A RESEARCH PAPER ON Smart Kitchen Assistant for Ingredient Detection and Recipe Guidance Using Edge Artificial Intelligence

Vijay Chakole[1], Ayush Sarode[2], Raju Malekar[3], Muskan Kulkarni [4], Ravisha Kolhe[5], Khushi Chakole[6]

[1]Head of Dept , Dept of Electronics and Telecommunication, KDK College of Engineering, Maharashtra, India
[2345] Dept of Electronics and Telecommunication, KDK College of Engineering, Maharashtra, India

---***---

Abstract - *Rapid advancements in artificial intelligence and embedded computing have enabled the development of intelligent systems capable of performing complex tasks directly on edge devices. In the context of smart homes, cooking assistance remains an area where intelligent automation can significantly enhance efficiency and reduce food wastage. This research presents the design and implementation of a Smart Kitchen Assistant that detects food ingredients using computer vision and provides recipe guidance through an edge artificial intelligence framework. The proposed system employs a Raspberry Pi-based embedded platform integrated with a camera module and a lightweight convolutional neural network model optimized using TensorFlow Lite. Unlike conventional cloud-based solutions, the system performs inference locally on the device, ensuring reduced latency, improved privacy, and independence from internet connectivity. A structured offline recipe database is integrated with a similarity-based matching algorithm to recommend recipes based on detected ingredients. Experimental evaluation demonstrates reliable ingredient recognition accuracy while maintaining low computational overhead. The proposed framework demonstrates the feasibility of deploying intelligent cooking assistance systems in domestic environments using affordable hardware and edge AI techniques.*

***Key Words*: Edge Artificial Intelligence, Smart Kitchen, Ingredient Detection, Embedded Vision, Raspberry Pi, Recipe Recommendation System**

1. INTRODUCTION

Artificial Intelligence (AI) has become an essential component in modern technological systems, particularly in the domain of smart homes and intelligent automation. The integration of AI with embedded computing has enabled devices to perform complex decision-making processes locally without relying heavily on remote cloud servers. Edge AI represents a paradigm shift where machine learning models operate directly on local devices such as microcontrollers, embedded systems, and edge computing platforms.

Cooking is one of the most common daily activities in households. However, many individuals face challenges when deciding what meals to prepare using the available ingredients. Traditional recipe applications require manual searching and rely on internet connectivity, which limits accessibility and convenience. Moreover, these applications do not actively detect ingredients available in the kitchen.

Recent advances in computer vision have made it possible to recognize objects from images using convolutional neural networks (CNNs). By integrating these capabilities into a kitchen environment, it becomes possible to create intelligent systems capable of identifying ingredients and recommending appropriate recipes.

This research proposes a Smart Kitchen Assistant that utilizes edge artificial intelligence to detect ingredients placed in front of a camera and automatically suggest recipes that can be prepared using those ingredients. The system is designed to operate fully offline, ensuring privacy and reliability while reducing latency.

The main objectives of this research include:

- Designing an embedded AI system for ingredient recognition
- Implementing real-time image classification using lightweight CNN models
- Developing an offline recipe recommendation system
- Evaluating the performance of the proposed architecture on edge hardware

2. SYSTEM ARCHITECTURE

The proposed Smart Kitchen Assistant is designed using an edge computing architecture that enables real-time ingredient detection and recipe recommendation without relying on cloud-based processing. The system integrates both hardware and software components to perform image acquisition, data processing, ingredient classification, and recipe retrieval within a single embedded platform. The core hardware component of the system is the Raspberry Pi 4 Model B, which acts as the central processing unit responsible for executing image processing and machine learning inference tasks. A high-resolution camera module is connected to the Raspberry Pi to capture images of ingredients placed in front of the device. These captured images are transferred to the processing pipeline where they undergo preprocessing operations such as resizing, normalization, and noise reduction in order to improve the performance of the machine learning model.

After preprocessing, the processed image is passed to a convolutional neural network model optimized for edge deployment. In this research, a lightweight deep learning architecture based on MobileNetV2 is utilized because it offers a balance between computational efficiency and classification accuracy. The trained model is converted into TensorFlow Lite format, allowing it to run efficiently on the Raspberry Pi with reduced memory usage and faster inference speed. The model analyzes the visual features of the input image and predicts the ingredient class by generating a probability distribution across all possible ingredient categories. The ingredient label with the highest probability is selected as the final classification output.

