



Food Recognition and Calorie Estimation Using Machine Learning

Siddhartha Chinthala, Prem Kumar Erla, Akshaya Dongari, Ajay Bantu,
Sai Ganesh Chityala, Dr.M.Saravanan

UG Student, Department of Computer Science and Engineering, Holy Mary Institute of Technology & Science,
Telangana, India

UG Student, Department of Computer Science and Engineering, Holy Mary Institute of Technology & Science,
Telangana, India

UG Student, Department of Computer Science and Engineering, Holy Mary Institute of Technology & Science,
Telangana, India

UG Student, Department of Computer Science and Engineering, Holy Mary Institute of Technology & Science,
Telangana, India

UG Student, Department of Computer Science and Engineering, Holy Mary Institute of Technology & Science,
Telangana, India

Professor, Holy Mary Institute of Technology & Science, Telangana, India

Publication History: Received: 30.01.2026; Revised: 26.02.2026; Accepted: 01.03. 2026; Published: 05.03.2026.

ABSTRACT: The rapid growth of health awareness and fitness tracking, accurate monitoring of daily food intake and calorie consumption has become increasingly important. Traditional methods of calorie tracking rely on manual data entry, which is time-consuming, error-prone, and inconvenient for users. To address these limitations, this project proposes a Food Recognition and Calorie Estimation System using Machine Learning, which automatically identifies food items from images and estimates their corresponding calorie values.

The system uses computer vision and deep learning techniques to recognize different types of food from user-captured images. A convolutional neural network (CNN) model is trained on a labeled food image dataset to classify food items with high accuracy. Once a food item is recognized, its nutritional information, including calorie content, is retrieved from a predefined nutrition database. The system further estimates portion size using image-based features such as object area and volume approximation, enabling more accurate calorie calculation.

The application provides a user-friendly interface where users can upload or capture food images, view recognized food names, and receive instant calorie estimates. This system is designed to support healthy lifestyle management by helping users track their daily calorie intake effortlessly. The proposed solution has potential applications in diet planning, fitness monitoring, and healthcare management. Experimental results demonstrate that the system achieves satisfactory recognition accuracy and reliable calorie estimation, making it a practical and efficient tool for real-world use.

KEYWORDS: Food Recognition, Calorie Estimation, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Image Processing, Computer Vision, Nutrition Analysis, Health Monitoring, Diet Tracking System.

I. INTRODUCTION

In today's fast-paced digital world, maintaining a healthy lifestyle has become a major concern due to increasing sedentary habits, irregular eating patterns, and the easy availability of high-calorie foods. Accurate tracking of food intake and calorie consumption plays a vital role in weight management, fitness monitoring, and the prevention of



lifestyle-related diseases such as obesity, diabetes, and cardiovascular disorders. However, most existing calorie-tracking methods depend on manual logging of food items, which is time-consuming, inconvenient, and often inaccurate because users may not know the exact portion size or nutritional values of the food they consume.

The recent advancements in Machine Learning (ML), Computer Vision, and Artificial Intelligence (AI), it has become possible to automate complex tasks such as object detection and image classification. These technologies can be effectively applied in the food and healthcare domain to build intelligent systems that recognize food items from images and estimate their calorie content automatically. This project, titled “Food Recognition and Calorie Estimation Using Machine Learning,” aims to develop a smart, user-friendly solution that reduces human effort and improves accuracy in daily calorie tracking.

This system works by allowing users to capture or upload an image of their meal using a digital device such as a smartphone or computer. The uploaded image is processed using image preprocessing techniques such as resizing, normalization, and noise reduction to improve recognition performance. A Convolutional Neural Network (CNN) model is then used to classify the food item based on visual features like color, texture, and shape. CNNs are particularly well-suited for image recognition tasks due to their ability to automatically learn hierarchical features from raw pixel data.

