International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 06, June 2026
Received: 06-05-2026 Accepted: 12-06-2026 Published: 19-06-2026

NUTRIBOT ASSISTANT BY USING DEEP LEARNING MODELS

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ABSTRACT

This project aims to develop a deep learning-based intelligent assistant, **Nutribot**, for automated food image classification and nutritional information prediction. The Nutribot system assists users by classifying food items into twelve predefined categories
Apple Pie, Cannoli, Cheese Plate, Cheesecake, Chicken Wings, Chocolate Cake, Deviled Eggs, Donuts, French Fries, Frozen Yogurt, Ice Cream, and Macarons — and instantly providing their nutritional breakdown including calories, fat, carbohydrates, and protein content per 100 grams.

To achieve this, three deep learning architectures were designed and implemented: a Custom Convolutional Neural Network (CNN), SqueezeNet, and VGG16. These models were trained, validated, and tested on a curated food image dataset. Transfer learning was applied to VGG16 and SqueezeNet to improve classification accuracy with limited data. The Custom CNN was built from scratch to demonstrate the flexibility of tailored architectures for food recognition tasks.

The system is deployed as a Flask-based web application with an intuitive interface developed using HTML, CSS, Bootstrap, and JavaScript. Users can register, log in, upload food images, receive instant predictions with confidence scores, and download results. A MySQL database stores user accounts, prediction history, and nutritional reference data. The backend supports export of results in JSON and CSV formats.

Experimental results demonstrate that VGG16 achieves the highest accuracy of 91.4%, followed by Custom CNN at 86.7% and SqueezeNet at 84.2% on the test set. The system proves efficient in real-world scenarios with response times under 3 seconds per prediction. This Nutribot platform promotes healthier dietary habits by enabling precise food tracking and nutritional awareness.

KEYWORDS: Food classification, Deep learning, Squeeze net, Flask, Diet tracking

INTRODUCTION

The rapid growth of artificial intelligence (AI) and deep learning technologies has transformed the healthcare and nutrition sectors by enabling intelligent virtual assistants capable of providing personalized dietary recommendations and health guidance. In recent years, AI-powered nutrition chatbots have gained significant attention due to their ability to analyze user preferences, calorie intake, medical conditions, and lifestyle habits in real time. These systems help users maintain healthy eating behaviors, improve weight management, and receive continuous nutritional support without requiring direct interaction with healthcare professionals.

Deep learning models, particularly Natural Language Processing (NLP) and Large Language Models (LLMs), play a major role in improving chatbot communication and personalization. Research by ChatDiet: Empowering Personalized Nutrition-Oriented Food Recommender Chatbots through an LLM-Augmented Framework demonstrated that LLM-based nutrition chatbots can provide personalized and explainable food recommendations with nearly 92% effectiveness in recommendation accuracy.

Similarly, a systematic review published in the International Journal of Behavioral Nutrition and Physical Activity[1]analyzed AI chatbot interventions for healthy diet management and concluded that intelligent chatbots positively influence healthy eating habits, physical activity, and weight management behaviors.

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Recent advancements also show the application of AI chatbots in disease-specific nutritional guidance. A study published in the European Journal of Clinical Nutrition[2] evaluated AI chatbots for diabetes and metabolic syndrome nutrition management and highlighted the growing importance of AI-driven dietary counseling systems.

Moreover, emotionally intelligent nutrition assistants are becoming increasingly important. The research work titled SlimMe, a Chatbot With Artificial Empathy for Personal Weight Management[4] introduced a chatbot capable of providing motivational and empathic responses to users during diet management. The study reported improved user engagement and interactive dietary support through NLP-based emotional analysis.

Despite these advancements, existing nutrition chatbots still face challenges such as limited contextual understanding, inaccurate dietary recommendations, lack of personalization, and insufficient real-time adaptation to user health conditions. [7]Researchers have emphasized the need for more robust deep learning architectures and contextual intelligence to improve chatbot reliability and healthcare accuracy.

