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Original Article

Innovative IoT-Enabled Food Nutrient Profiling with Deep Learning Techniques

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Abstract - *As living costs in large cities continue to rise, and the health and safety concerns associated with eating fast food become more apparent, an increasing number of office workers are opting to bring their lunches from home. Traditionally, these lunches are reheated using microwaves, thermal lunch boxes, or electric heating containers. This device introduces a novel solution by enabling users to control the temperature of their lunchbox remotely via a smartphone application. This innovative device automates several conventional functions, such as setting timers for food heating, thus providing a more convenient alternative to traditional microwaves. Not only does it eliminate the need for an external power source during heating, but it also promotes healthier eating habits by tracking the nutritional content of the meals. The device is ideal for users seeking the convenience of enjoying hot meals on the go, making it a significant advancement in personal meal management.*

Keywords - *Dietary management technology, Food detection, Machine learning in food analysis, Nutritional analysis, Remote temperature control, Smart tiffin box.*

1. Introduction

In the pursuit of healthier lifestyles, technology has emerged as a critical ally. Recently, innovative applications such as smart tiffin boxes, which measure the nutritional value of food items, have gained prominence. These devices, integral to the modern Internet of Things (IoT) ecosystem, utilize Artificial Intelligence (AI) and machine learning to offer precise nutritional tracking crucial in scenarios where traditional methods fall short.

Amidst rising obesity rates and health risks associated with poor dietary habits, the ability to accurately measure and manage food intake is more essential than ever. This paper introduces an advanced smart tiffin box that not only stores food but also performs real-time analysis of meal contents through integrated sensors and sophisticated data algorithms.

This system provides detailed nutritional information, empowering users to make informed dietary choices. The development of such technology faces challenges, including sensor integration, algorithm reliability, and user interface design. Despite these hurdles, the enhanced functionality of smart tiffin boxes could significantly improve dietary management and overall well-being, marking a step forward in human-oriented product design and health maintenance.

This paper systematically examines various aspects: Section 2 reviews existing research, Section 3 elaborates on system design, Section 4 discusses methodology, Section 5 outlines database creation, Section 6 addresses practical implementation, and Section 7 analyzes results, concluding with the significance of key findings.

2. Related Work

The literature survey delved into scholarly works and market products related to smart tiffin boxes, identifying gaps for advanced nutritional analysis, with limited existing research but valuable insights from related technologies. Here, we summarize key findings from different research papers and discuss their relevance to our project.

This paper [1] explores ensemble machine-learning techniques like decision trees and logistic regression to customize meal services, demonstrating enhanced accuracy by combining these models with a simulated dataset. It highlights AI's potential to tailor meals to individual dietary needs, promote healthier lifestyles, and address computational demands for scalability in various sectors. Authors in this paper [2] examine the impact of Artificial Intelligence (AI) on healthcare and nutrition, utilizing machine learning, neural networks, and natural language processing to enhance diagnostics, treatment, and service accessibility.

It leverages extensive data to showcase AI's potential in reducing healthcare costs and improving patient care. The research also underscores the importance of maintaining ethical standards and the essential role of human empathy in healthcare, advocating for AI to complement rather than replace human interaction.

[3] Ensemble machine learning aids in personalizing meal services within food delivery and restaurants, showing improved customization and health promotion through many models integrated into one model. The paper underlines the mentioned AI potential to ensure consumer satisfaction with simultaneous acknowledgement of computational challenges. It, therefore advocates more extensive utilization of ML in the food industry for these industry-altering socio-economic benefits. This paper [4] reviewed the transformative potential of AI-enabled food systems and highlights the scaling of productivity, safety, waste management, and so on. The scholars highlight technological and IT solutions of this innovation by coupling AI with nanotechnology as well as biotechnology towards attaining sustainable agriculture. Many other challenges, such as the ethical one, support balanced AI adoption to maximize benefits in sustainable food systems.

The paper [5] follows and discusses the implementation of neural networks for the recognition of food types and the estimation of calorie content. In this work, a method is presented that uses a neural network to conduct image analysis and classification of food images into different types of food. Second, a model is developed to estimate the calorie content of the identified food. The paper now proceeds with its description and evaluation, showing its effectiveness in recognizing different types of food and accurately approximating calorie content. In this paper [6], Jiang et al. report a 2020 IEEE Access publication on "Deep Food," which is a model designed using deep learning methods to analyze food images for dietary assessment. It also presents convolutional neural network architecture for classifying food items and estimating food nutrition content from images.