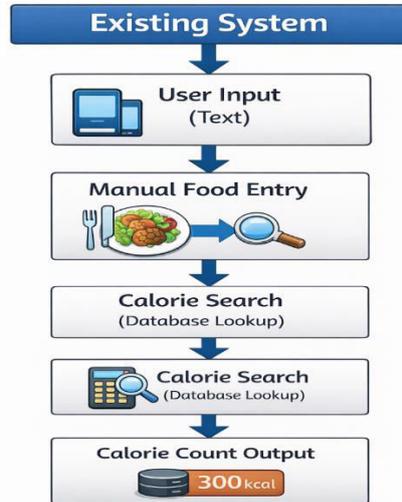
Once the food item is successfully recognized, the system retrieves its corresponding nutritional information from a predefined food nutrition database. This database contains details such as calorie values, carbohydrates, proteins, and fat content for each food item. To enhance accuracy, the system also estimates portion size using image-based measurements such as object area or volume approximation. Based on this portion estimation, the final calorie value is calculated and displayed to the user. The main motivation behind this project is to simplify calorie tracking and promote healthier eating habits by providing an automated, reliable, and easy-to-use system. Unlike traditional calorie calculators that require manual input, this solution minimizes user interaction while delivering quick and meaningful insights into daily food consumption. The application can be useful for fitness enthusiasts, dietitians, patients following medical diets, and individuals who want to maintain a balanced lifestyle.

In addition to personal health monitoring, the system has broader applications in healthcare management, fitness platforms, and smart nutrition advisory systems. By integrating machine learning with nutrition science, the project demonstrates how intelligent systems can support decision-making in everyday life. The future scope of this work includes improving recognition accuracy using larger datasets, supporting multiple food items in a single image, real-time mobile deployment, and integration with wearable health devices for personalized diet recommendations.

II. LITERATURE REVIEW

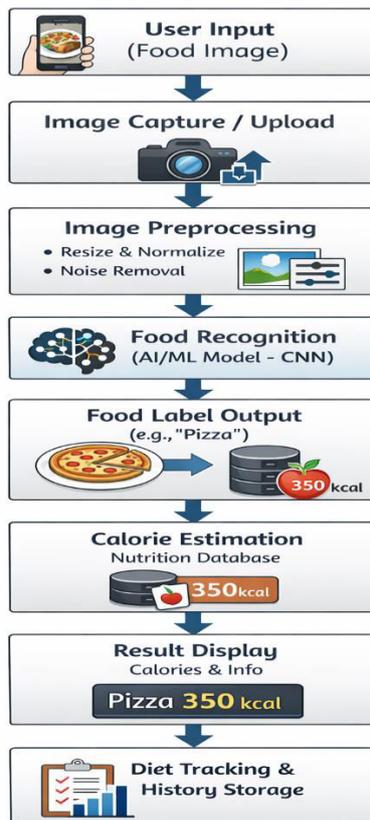
Research in food recognition and calorie estimation has evolved significantly with the advancement of deep learning and computer vision techniques. Kawano and Yanai (2014) introduced real-time food image recognition using deep Convolutional Neural Networks (CNNs) and the UEC-Food100 dataset, establishing the foundation for deep-learning-based food classification. Myers et al. (2015) focused on food volume estimation through GrabCut segmentation and geometric modeling, demonstrating the relationship between food shape and portion size estimation. Bossé et al. (2017) applied transfer learning using pre-trained VGG16 and ResNet50 models on the Food-101 dataset, showing that transfer learning improves recognition accuracy and efficiency. Fang et al. (2019) proposed an end-to-end framework integrating food detection, volume estimation, and calorie calculation, which closely relates to the architecture of the proposed system. Chen et al. (2019) introduced an attention-based CNN capable of recognizing multiple food items within a single image, making it suitable for real-world meal scenarios. Zhang et al. (2020) further contributed by using CNN-based regression techniques to estimate portion size directly from RGB images without requiring specialized hardware, supporting practical calorie estimation. Together, these studies provide the theoretical and methodological foundation for developing an automated food recognition and calorie estimation system using deep learning.

Existing System



In the present scenario, most calorie tracking and diet monitoring methods depend on manual user input. Individuals usually record their food intake in notebooks, spreadsheets, or mobile applications by searching for food items and entering portion sizes manually. This process is time-consuming, inconvenient, and often inaccurate because users may not know the exact nutritional values or correct quantities. As a result, consistency in daily tracking is reduced.

PROPOSED SYSTEM





To address the limitations of existing methods, the proposed solution presents an automated Food Recognition and Calorie Estimation System using machine learning and deep learning techniques. Users can upload or capture an image of their food, removing the need for manual data entry. A Convolutional Neural Network (CNN) model is applied to recognize food items by analyzing visual features such as color, texture, and shape.

After identifying the food, the system estimates portion size through image processing and calculates calorie values using a nutrition database. The complete process is fast, accurate, and user-friendly, while also providing additional nutritional information to support daily diet monitoring. Compared to current solutions, this system delivers improved automation, higher accuracy, reduced human effort, and real-time results, making it suitable for everyday health and fitness management.