The proposed paper, “NUTRIBOT ASSISTANT BY USING DEEP LEARNING MODELS,” aims to develop an intelligent nutrition assistant capable of delivering personalized dietary suggestions, calorie analysis, meal recommendations, and health monitoring using advanced deep learning algorithms. The system integrates NLP techniques, user profiling, and predictive analytics to provide accurate and interactive nutritional guidance. By leveraging deep neural networks and AI-driven conversational models, the proposed NutriBot Assistant seeks to enhance healthcare accessibility, improve dietary awareness, and support healthy lifestyle management efficiently.

LITERATURE REVIEW

The literature review examines prior research and published work related to deep learning-based food image classification, nutritional prediction, and diet management systems. This review covers key papers that have directly informed the design choices and model selection for the Nutribot system. The review is organized thematically to highlight the evolution of techniques from traditional image processing to modern deep learning approaches.

Detailed Review of Related Work

[8] A survey Comprehensive survey of 350+ studies on CNN-based food recognition. Reviews tasks including food type detection, ingredient identification, and quantity estimation. Evaluates CNN architectures, transfer learning, and semi-supervised learning approaches.Establishes the theoretical foundation for using CNNs and transfer learning in food classification tasks relevant to Nutribot.

[9] Author Introduces MLP-TF-SE (Multi-layer Perceptron with Transformer and SqueezeExcitation) achieving 99% classification accuracy and R^2=0.93–0.98 for nutrient prediction from ingredient statements. Validates the feasibility of combining food classification with nutritional value prediction, directly supporting Nutribot's dual-output design.

[10] Reviews state-of-the-art deep learning techniques for food image recognition including classification, calorie estimation, and health management applications. Discusses challenges like intra-class variability. Provides current benchmark performance expectations and highlights SqueezeNet and VGG-family models as effective choices for food recognition.

[11] AuthorCompares SqueezeNet and VGG-16 for food classification with data augmentation and hyperparameter tuning. Evaluates on health and medical diet monitoring applications.Directly informs the model selection in Nutribot by demonstrating

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the comparative performance of SqueezeNet vs VGG-16 on food datasets.

[12] Reddy et al. Demonstrates VGG-16 and SqueezeNet effectiveness in real-time food classification for dietary analysis and calorie monitoring. Shows VGG-16 achieves higher accuracy while SqueezeNet offers better efficiency. Supports the Nutribot architecture decision to include both models and validates real-time deployment feasibility.

[13] Samundi & G.S. (2024) Presents an automated food prediction system combining image classification with a calorie estimation algorithm. Demonstrates integration of classification output with nutritional data lookup.Validates the nutritional lookup approach used in Nutribot and demonstrates calorie estimation accuracy benchmarks.

[14] Jakka et al. (2022) AppliesSqueezeNet and VGG-16 to food image datasets. Evaluates accuracy, precision, and recall. Includes data augmentation and model fine-tuning strategies. Provides implementation-level insights into training SqueezeNet and VGG-16 for food classification adopted in Nutribot.

[15]Haque et al. (2022) Develops a parameter-optimized lightweight CNN for real- time calorie estimation. Achieves competitive accuracy with significantly fewer parameters, demonstrating importance of efficiency-accuracy trade-offs.Influences the Custom CNN design in Nutribot, particularly the emphasis on lightweight architecture for real-time web deployment.

Literature Review Summary

The literature review confirms that deep learning — particularly CNN-based architectures — is the dominant and most effective approach to food image classification. VGG16 consistently achieves higher accuracy while SqueezeNet offers computational efficiency advantages. No existing publicly documented system combines all three architectures (Custom CNN, SqueezeNet, VGG16) with a full-stack web deployment, user authentication, nutritional database, and multi-format export in a single integrated platform. Nutribot addresses this gap by providing a complete, practical, and deployable food nutrition assistant.

METHODOLOGIES

Custom CNN:

Custom CNN is a specialized deep learning architecture designed to optimize performance for specific tasks. Unlike standard pre-trained models, the Custom CNN can be tailored to extract relevant features from food images for classification and nutritional analysis. In this project, the Custom CNN is trained on a diverse dataset of food images, learning to differentiate between food categories like "Apple Pie," "Cheese Plate," and "Chocolate Cake." The model's unique architecture allows it to perform real-time predictions while maintaining high accuracy. Its flexibility enables it to adapt to new food items and efficiently process images for both classification and nutritional information extraction.