The research outlines the high accuracy of the model in the classification of food and types of quantities, which is of importance for real-time dietary tracking applications. "Deep Food" has proven to make compelling improvements in nutritional assessment, with strong, valuable applications in health and monitoring of nourishment due to wide validation against real-world datasets. It [7] introduces a deep learning framework, namely MSMV-DFA, that fuses the features from multiple scales and viewpoints learned by advanced CNNs to enhance the accuracy of food recognition. In the current era, the traditional methods for recognizing food by using food image datasets do not take care of the appearance variation that occurs due to diverse serving sizes and preparation styles; however, the proposed framework does so. Therefore, its recognized performance against traditional benchmarks is outstanding.

MSMV-DFA shows promise for broader image recognition tasks, suggesting potential applications beyond food recognition. [8] Tasci presents a novel approach for food image recognition using an ensemble of fine-tuned CNN. The authors propose a method that combines the outputs of multiple CNNs using a voting combinations-based ensemble technique. This ensemble approach aims to improve the overall accuracy and robustness of food image recognition systems. The effectiveness of their approach is demonstrated through experiments on food image datasets, showing improved performance compared to individual CNN models.

[9] UECFOOD-100 and UECFOOD-256 datasets can be utilized to train a deep learning model employing a region proposal network, part of the Faster RCNN model. This three-step process demonstrated effective food detection. [10] Focus is laid upon comparing various attributes for food recognition and calorie estimation. The study assessed the effectiveness of current vision-based methods in dietary assessments. This research introduces a system evaluated on the MADiMa database and a custom fast-food database, achieving a top-3 accuracy of 71.8% for fine-grained food categories. In this paper [11] author, explored the use of CNNs for food detection, suggesting the use of MSMVFA (Multi-Scale Multi-View Feature Aggregation) to overcome detection issues related to common pattern recognition in varied food appearances.

The scholars [12] addressed the challenges of intraclass variation in food detection using two modules: ingredient detection and food classification. The process involved texture verification and a base model for ingredient scanning, followed by multi-view multi-kernel SVM for classification. Testing on 15,262 images showed high accuracy in detecting complex food items. Authors in this paper [13] address a unique approach combining data from food with additional variables such as temperature and brightness captured by thermal and CCD cameras. This hardware-software fusion enhanced the accuracy of traditional food recognition methods.

It also [14] explores enhancing food recognition through Convolutional Neural Networks (CNNs) by combining multiple classifiers. Using a fusion strategy, the authors improve accuracy, outperforming individual classifiers. Experimental results on benchmark datasets demonstrate significant advancements in food recognition accuracy.

Another research [15] addresses the combined traditional methods and neural networks to estimate food and nutrient content, highlighting challenges in volume estimation. SVM and MLP models were developed using MATLAB, showing promising results. Ao and Ling [16] introduce a method to efficiently integrate new food categories into deep neural networks using deep representation and transfer learning. Tested on a standard food image dataset, their approach significantly improves model accuracy with minimal additional data, highlighting the potential of adaptable AI systems in food recognition.

[17] Research has been conducted on collecting data from 1027 canteen trays containing various food items, primarily fruits. Neural networks and edge computing were employed for detection, with segmentation ensuring image quality. The system utilized CNN-based algorithms, watershed-based segmentation, and communication components, achieving accuracy ranging from 63% to 94%. This paper [18] study utilized SVM and Gabor filters for food identification. Gabor filters are particularly effective for texture analysis, crucial for distinguishing between different food items. The nutritional content was calculated by correlating food portions with nutritional tables, with a thumb placed in images as a reference for size estimation.

For example, this approach has reported an accuracy of 86%. The working paper [19] being reported here is a report on a study regarding the effect of big data on health analytics concerning HealthCare 4.0. It has analyzed 2212 respective articles from Scopus published from 2014–2023. What is reported here is the emphasis on "Machine Learning" and "Artificial Intelligence," and emerging areas are "Wearable Sensors" and "Privacy-Preserving". It highlights the related challenges regarding the privacy of data and the need for skilled professionals with a global perspective to make use of technology in a way that brings out better impacts on health in general. These two studies underline the potential and challenges lying in the use of AI/ML for food recognition and nutritional analysis. Insights from either system could help in building our smart tiffin box, especially in aiming for better accuracy, robustness to a variety of food types, and the fusion of multiple types of data for comprehensive nutritional analysis.