Once the ingredient has been detected, the system interacts with a local recipe database stored within the Raspberry Pi. The database contains multiple recipes along with their required ingredients and preparation steps. A similarity-based matching algorithm is used to compare the detected ingredient with the ingredients listed in the recipes. Based on this comparison, the system identifies recipes that can be prepared using the detected ingredient and ranks them according to their similarity score. The recommended recipes are then displayed to the user through a graphical interface on the connected display screen.

The entire system operates locally on the embedded device, which eliminates the need for internet connectivity and enhances data privacy. By performing all computational tasks at the edge, the architecture reduces latency and ensures real-time performance suitable for interactive kitchen environments. This modular architecture also allows future expansion such as multi-ingredient detection, voice interaction, and integration with smart kitchen appliances.

3. System Workflow

The workflow of the proposed Smart Kitchen Assistant begins with the initialization of the system and activation of the camera module installed in the kitchen environment. When the user places food ingredients in front of the camera, the system captures an image of the ingredients in real time. This captured image acts as the primary input for the intelligent processing pipeline. The system ensures that the captured image is clear and suitable for further processing before it proceeds to the next stage.

After the image is captured, it undergoes an image preprocessing stage where operations such as resizing, normalization, and noise reduction are applied. These preprocessing steps ensure that the image is compatible with the input requirements of the deep learning model. Once the preprocessing is completed, the edge artificial intelligence model is loaded on the embedded device. A trained convolutional neural network (CNN) model is then used to analyze the image and perform ingredient classification. The model detects different food ingredients present in the image and generates prediction labels corresponding to each identified ingredient.

Following ingredient detection, the system sends the identified ingredient list to the recipe recommendation module. In this stage, the system searches a structured recipe database containing multiple recipes and their required ingredients. A matching algorithm evaluates the similarity between the detected ingredients and the ingredients required for different recipes. Based on this comparison, a match score is calculated to determine which recipes can be prepared using the available ingredients.

Finally, the system displays the most suitable recipes to the user through a graphical interface or connected mobile application. The suggested recipes include step-by-step cooking instructions and may also provide additional information such as preparation time and nutritional value. This workflow enables the Smart Kitchen Assistant to automatically recognize ingredients and guide users toward suitable meal options while operating efficiently on edge computing devices without heavy reliance on cloud processing.

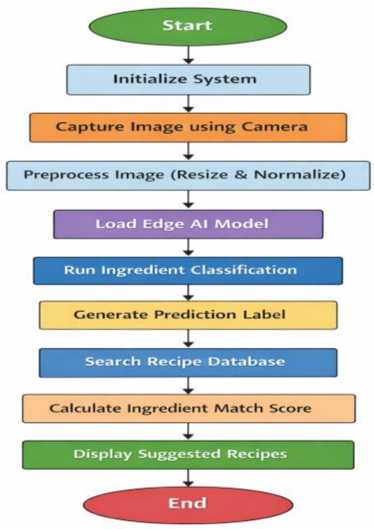

Fig-1: Workflow Diagram

4. Methodology

The proposed Smart Kitchen Assistant system is designed to automatically detect food ingredients and generate suitable recipes using edge artificial intelligence. The system begins with an image acquisition stage where a camera module captures real-time images of ingredients placed on the kitchen counter. These images are processed using an edge computing device such as a Raspberry Pi or embedded AI processor. A pre-trained deep learning model based on convolutional neural networks (CNN) is used to identify and classify the ingredients present in the image. The detected ingredients are then converted into structured data that represents the available food items for further processing.

Once the ingredients are identified, the system utilizes a recipe recommendation module that matches the detected ingredients with a recipe database. Natural Language Processing (NLP) techniques and rule-based filtering are applied to determine the most suitable recipes that can be prepared with the available ingredients. The final output is presented to the user through a display interface or mobile application, which provides recipe instructions, preparation steps, and optional nutritional information. By performing inference on the edge device rather than relying entirely on cloud computing, the system ensures faster response time, reduced internet dependency, and improved user privacy while assisting users in making efficient cooking decisions.

5. DISCUSSION

The proposed Smart Kitchen Assistant for Ingredient Detection and Recipe Guidance Using Edge Artificial Intelligence demonstrates how computer vision and edge computing can be applied to simplify everyday cooking activities. By deploying a convolutional neural network model on an edge device, the system is capable of detecting food ingredients in real time and recommending appropriate recipes without relying on continuous internet connectivity. This approach reduces processing latency and improves user privacy because the captured images are processed locally on the device rather than being sent to external cloud servers.

