CV-based food detection, identification, and quantification and the most recent research on MR-based interventions to drive users towards better food options. Second, an integrated framework was proposed for simultaneously using automatic CV-based food recognition and visual interventions in real-time in a vending machine (VM) environment through MR headsets. Third, to gauge such a system's capability to recognize packaged food items, technical feasibility study results was demonstrated. Fourth, to evaluate the capability of visual interventions to change user behavior, a user study performed with 61 participants in realistic settings.

A review was done in [11] on CNN for fruit classification and fruit image processing, different use cases for deep learning based fruit classification were found. Auto classification of fruit [12] into fresh and rotten category is challenging as well as crucial task in agricultural sector. The present research compares the performance of a CNN based model with pre-trained transfer learning model for fruit classification. AlexNet, LeNet-5, VGG-16, and VGG-19 are the transfer learning models used in this research. The proposed model is compared against the performance of current models, and the effects of different hyper parameters are tested. The comparisons' results demonstrate that the proposed CNN model's classification accuracy is superior and stronger than transfer learning methods in classifying fruits. The accuracy level of 98.23 % is attained by proposed CNN model.

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In the paper [13], MobileNet has been applied on Fruit Dataset to find the improved classification performance of the network. From fruits dataset, here 1260 images have been taken from 7 categories: 85 % of these images are taken for training, and 15 % for testing the model. The network is trained for 10 epochs with a batch size of 14. The accuracy of the suggested model was 98.74 %. The comparison of the suggested model with the traditional models indicates that the performance of this model is exceptionally good and promising to implement in real-world applications. This type of higher accuracy and precision will function to enhance the machine's overall efficiency in fruit recognition more suitably. As a prototype, a Python program was created using PyQt library in Visual Studio environment.

In [14] YOLO have highest accuracy, compared to other algorithm such as CNN and color detection using MATLAB and MATLAB implementation is for circle shape fruits only and it can identify all the ripen fruit in YIQ value used. Thus YOLO have advantages in object classification than any other algorithm and additional image classification can be done using increase in dimensions such as 3D by maintaining much more objective or parameters. After the simulation classifying the fruit is done, a camera can be mounted on a drone to take the picture of the fruit, classify the fruit and harvest the fruit by utilizing gripper attached to the drone. This research can result in autonomous drone that can assist in the harvesting process.

In the paper [15], we introduce a system that classifies fruit with an accuracy rate of 88% (mango), 83%(limes), 99% (pitaya) and with an average computation cost of 0.0131 m/s. Faster R-CNN is one such model that became possible in tackling complex computer vision issues with the same concept and exhibits amazing performance at the dawn of deep learning revolution. The algorithm presents a solution for addressing instances of real-time fruit quality detection using multi-classes.

The research introduced in [16] is a double-track approach to classify fruit varieties in a retail selling system. The technique employed two nine-layer CNNs with identical structure and distinct weight matrices. Initially, the network distinguished fruits according to images of fruits against the background and the second one for images with the ROI (single fruit). Results were combined using suggested values for neuron weights (significance). The technique therefore returned predicted class/classes (varieties of fruits) along with their Certainty Factor (CF). The proposed approach merged the detection and classification techniques and calculated the certainty factor of the prediction outcomes from original and cropped image ROIs, which was the contribution of this paper.

III. METHODOLOGY

SYSTEM ARCHITECTURE

NutriVision mobile application is designed for real-time food classification and nutritional analysis using CNNs and Transfer Learning. As represented in figure 1 users can photograph foods or scan barcodes, and these are processed by a pre-trained model to classify them. A Barcode API retrieves the product details, and a database system stores the classified images, nutritional data, and user

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information. The system is cloud-based for scalability and efficient data storage. Once a food item is classified, nutritional content is scanned using Gemini AI for macronutrient composition, dietary impact, and personalized health advice. An in-app recipe recommendation feature pulls appropriate healthy meals from accessed food items, offering a friendly and personalized experience. The whole range of results, ranging from classification to nutrition facts to recipes, is presented within the app. In its mission to be efficient, real-time processing, and scalable, NutriVision utilizes deep learning models, AI-based analysis, and cloud databases to promote food awareness and healthy diets. The merging of image recognition, barcode reading, and AI-generated insights brings about an intuitive, accurate, and informative experience.