3. Overview of the Proposed System

We are developing an AI-driven smart tiffin box, merging IoT, AI, and ML not just to store and warm food but also to assess its nutritional value. It features a password-based lock, automatic warming, and a mobile app offering nutritional insights based on the user's body temperature.

Figure 1 illustrates its structure, integrating an inbuilt heating provision, IoT hardware for connectivity, and a rechargeable battery.

The arrows symbolize data and power flow, with the Raspberry Pi as the central processor, ensuring seamless device control. Designed for integration, each component contributes to the tiffin box's smart functionalities.

The proposed smart tiffin box system involves several key components, including a Raspberry Pi, a camera module, a heating module, temperature sensors, and IoT connectivity modules.

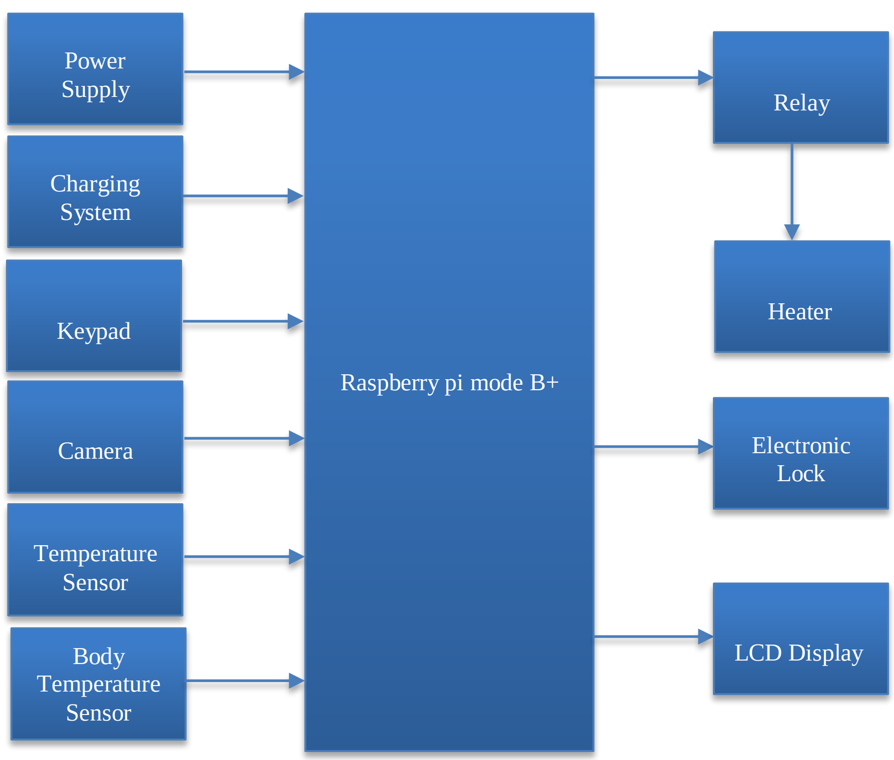

Fig. 1 Architecture diagrams

Key Components:

- Raspberry Pi 3 Model B+
- Camera Module
- Heating Module (Relay and Heater)
- Temperature Sensors (MLX90614)
- Keypad (for passcode entry)
- OLED Display (for displaying messages)
- Power Supply and Battery Management System
- Wi-Fi Module (built-in on Raspberry Pi)

3.1. Configurations and Specifications of the Proposed IoT System Components

Raspberry Pi 3 Model B+:

- Processor: 1.2GHz 64-bit quad-core ARM Cortex-A53 CPU
- Memory: 1GB RAM
- Connectivity:
- Wi-Fi: 802.11n Wireless LAN
- Bluetooth: 4.1
- Ethernet: 10/100 Mbps
- USB: 4 USB ports
- GPIO: 40-pin GPIO header
- Storage: microSD slot

The camera Module consists of a sensor with 8-megapixel IMX219 sensor with a resolution of 3280 x 2464 with a video rating of 1080p30, 720p60, and 640x480p90. This uses a CSI interface for connection to Raspberry Pi. The heating Module consists of a Relay Module with a 5V relay to control the heater. The electrical resistance heater and power rating are selected as per the requirement (typically 5-12V). The heating control is done via the GPIO pins of the Raspberry Pi.