SqueezeNet:

SqueezeNet is a lightweight convolutional neural network designed for fast and efficient performance, making it ideal for mobile and edge devices with limited computational resources. By using fire modules, which consist of squeeze and expand layers, SqueezeNet reduces the number of parameters while preserving performance. In the Nutribot project, SqueezeNet is used to classify food images and predict nutritional data, such as calories, fats, and carbohydrates. Its efficient design enables real-time classification, making it well-suited for applications where computational resources are constrained, such as mobile apps for dietary tracking and health management.

VGG16:

VGG16 is a widely recognized deep convolutional neural network known for its simplicity and effectiveness in image classification tasks. With 16 layers, VGG16 is designed to extract deep features from images by stacking convolutional layers followed by pooling layers. In this project, VGG16 is

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utilized to classify food items, such as "Donuts," "Ice Cream," and "Chicken Wings." Its deep architecture allows the model to capture intricate patterns in food images, ensuring accurate categorization of food types. VGG16's well-established performance and reliability make it a crucial model for food recognition and nutritional information extraction in Nutribot.

RESULTS

System Workflow

The Nutribot system was evaluated through complete end-to-end workflow demonstrations. The system consistently handled user registration, login, image upload, prediction, nutritional data display, history retrieval, and export without errors across 200 test sessions. API response times remained within specification for all three models.

Performance Evaluation

Model performance was evaluated on the held-out test set of 1,695 images (15% of total dataset). The following metrics were computed for each model and each food category:

Food Category	CNN Acc %	SqNetAcc %	VGG16 Acc %
Apple Pie	84.7	82.0	90.7
Cannoli	81.3	79.2	88.7
Cheese Plate	85.9	83.7	91.1
Cheesecake	82.0	78.7	89.3
Chicken Wings	88.7	86.0	93.3
Chocolate Cake	90.0	88.0	94.7
Deviled Eggs	87.3	85.3	92.7
Donuts	92.0	90.7	96.0
French Fries	88.0	86.7	92.0
Frozen Yogurt	83.3	81.3	89.3
Ice Cream	84.7	82.7	90.0
Macarons	91.3	89.3	95.3
Overall Average	86.7	84.5	91.4

Comparison with Manual Dietary Tracking

Feature	Manual Tracking	Nutribot AI System
Input Method	Text search / barcode scan	Image upload — zero manual input
Time to Log	2–5 minutes per item	Under 3 seconds

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Food Coverage	Packaged foods (barcode)	All 12 visual food categories
Nutritional Data	Calories only (most apps)	Calories, Fat, Carbs, Protein
Accuracy	Highly dependent on user	86.7%–91.4% automated accuracy
Consistency	Variable (user fatigue)	Consistent across all predictions
Export	Limited	JSON and CSV export available
History Tracking	Manual diary	Automatic prediction history
Usability	Requires nutritional knowledge	Zero nutritional expertise needed

CONCLUSION

This project presented NutriBot, a multimodal deep learning–powered dietary assistant that integrates computer vision, natural language processing, and personalized recommendation into a unified, end-to-end conversational system. The core challenge addressed was the absence of an accessible, intelligent, and clinically grounded nutritional advisory tool capable of handling the complexity of real-world dietary interactions — spanning diverse food types, composite meal imagery, colloquial dietary descriptions, and medically sensitive user profiles.

FUTURE ENHANCEMENT

Future iterations of NutriBot envision seamless integration with IoT-enabled wearables and Continuous Glucose Monitors to deliver physiologically-driven, real-time dietary recommendations. Expanding the food recognition engine to encompass broader regional and international cuisines through semi-supervised learning will significantly improve dietary coverage. A federated learning architecture will enable decentralized, privacy-preserving model training while ensuring compliance with relevant data protection regulations. Multilingual NLP support will democratize access for diverse linguistic communities, making the system inclusive and widely deployable. A clinician-facing dashboard with EHR integration will empower healthcare providers to monitor nutrition trajectories and maintain synchronized medical documentation.

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