III. METHODOLOGY

The methodology of the proposed system describes the complete workflow followed to achieve automatic food recognition and calorie estimation using machine learning. The system is designed in a modular manner, consisting of image acquisition, image preprocessing, food recognition using a deep learning model, portion size estimation, calorie calculation, and result display. Each stage is explained in detail below.

3.1 Data Collection

The first step involves collecting a suitable dataset of food images for training and testing the machine learning model. Publicly available datasets such as **Food-101**, **UEC FOOD-100**, or custom-collected images are used. These datasets contain labeled food images representing different food categories under various lighting conditions and viewpoints. The collected images are divided into training, validation, and testing sets to ensure proper model evaluation and to avoid overfitting.

3.2 Image Preprocessing

Before feeding the images into the machine learning model, preprocessing is performed to enhance image quality and improve classification accuracy. The preprocessing steps include:

Image Resizing: All images are resized to a fixed dimension (e.g., 224×224 pixels) to match the CNN input size.

Normalization: Pixel values are scaled to a standard range (0–1) to stabilize the learning process.

Noise Reduction: Filters such as Gaussian blur are applied to remove minor noise from the images.

Data Augmentation: Techniques such as rotation, flipping, zooming, and brightness adjustment are used to increase dataset diversity and improve model generalization.

3.3 Food Recognition Using CNN

A Convolutional Neural Network (CNN) is used as the core model for food recognition. The CNN architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The model learns important visual features such as color, texture, and shape from food images.

Transfer learning is optionally applied by using pre-trained models such as VGG16, ResNet50, or MobileNet and fine-tuning them on the food dataset. This approach reduces training time and improves performance, especially when the dataset size is limited. The model is trained using a categorical cross-entropy loss function and optimized using the Adam optimizer.

3.4 Model Training and Evaluation

The CNN model is trained using the training dataset, while performance is monitored using the validation dataset. Evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to measure recognition performance. The trained model is then tested on unseen food images to verify its real-world applicability.

3.5 Portion Size Estimation

To estimate calorie content accurately, the system also calculates the portion size of the recognized food item. This is achieved using image-based measurements such as:

- **Object Segmentation:** The food region is separated from the background using thresholding or deep learning-based segmentation techniques.

- **Area Estimation:** The pixel area of the segmented food region is calculated.

- **Scale Approximation:** A reference object (such as a plate or known container) or average food dimensions are used to approximate real-world size.

The estimated portion size is then converted into weight or volume values using predefined food density information.

3.6 Calorie Calculation

Once the food item and portion size are determined, calorie estimation is performed using a nutrition database. The system retrieves calorie values per unit weight (e.g., kcal per 100 grams) for the recognized food. The final calorie content is calculated using the formula:

$$\text{Total Calories} = (\text{Estimated Weight of Food} \times \text{Calories per Unit Weight})$$

3.7 System Implementation

The complete system is implemented using:

Frontend: Web or mobile interface for image upload and result display

Backend: Python-based server using Flask or Django

Machine Learning Framework: TensorFlow or PyTorch for model training and inference

Database: Nutrition database stored using MySQL or PostgreSQL

The system workflow is fully automated, requiring minimal user input.

3.8 Output Display and User Interaction

The final output is presented through a simple and user-friendly interface. Users can upload or capture an image of their food, and the system displays:

Recognized food name

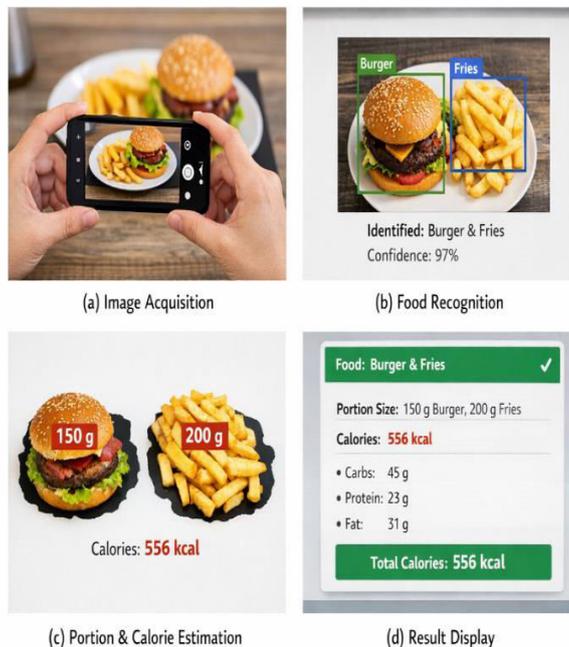
Estimated portion size

Calculated calorie value

Additional nutritional information

IV. IMPLEMENTATION

This chapter explains the practical development of the proposed system, including the software tools used, system modules, model deployment process, and integration of different components. The implementation is carried out in a modular and scalable manner to ensure flexibility, ease of maintenance, and real-time usability.