A typical temperature Sensors (MLX90614) is used in the smart tiffin box with a built-in Infrared temperature sensor with a temperature range of -70°C to 382.2°C and accuracy of ±0.5°C for (0°C to +50°C) with built-in I2C interface. The Keypad consists of a 4x4 matrix keypad with a GPIO pins interface for connecting to Raspberry Pi. The display system consists of an OLED Display with a size of 0.96 inches and a resolution of 128x64 pixels. This uses the I2C interface for connection. The Power Supply and Battery Management System consists of a 5V/2.5A power adapter with a rechargeable lithium-ion battery with a charging circuit as a battery management unit.

3.2. Data Transmission Protocol

The following Communication Protocols are used in the proposed system.

I2C protocol: This protocol is used for communication between the Raspberry Pi and sensors, for example, the MLX90614 temperature sensor OLED display; every I2C device has its unique address. MLX90614 has an address of 0x5A—the data rate with a Standard mode of 100 kbps fast mode of 400 kbps. The SDA (data line) and SCL (clock line) pins will be interfaced to the corresponding GPIO pins. GPIO Pins **a**re used for direct communication with components like the relay module, keypad, and potentially other peripherals. The Digital I/O is used for reading inputs from the keypad and controlling the relay.

Wi-Fi Communication: The built-in Wi-Fi module of the Raspberry Pi is used for network connectivity with TCP/IP for communication between the Raspberry Pi and the mobile application.

MQTT Protocol is also considered Lightweight, real-time communication between the IoT backend and the Raspberry Pi. Here, Raspberry Pi acts as an MQTT client, communicating with an MQTT broker hosted on the cloud or a local server. Specific topics for data like "tiffinBox/temperature", "tiffinBox/nutrition", and "tiffinBox/control" are used.

3.2.1. Data Flow

The Raspberry Pi module does the initialization by connecting Wi-Fi network. The user does Heating Control by setting a heating time via the mobile app. Then a Command is sent to the Raspberry Pi over Wi-Fi. The Raspberry Pi triggers the relay to turn on the heater. The Nutritional Analysis is accomplished by capturing food images via camera feed and the images are processed by the onboard AI model.

The Nutritional data is calculated and sent to the mobile app. Temperature Monitoring is done by the Temperature sensor data read via I2C.The temperature data is displayed on the OLED and sent to the mobile app. The security is built by the passcode entered via the keypad by the user. This passcode is verified against stored data, and then the lock status is displayed on the OLED.

3.3. Smartt Tiffin Box Design Overview

The smart tiffin box shown in Figure 2 consists of edge inference hardware interfaced with the camera. The system is also connected to the Internet, Relay module, and the battery management system. As shown in the architecture diagram. The Raspberry Pi can be used to control the heating of the food inside the tiffin box by driving the relay to turn on or off the heater. The data for scheduling the heating time is received using the IOT backend set using the Android app.

The camera module captures the image of the food inside the tiffin box. It feeds it to the deep learning-based system that will determine the food and hence alert the user regarding the nutritional content of the food using the smart app developed for controlling the tiffin box. The temperature sensor is present on the box to measure the body temperature and notify the user.