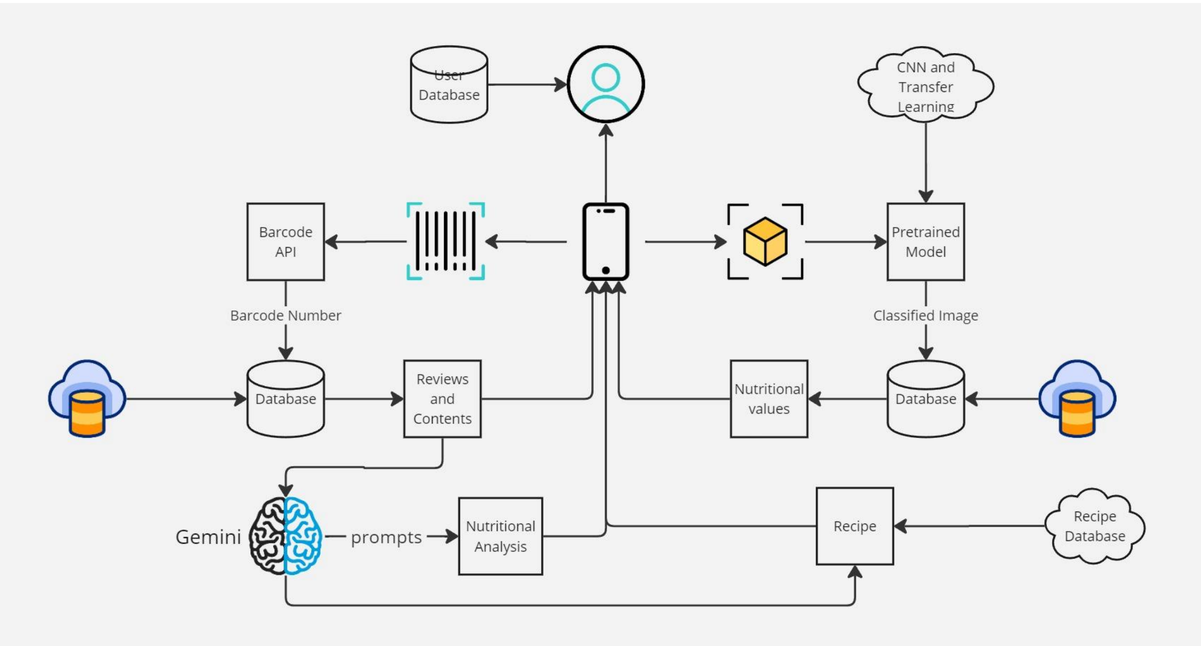

Figure 1: System Architecture

DATA COLLECTION

The effectiveness and performance of any machine learning model to a great extent depend on the dataset quality and diversity upon which training and testing are done. For NutriVision app, two commonly tested datasets were selected to provide end-to-end food recognition and classification:

1. Fruits and Vegetables Dataset (Used by jazzmacedo/fruits-and-vegetables-detector-36)

2. Food-101 Dataset (Used by nateraw/food)

These data sets were chosen for their diversity, scalability, and utility in practical scenarios, which allowed the model to generalize across a wide range of environments. The Food-101 dataset on Kaggle is one of the widely used benchmark data sets for food classification in machine learning and computer vision. The data set contains 101 categories of foods, each covered by 1,000 images, resulting in a total of 101,000 images. This dataset provides a realistic and diverse collection of food images and thus is a great option for training deep learning model for food recognition and classification.

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Food-101 is a properly organized and large dataset providing a real challenge to food classification models. It is well recognized within computer vision and deep learning communities as an awesome training resource for building AI-driven food recognition systems. The richness of food categories, natural image variations, and challenging classification scenarios in the dataset render it an ideal choice for researchers and developers working on AI-driven food analysis tasks. Food 101 dataset include images of food like caesar salad, nachos, ramen, chocolate cake, chicken wings, dumplings etc. Fruit and vegetables dataset has images of many fruits and vegetables and offers a diverse range for use in image recognition. The foods covered in the dataset are:

1. Fruits: Banana, Apple, Pear, Grapes, Orange, Kiwi, Watermelon, Pomegranate, Pineapple, Mango.
2. Vegetables: Cucumber, Carrot, Capsicum, Onion, Potato, Lemon, Tomato, Radish, Beetroot, Cabbage, Lettuce, Spinach, Soybean, Cauliflower, Bell Pepper, Chilli Pepper, Turnip, Corn, Sweetcorn, Sweet Potato, Paprika, Jalapeño, Ginger, Garlic, Peas, Eggplant.

The dataset is categorized into three principal directories:

- Train: It includes 100 images per class.
- Test: It includes 10 images per class.
- Validation: It includes 10 images per class.