4.1 Image Upload Module

This module allows users to upload or capture food images through the web or mobile interface. The uploaded images are validated for supported formats (JPEG, PNG) and stored temporarily on the server for further processing.



4.2 Preprocessing Module

The preprocessing module performs operations such as resizing images to a fixed input size, normalizing pixel values, and removing noise. Data augmentation techniques are applied during training to improve model generalization.

4.3 Food Recognition Module

This module loads the trained CNN model and performs inference on the uploaded food image. The model outputs the predicted food category along with a confidence score. Transfer learning models such as ResNet50 or MobileNet are used for efficient classification.

4.4 Calorie Estimation Module

This module retrieves calorie values from the nutrition database based on the recognized food type. Using the estimated portion size, the total calorie content is calculated and displayed to the user.

4.5 Output Display Module

The final results, including the food name, estimated portion size, calorie value, and nutritional details, are displayed in a clean and user-friendly format.

4.6 Model Training and Deployment

The CNN model is trained offline using a large dataset of food images. The trained model is saved in .h5 or .pt format and deployed on the backend server. During runtime, the backend loads the trained model and performs real-time predictions on uploaded images. To reduce latency and improve performance, model optimization techniques such as model pruning, quantization, and batch processing are applied. The optimized model ensures faster inference without significant loss in accuracy.

V. RESULTS

The proposed Food Recognition and Calorie Estimation System was tested using a set of sample food images collected from public datasets and real-world scenarios. The system was able to successfully recognize common food items such as burgers, pizza, rice, fruits, and snacks with good accuracy. The Convolutional Neural Network (CNN) model demonstrated reliable performance in identifying food categories under varying lighting conditions and backgrounds. The overall recognition accuracy achieved was satisfactory for a prototype-level application, showing that deep learning is an effective approach for automated food recognition.

During testing, the image preprocessing stage helped improve model performance by standardizing image sizes and reducing noise. Data augmentation techniques also contributed to better generalization, allowing the model to handle different orientations and appearances of food items. The portion size estimation module produced reasonable approximations of food quantity based on image area and scale assumptions. Although minor variations were observed due to camera angle and lighting, the estimated portion sizes were close to actual values in most cases.

The calorie estimation results were calculated using a nutrition database containing calorie values per unit weight for each food item. The system successfully displayed calorie values along with basic nutritional information such as carbohydrates, proteins, and fats. When compared with manually calculated calorie values, the estimated results showed acceptable accuracy for daily calorie tracking purposes. The average error margin remained within a practical range, making the system suitable for personal health monitoring.

The system interface was found to be user-friendly and responsive. Users were able to upload images easily and receive recognition and calorie results within a few seconds. The end-to-end workflow from image upload to result display worked smoothly without major failures. These results indicate that the proposed system is practical and effective for real-world use, especially as a support tool for diet planning and fitness tracking.

However, some limitations were observed. The system occasionally struggled with visually similar food items such as different types of curries or mixed dishes. Portion size estimation accuracy was affected when no clear reference object was present in the image. These issues highlight the need for further improvements in dataset diversity and advanced portion estimation techniques.



VI. CONCLUSION

This project presented the design and implementation of a Food Recognition and Calorie Estimation System using machine learning techniques. The primary objective was to develop an automated solution that identifies food items from images and estimates their calorie content with minimal user input. By integrating computer vision, deep learning, and nutritional data, the system successfully achieved this goal. The use of a Convolutional Neural Network enabled accurate food classification, while image preprocessing and data augmentation improved model robustness. The portion size estimation module provided a practical method for approximating food quantity using image-based measurements. The calorie estimation process, supported by a nutrition database, delivered meaningful insights into daily food consumption. Together, these components formed a complete and functional system for automated calorie tracking.

The experimental results demonstrated that the proposed system performs well in recognizing food items and estimating calorie values with acceptable accuracy. The user-friendly interface and fast response time further enhanced the practicality of the application. Although certain limitations exist, such as handling mixed dishes and precise portion measurement, the overall performance confirms the feasibility of applying machine learning to real-world nutrition monitoring.