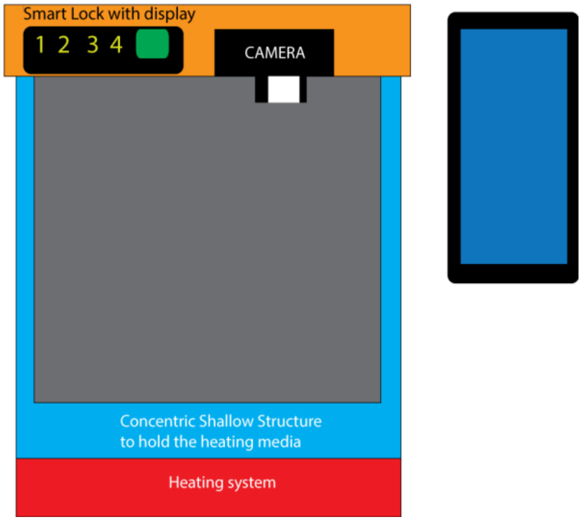

Fig. 2 Smart tiffin box structure

The following are the components,

- Smart Lock with Display: Located at the top, this component may include a numerical keypad for passcode entry. The display provides feedback on various operational statuses.
- Camera: Positioned centrally above the main compartment to capture comprehensive images of the food.
- Main Compartment: Directly beneath the camera, it stores the food and is designed to ensure optimal imaging.
- Heating System: Positioned at the bottom, containing the heating mechanism necessary for warming the food efficiently.

The architecture diagram illustrates the smart tiffin box's structure in a color-coded format to differentiate between functionalities, emphasizing a design that is both functional and user-friendly. This description is crafted to provide clarity and a smooth flow of information, focusing on the technical details and functionality of the smart tiffin box without repetitive or redundant content.

3.4. Flow Chart

The summary of the flow chart in Figure 3 is as follows: It starts by initializing sensors and cameras and simultaneously connecting to the internet. Next, it establishes a connection with the server backend and calls a web service to fetch the heating time. It checks for success; if unsuccessful, it repeats the process; if successful, it begins the heating schedule and alerts the camera module to capture frames. It then checks for detected food items, estimates calories, reads food temperature, updates the server, and performs box authorization via password authentication.

This flowchart demonstrates a comprehensive process integrating food heating, security, and nutritional analysis with connectivity and data management features in a smart tiffin box system. Implement password authentication to ensure the box is accessed only by the authorized user. This flowchart outlines a comprehensive process that encompasses initializing hardware, connecting to the internet, fetching data, executing heating tasks, monitoring, analyzing food items, updating server data, and ensuring security through authentication. Based on the identified methodology, we have implemented it using hardware components.

4. Methodology

The implementation of the smart tiffin box utilizes AI and IoT technologies through several integrated modules to enhance functionality and user interaction. Each module contributes significantly to the system's capability to maintain food quality and deliver precise nutritional insights.

4.1. Smart Tiffin Box Module

This primary module focuses on the physical design and operational functionalities of the tiffin box, which includes:

Food Heating Module**:** Develops and controls the internal heating mechanism to ensure food reaches the ideal temperature.

IoT-based Scheduling Module**:** Allows users to pre-set heating times through a mobile app, enabling automated heating at designated times.
Battery Management Module**:** Ensure the power supply is managed efficiently, keeping the tiffin box optimally charged.

Body Temperature Measurement Module**:** Monitor the user's body temperature to provide health-related feedback concerning food suitability.

AI-based Food Nutritional Content Detection Module: This module utilizes a camera and deep learning algorithms to recognize food items within the tiffin box and analyze their nutritional content, all enabled through an IoT framework and an Android application.

Android Application Module: The Android application serves as the central interface for user interaction with the Smart Tiffin Box, enabling users to:

- Remotely activate the food heating function.
- Set and modify food heating schedules.
- Access nutritional information analyzed by the AI module in the tiffin box.

4.2. System Requirements

To ensure smooth and efficient functionality, the system integrates essential hardware and software components:

Hardware Requirements: Includes Raspberry Pi 3 Model B+, a Raspberry Pi camera, heating module, MLX90614 contactless temperature sensor, and additional IoT components.