These folders are further divided into specific folders for each category of fruit and vegetable with respective images.

DATASET PREPROCESSING

Preprocessing was performed on the dataset for improved generalization of the model with traditional image processing techniques. All images were resized to 224x224 pixels to have a common input size, and pixel intensities were normalized in the range [0, 1] for uniform input distribution. Data augmentation methods were used to increase model robustness, such as rotation (±15°), horizontal and vertical flipping, brightness modification (±20%), random zoom-in/out, and addition of Gaussian noise to mimic real-world variability. These preprocessing operations guaranteed enhanced adaptability and performance of the model under varied conditions.

MODEL TRAINING

In this research study, we experimented with different deep learning models to identify the best approach to fruit/vegetable detection and food item categorization. The training of NutriVision was done by applying deep learning-based image classification using a mix of conventional CNN architectures and transfer learning models. The major objective was to create a robust and efficient system to recognize fruits and vegetables correctly under real-world scenarios. The below-described models were tested:

- jazzmacedo/fruits-and-vegetables-detector-36 (Hugging Face, Transfer Learning)
- tnateraw/food (Hugging Face, Transfer Learning)
- VGG-16 (Traditional CNN)
- ResNet-50 (Transfer Learning)
- EfficientNet-B0 (Transfer Learning)

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The Hugging Face models (Jazzmacedo/fruits-and-vegetables-detector-36 and Nateraw/food) were neither fine-tuned nor utilized but directly applied in inference, using their pre-trained weights.

MODEL TRAINING STRATEGY

Training VGG-16 (Traditional CNN Model): The VGG-16 model, which is a 16-layer Convolutional Neural Network (CNN), was trained with small 3x3 filters to extract efficient deep hierarchical features. The Categorical Crossentropy loss function was utilized since it is optimal for multi-class classification problems. The model was trained using the Adam optimizer with a learning rate of 0.0001 and was trained with a batch size of 32 for 50 epochs. Dropout (0.5) was used to prevent overfitting. VGG-16 was computationally intensive, however, and required adequate regularization to prevent overfitting without excessively complicated training.

Training ResNet-50 (Transfer Learning Model): The deep residual network, ResNet-50, was employed since it can avoid vanishing gradients through the utilization of skip connections. Training consisted of freezing lower layers to retain pre-trained feature representations and fine-tuning the higher layers over the dataset. The SGD optimizer with momentum (learning rate = 0.001) was used for training for over 30 epochs. The architecture facilitated improved feature learning, rendering the training process more stable and capable of applying transfer learning for greater accuracy and efficiency.

Training EfficientNet-B0 (Transfer Learning Model): EfficientNet-B0 was used because of its compound scaling approach that scales depth, width, and resolution in a balanced manner for maximizing the balance between performance and efficiency. The training process focused on feature extraction using progressive image resizing to allow the model to learn optimally. The Adam optimizer was employed at a learning rate of 0.0003, and training was done for 25 epochs. EfficientNet-B0 was found to be extremely appropriate for mobile use due to its high accuracy and low computational cost, with the possibility of doing smooth real-time inference with fewer resources.


```
Epoch 15/20
49/49 ━━━━━━━━━━━━━━━━━━━━ 151s 2s/step - accuracy: 0.9757 - loss: 0.1857 - val_accuracy: 0.9658 - val_loss: 0.1586
Epoch 16/20
49/49 ━━━━━━━━━━━━━━━━━━━━ 132s 2s/step - accuracy: 0.9800 - loss: 0.1771 - val_accuracy: 0.9715 - val_loss: 0.1550
Epoch 17/20
49/49 ━━━━━━━━━━━━━━━━━━━━ 141s 2s/step - accuracy: 0.9781 - loss: 0.1624 - val_accuracy: 0.9715 - val_loss: 0.1506
Epoch 18/20
49/49 ━━━━━━━━━━━━━━━━━━━━ 143s 2s/step - accuracy: 0.9820 - loss: 0.1529 - val_accuracy: 0.9687 - val_loss: 0.1433
Epoch 19/20
49/49 ━━━━━━━━━━━━━━━━━━━━ 141s 2s/step - accuracy: 0.9849 - loss: 0.1405 - val_accuracy: 0.9687 - val_loss: 0.1470
Epoch 20/20
49/49 ━━━━━━━━━━━━━━━━━━━━ 114s 2s/step - accuracy: 0.9869 - loss: 0.1287 - val_accuracy: 0.9744 - val_loss: 0.1352
```