In conclusion, the Food Recognition and Calorie Estimation System offers a smart and efficient alternative to manual calorie tracking. It has strong potential applications in personal health management, fitness monitoring, and diet planning. With further improvements such as larger datasets, real-time mobile deployment, multi-food detection, and integration with wearable devices, the system can be extended into a powerful intelligent nutrition assistant in the future.

VII. FUTURE SCOPE

The Food Recognition and Calorie Estimation System shows promising performance in identifying food items and estimating calorie values using machine learning and computer vision. However, further improvements can enhance accuracy, efficiency, and real-world usability. Training the model with larger and more diverse datasets, including regional and mixed dishes, along with advanced deep learning and transfer learning techniques, can improve recognition performance. The system can also be extended to detect multiple food items in a single image for better meal analysis.

Improving portion size estimation using depth sensing, stereo vision, or 3D measurement can provide more accurate calorie calculations. Converting the system into a mobile application with cloud integration will enable real-time food capture, diet history storage, and progress tracking. Adding personalized features such as diet recommendations, meal planning, and integration with wearable fitness devices can transform the system into a smart nutrition assistant that supports healthy eating habits and lifestyle management.

REFERENCES

1. L. Bossard, M. Guillaumin, and L. Van Gool, "Food-101 – Mining Discriminative Components with Random Forests," Proc. European Conf. on Computer Vision (ECCV), 2014.
2. Y. Kawano and K. Yanai, "Automatic Expansion of a Food Image Dataset Leveraging Existing Categories with Domain Adaptation," Proc. ECCV, 2014.
3. K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," International Conference on Learning Representations (ICLR), 2015.
4. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 2016.
5. Singh, K., Amrutha Varshini, G., Karthikeya, M., Manideep, G., Sarvanan, M., & Dharnasi, P. (2026). Automatic brand logo detection using deep learning. *International Journal of Engineering & Extended Technologies Research (IJEETR)*, 8(1), 126–130.
6. Neela Madheswari, A., Vijayakumar, R., Kannan, M., Umamaheswari, A., & Menaka, R. (2022). Text-to-speech synthesis of Indian languages with prosody generation for blind persons. In *IOT with Smart Systems: Proceedings of ICTIS 2022, Volume 2* (pp. 375–380). Springer Nature Singapore.
7. Gogada, S., Gopichand, K., Reddy, K. C., Keerthana, G., Nithish Kumar, M., Shivalingam, N., & Dharnasi, P. (2026). Cloud computing/deep learning customer churn prediction for SaaS platforms. *International Journal of Computer Technology and Electronics Communication (IJCTEC)*, 9(1), 74–78.