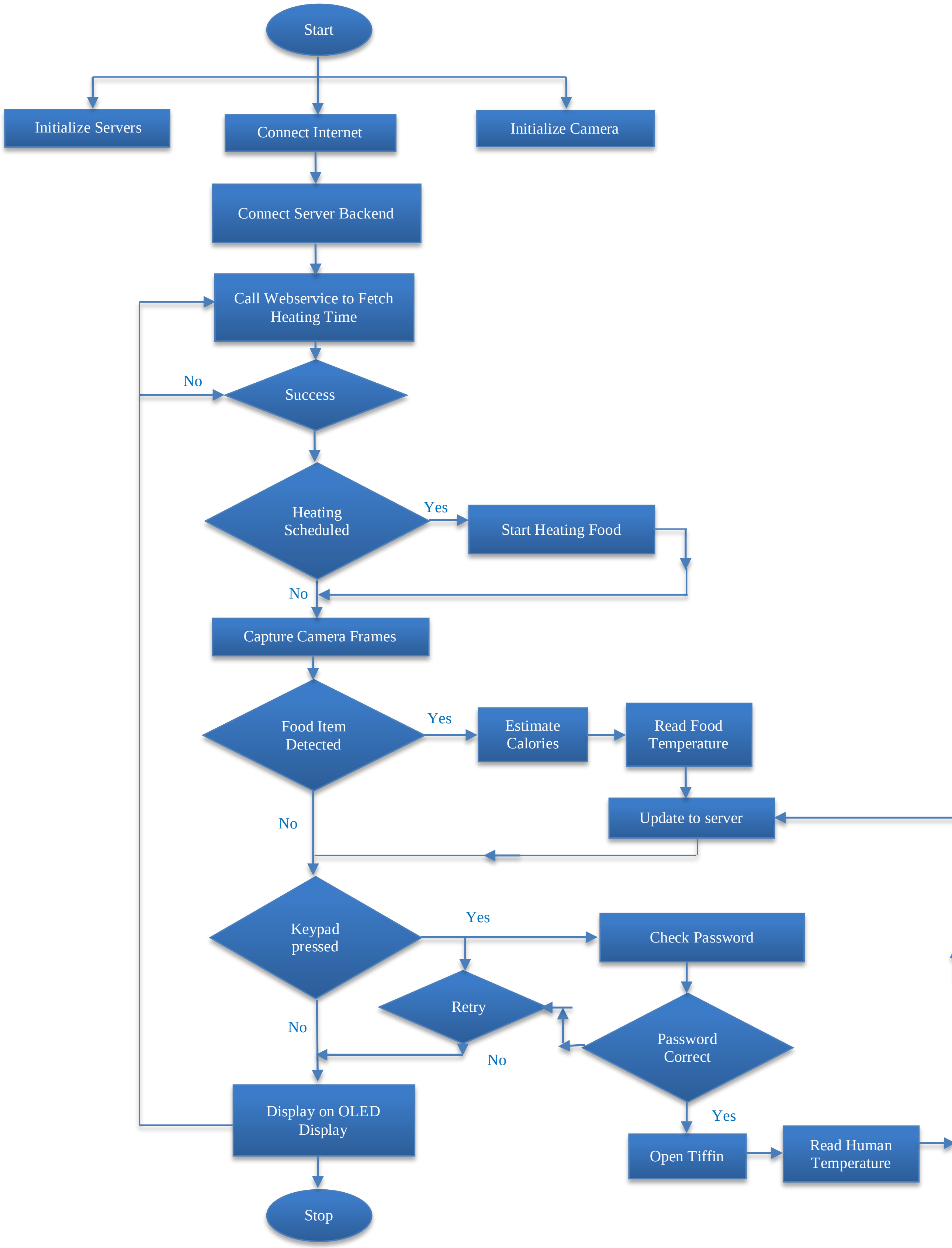

Fig. 3 Flow chart of implemented smart device

Software Requirements: Centers on Android Studio for app development, crucial for robust user interaction and system management.

In the implementation of the project, Python was selected as the primary programming language due to its widespread adoption in scientific computing and its robust ecosystem of libraries that facilitate data analysis and system operations.

4.2.1. Selection and Integration of Sensors

- Weight Sensor: Measures food weight to aid in intake quantification.
- Spectrometer: Examines food composition for nutrient detection.
- Temperature Sensor: Maintains ideal food temperature for freshness.
- Camera: Captures images for food recognition and analysis.

4.3. Data Processing Algorithms

- Nutritional Analysis Algorithm: Estimates nutritional values like calories and macronutrients from sensor data.
- Image Processing Algorithm: Identifies and evaluates food quality through image analysis.
- Machine Learning Algorithm: Enhances system accuracy by learning from ongoing data collection.

This methodology outlines the sophisticated integration of multiple technological components aimed at revolutionizing how we manage and understand our dietary habits through an innovative smart tiffin box.