Figure 2: Model Training (Epochs)

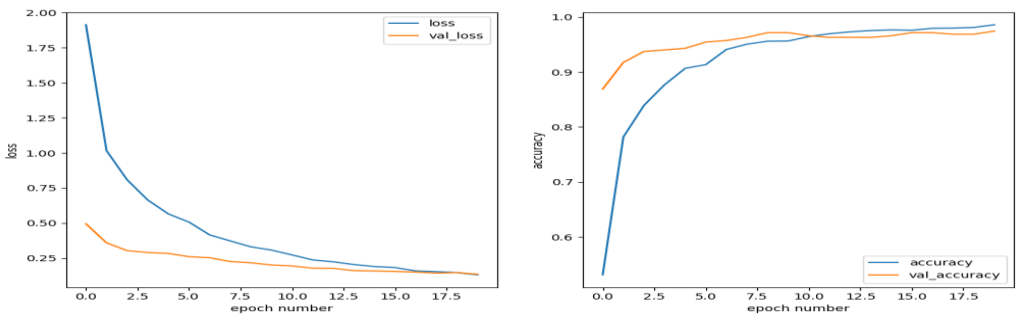

Figure 3: Learning Curve

MODEL EVALUATION

Out of all the models, jazzmacedo/fruits-and-vegetables-detector-36 produced the highest accuracy of 94.5%, high precision (0.92), recall (0.93), and an F1-score of 0.925 and thus is the most accurate model for fruit and vegetable detection. The nateraw/food model also performed well with accuracy of 91.2% and balanced precision (0.89), recall (0.90), and F1-score (0.895), again demonstrating the success of transfer learning in food classification tasks. Out of the CNN models, EfficientNet-B0 worked best with an accuracy of 90.1%, and balanced recall, precision, and F1-score (0.89 each). ResNet-50 came close with 88.2% accuracy and an F-1 score of 0.875, which indicates its ability to perform well in extracting deep features.

VGG-16, despite working, recorded the lowest accuracy (86.7%), which indicates its lack of efficiency in handling complex food image variations. The Hugging Face models were chosen for production deployment because had higher accuracy and were more efficient during real-time inference. The models utilize transfer learning. With pre-trained weights of larger dataset being utilized to identify fruits, vegetables and foods. No fine-tuning into inference done and the models were deployed straight into inference using their pre-trained weights.

Table 1: Model Evaluation Table

Model	Accuracy (%)	Precision	Recall	F1-Score
jazzmacedo/fruits-and-vegetables-detector-36	94.5	0.92	0.93	0.925
nateraw/food	91.2	0.89	0.90	0.895
VGG-16	86.7	0.84	0.85	0.845
ResNet-50	88.2	0.87	0.88	0.875
EfficientNet-B0	90.1	0.89	0.89	0.89

IV. CONCLUSION

To conclude NutriVision presents a new AI-powered approach for automatic food identification and nutrition analysis with Convolutional Neural Networks (CNNs) and Transfer Learning to accurately classify fruits, vegetables, and processed food. The application blends pretrained models such as jazzmacedo/fruits-and-vegetables-detector-36 (94.5%), nateraw/food (91.2%) to enable accurate classification of foods. The system takes images through a mobile interface, where the pretrained model recognizes the food and extracts nutrition values from a structured database. Barcode scanning also enhances user experience by providing detailed product information, while the recipe suggestion system offers meal suggestions tailored based on user requirements and dietary needs. Future growth will focus on optimizing model efficiency, expanding the dataset, and enhancing individualized recommendations to make NutriVision a worthwhile resource for promoting informed and healthier food choices.

V. FUTURE SCOPE

Some future enhancements for NutriVision are enhancing the model's accuracy, expanding the dataset, and integrating state-of-the-art AI-powered functionalities. At its core will be the improvement of the recipe suggestion mechanism by leveraging user interest, dietary constraints, and available ingredients to make more personalized and nutritious meals available. In addition, adding multi-modal learning from a fusion of image and text-based identification of food items has the potential to improve the classification accuracy, especially for complex or ambiguous food products. Furthermore, real-time performance can be improved by using lightweight deep learning models on mobile devices that reduce inference time without loss of accuracy. Expanding the barcode database to cover global food products and including a user feedback system will enhance the accuracy of product information and nutritional facts. Finally, incorporating real-time nutritional advice will make NutriVision an even better and informative instrument in driving healthy and well-informed food decisions.

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