Another important benefit of the system is its potential to improve kitchen efficiency and reduce food wastage. Many users are often unsure about what meals can be prepared with the ingredients available in their kitchen. The proposed system addresses this challenge by automatically identifying ingredients and matching them with a structured recipe database. This allows the system to recommend suitable recipes that can be prepared with the detected ingredients, thereby helping users utilize available food items effectively and simplifying the decision-making process during cooking.

However, certain challenges remain in the practical implementation of the system. Ingredient recognition accuracy may vary depending on lighting conditions, background clutter, and variations in ingredient appearance. Additionally, real kitchen environments often involve multiple ingredients at once, which may require more advanced multi-object detection techniques. Future improvements could focus on enhancing model accuracy, supporting multiple ingredient detection, and incorporating personalized recipe recommendations based on user preferences and dietary requirements, which would further improve the usability and effectiveness of the Smart Kitchen Assistant system.

6. CONCLUSION

This research presents the development of a Smart Kitchen Assistant for Ingredient Detection and Recipe Guidance Using Edge Artificial Intelligence, designed to assist users in identifying food ingredients and generating suitable recipes automatically. The proposed system integrates computer vision and deep learning techniques to detect ingredients using images captured through a camera module. By deploying the trained model on an edge computing device, the system performs ingredient recognition locally, enabling real-time processing while reducing dependency on cloud-based services. This edge-based approach improves response time, enhances data privacy, and makes the system suitable for practical kitchen environments.

The system further utilizes a recipe recommendation module that matches the detected ingredients with a structured recipe database to suggest appropriate dishes along with preparation instructions. This feature helps users make better use of available ingredients, reduces food wastage, and simplifies the cooking process, especially for beginners. Although the system demonstrates promising results, future enhancements such as multi-ingredient detection, improved model accuracy, and personalized recipe recommendations can further improve its effectiveness. With continued advancements, the proposed Smart Kitchen Assistant can contribute significantly to the development of intelligent and automated smart kitchen systems.

REFERENCES

[1] A. G. Howard et al., “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” arXiv preprint arXiv:1704.04861, 2017.

[2] M. Sandler et al., “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 4510–4520.

[3] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," Proceedings of the IEEE CVPR, 2017, pp. 1251–1258.

[4] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," International Conference on Learning Representations (ICLR), 2015.

[5] C. Szegedy et al., "Going Deeper with Convolutions," Proceedings of the IEEE CVPR, 2015, pp. 1–9.

[6] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," Google Research, 2016.

[7] B. Zoph et al., "Learning Transferable Architectures for Scalable Image Recognition," Proceedings of the IEEE CVPR, 2018.

[8] J. Redmon et al., "You Only Look Once: Unified, Real-Time Object Detection," Proceedings of the IEEE CVPR, 2016, pp. 779–788.

[9] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems, 2012.

[10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[11] W. Shi et al., "Edge Computing: Vision and Challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, 2016.

[12] M. Satyanarayanan, "The Emergence of Edge Computing," Computer, vol. 50, no. 1, pp. 30–39, 2017.

[13] H. Chen et al., "Deep Learning on Embedded Systems: A Survey," IEEE Transactions on Emerging Topics in Computing, 2020.

[14] S. Han et al., "Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding," International Conference on Learning Representations, 2016.

[15] J. Dean et al., "Large Scale Distributed Deep Networks," Advances in Neural Information Processing Systems, 2012.

[16] R. Want, "An Introduction to RFID Technology," IEEE Pervasive Computing, vol. 5, no. 1, pp. 25–33, 2006.

[17] S. K. Datta et al., "Smart Home Automation Using IoT," IEEE Consumer Electronics Magazine, vol. 5, no. 1, pp. 48–55, 2016.

[18] P. Viola and M. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," Proceedings of the IEEE CVPR, 2001.

[19] D. G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," International Journal of Computer Vision, vol. 60, no. 2, pp. 91–110, 2004.

[20] N. Lane et al., "Deep Learning for Mobile and Embedded Devices: A Survey," IEEE Pervasive Computing, vol. 17, no. 3, pp. 35–44, 2018.