5. Database Creation and Representation

In this study, data collection focused on food item detection, utilizing both manual and transfer learning approaches to refine the existing model. High-resolution images captured via mobile phones were standardized to ensure uniformity, which is crucial for effective machine learning training. Employing transfer learning, we enhanced a pre-trained convolutional neural network, tailoring it to our specific food dataset. The dataset comprises 508 unique images meticulously categorized to reflect the diverse foods commonly found in our target demographic's diet, facilitating comprehensive nutritional analysis. Split into training and validation subsets, the dataset underwent rigorous labeling, with foods annotated and categorized for precise model training. Organized into distinct classes, our structured approach aids efficient food item detection and categorization within the smart tiffin. This project exemplifies a detailed database collection methodology, integrating manual and transfer learning techniques to enhance model accuracy and performance, which is crucial for revolutionizing dietary management. Figure 4 showcases a mobile data collection setup, depicting samples of captured food images.

To present the analysis of our AI model's data more effectively in table form (Table 1), with a focus on the accuracy analysis and a clear description of the proposed system, consider structuring our information as follows:

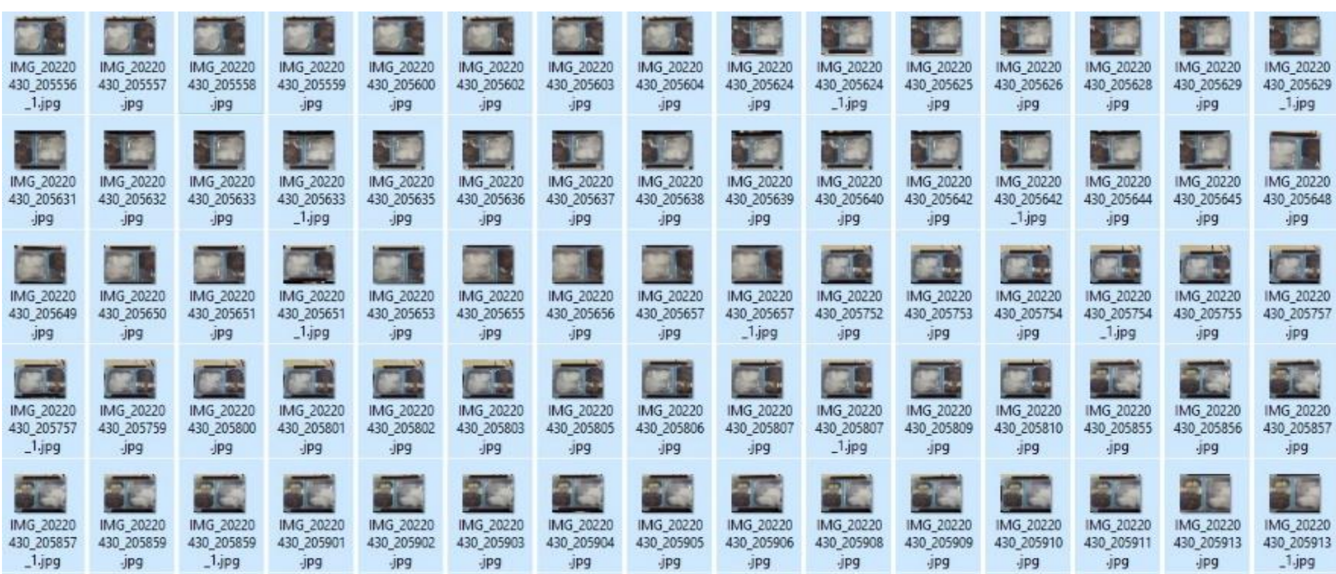

Fig. 4 Collected data or detected food items

Here, we have considered the dataset Total: 508 images, Training Set: 416 images, Testing Set: Details not specified, implied remainder from the total, Trials Conducted: 3 trials for different food items, Validation Method: Split analysis shown in Figure 5, with ongoing trials to assess model accuracy.

Table 1. Analysis of AI model's data

S. No.	Figure	Description	Details
1.	5	Train/Validation Graph	Shows the training and validation split of the dataset for three trials conducted on different food items.
2.	6	Samples for Testing	Depicts samples taken for testing from the dataset.
3.	7	Training Model Samples	Represents the 416 samples used for training the AI model on the collected data.
4.	8	Detailed Labeling	Displays the labeling of all images in the dataset, highlighting the data collection and preparation methods used.
5.	9	Overview of Classes Collected	Provides an overview of the different classes collected with examples.