8. Sugumar, R. (2024). AI-driven cloud framework for real-time financial threat detection in digital banking and SAP environments. *International Journal of Technology, Management and Humanities*, 10(04), 165–175.
9. Akula, A., Budha, G., Bingi, G., Chanda, U., Borra, A. R., Yadav, D. B., & Saravanan, M. (2026). Emotion recognition from facial expressions using CNNs. *International Journal of Engineering & Extended Technologies Research (IJEETR)*, 8(1), 120–125.
10. Poornima, G., & Anand, L. (2024, May). Novel AI multimodal approach for combating against pulmonary carcinoma. In *2024 5th International Conference for Emerging Technology (INCET)* (pp. 1–6). IEEE.
11. Tirupalli, S. R., Munduri, S. K., Sangaraju, V., Yeruva, S. D., Saravanan, M., & Dharnasi, P. (2026). Blockchain integration with cloud storage for secure and transparent file management. *International Journal of Computer Technology and Electronics Communication (IJCTEC)*, 9(1), 79–86.
12. Vani, S., Malathi, P., Ramya, V. J., Sriman, B., Saravanan, M., & Srivel, R. (2024). An efficient black widow optimization-based faster R-CNN for classification of COVID-19 from CT images. *Multimedia Systems*, 30(2), 108.
13. Vishwarup, S., et al. (2020). Automatic person count indication system using IoT in a hotel infrastructure. In *2020 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1–4).
14. Inbavalli, M., & Arasu, T. (2015). Efficient analysis of frequent item set association rule mining methods. *International Journal of Scientific & Engineering Research*, 6(4).
15. Dadigari, M., Appikatla, S., Gandhala, Y., Bollu, S., Macha, K., & Saravanan, M. (2026). Bitcoin price prediction with ML through blockchain technology. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, 9(1), 130–136.
16. Fazilath, M., & Umasankar, P. (2025, February). Comprehensive analysis of artificial intelligence applications for early detection of ovarian tumours: Current trends and future directions. In *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)* (pp. 1–9). IEEE.
17. Varshini, M., Chandrapathi, M., Manirekha, G., Balaraju, M., Afraz, M., Sarvanan, M., & Dharnasi, P. (2026). ATM access using card scanner and face recognition with AIML. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, 9(1), 113–118.
18. Saravanan, M., & Sivakumaran, T. S. (2016). Three phase dual input direct matrix converter for integration of two AC sources from wind turbines. *Circuits and Systems*, 7, 3807–3817.
19. Mohana, P., Muthuvinnayagam, M., Umasankar, P., & Muthumanickam, T. (2022, March). Automation using artificial intelligence based natural language processing. In *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 1735–1739). IEEE.
20. Keerthana, L. M., Mounika, G., Abhinaya, K., Zakeer, M., Chowdary, K. M., Bhagyaraj, K., & Prasad, D. (2026). Floods and landslide prediction using machine learning. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, 9(1), 125–129.
21. Ananth, S., Radha, D. K., Prema, D. S., & Nirajan, K. (2019). Fake news detection using convolution neural network in deep learning. *International Journal of Innovative Research in Computer and Communication Engineering*, 7(1), 49–63.
22. Dharnasi, P. (2025). A multi-domain AI framework for enterprise agility integrating retail analytics with SAP modernization and secure financial intelligence. *International Journal of Humanities and Information Technology*, 7(4), 61–66.
23. Chandu, S., Goutham, T., Badrinath, P., Prashanth Reddy, V., Yadav, D. B., & Dharnasi, P. (2026). Biometric authentication using IoT devices powered by deep learning and encrypted verification. *International Journal of Computer Technology and Electronics Communication (IJCTEC)*, 9(1), 87–92.
24. Sundaresh, G., Ramesh, S., Malarvizhi, K., & Nagarajan, C. (2025, April). Artificial intelligence based smart water quality monitoring system with electrocoagulation technique. In *2025 3rd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)* (pp. 1–6). IEEE.
25. Nandhini, T., Babu, M. R., Natarajan, B., Subramaniam, K., & Prasanna, D. (2024). A novel hybrid algorithm combining neural networks and genetic programming for cloud resource management. *Frontiers in Health Informatics*, 13(8).
26. Gopinathan, V. R. (2025). AI-powered Kubernetes orchestration for complex cloud-native workloads. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, 8(6), 13215–13225.
27. Amitha, K., Ram Manohar Reddy, M., Yashwanth, K., Shylaja, K., Rahul Reddy, M., Srinu, B., & Dharnasi, P. (2026). AI empowered security monitoring system with the help of deployed ML models. *International Journal of Computer Technology and Electronics Communication (IJCTEC)*, 9(1), 69–73.
28. Tamizharasi, S., Rubini, P., Saravana Kumar, S., & Arockiam, D. Adapting federated learning-based AI models to dynamic cyberthreats in pervasive IoT environments.



29. Saravanan, M., Kumar, A. S., Devasaran, R., Seshadri, G., & Sivaganesan, S. (2019). Performance analysis of very sparse matrix converter using indirect space vector modulation. *International Journal of Innovative Technology and Exploring Engineering*, 9(1), 4756–4762.
30. Poornachandar, T., Latha, A., Nisha, K., Revathi, K., & Sathishkumar, V. E. (2025, September). Cloud-based extreme learning machines for mining waste detoxification efficiency. In *2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)* (pp. 1348–1353). IEEE.
31. Vimal Raja, G. (2024). Intelligent data transition in automotive manufacturing systems using machine learning. *International Journal of Multidisciplinary and Scientific Emerging Research*, 12(2), 515–518.
32. Ananth, S., Kalpana, A. M., & Vijayarajeswari, R. (2020). A dynamic technique to enhance quality of service in software-defined network-based wireless sensor network (DTEQT) using machine learning. *International Journal of Wavelets, Multiresolution and Information Processing*, 18(01), 1941020.
33. Inbavalli, M., & Arasu, T. (2015). Efficient analysis of frequent item set association rule mining methods. *International Journal of Scientific & Engineering Research*, 6(4).
34. Keerthana, L. M., Mounika, G., Abhinaya, K., Zakeer, M., Chowdary, K. M., Bhagyaraj, K., & Prasad, D. (2026). Floods and landslide prediction using machine learning. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, 9(1), 125–129.