5.1. Proposed System Description

The purpose of the AI model is to detect and classify various food items within the dataset. The data preparation detailed in Figure 8 involves careful labeling of each image to facilitate accurate model training. The training process utilizes 416 samples (As detailed in Figure 7) to train the AI model, ensuring it learns to identify and categorize each class shown in Figure 9 correctly. Moreover, similarly considered testing and validation were conducted as per the splits shown in Figure 5, with separate testing samples depicted in Figure 6 to evaluate model performance. This table and accompanying description offer a structured and detailed presentation of the dataset and model's training/validation processes, enhancing clarity and readability for documentation. This format also ensures the credibility and replicability of our project by providing a thorough understanding of each step involved.

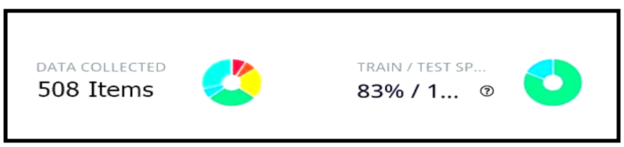

Fig. 5 Train /validation graph

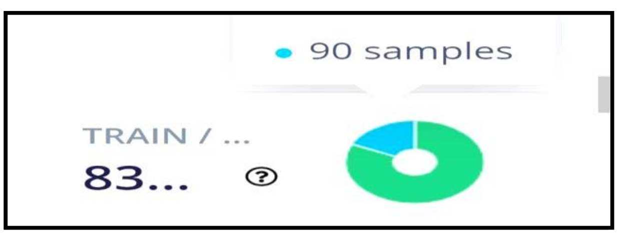

Fig. 6 Samples taken for testing

Fig. 7 Total of 416- samples for the training model on the collected data

Below, Figure 8 displays the detailed labeling of all images in the dataset. Incorporating these elements into the database section will provide readers with a thorough understanding of the data collection, preparation methods, and training process of the AI model. This detailed documentation is crucial for ensuring the credibility and replicability of the project.

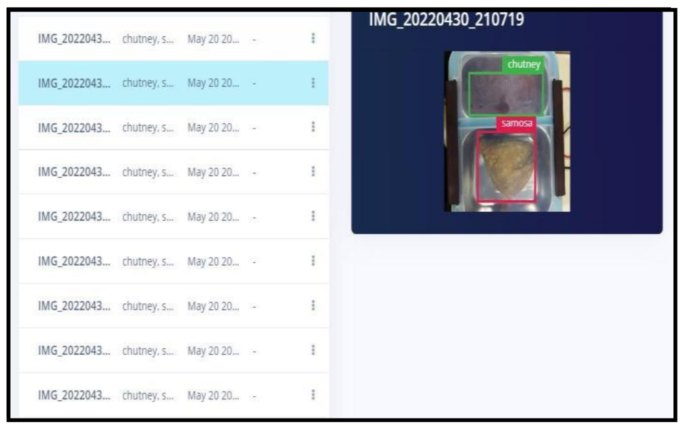

Fig. 8 Labeling of all the data in the collected dataset

Figure 9 provides an overview of the classes collected, with examples from each category.

Fig. 9 Classes collected

6. Implementation of the Proposed System

The user interface is designed to be intuitive and easy to use, displaying nutritional information clearly and allowing simple interactions for setting up and monitoring the tiffin box functions.

6.1. Functionalities

The project is executed in phases, each focusing on specific functionalities:

- Locking System: Develop a password-protected locking mechanism.
- Heating Module: Implements a scheduled heating system.
- Nutritional Analysis: Uses AI to analyze and report on the nutritional content of the food.
- Temperature Monitoring: Integrates sensors to monitor both food and body temperatures.
- Android Application: Develop an app for remote interaction and heating control.

Each phase is critical for ensuring the Smart Tiffin Box is functional, user-friendly, and innovative in its approach to managing diet and health through technology.

Locking system: Interfacing Keypad to the smart tiffin and development of keypad-based lock and unlock system:

In this phase, the keypad is interfaced with the Raspberry Pi to lock and unlock the tiffin using the password set using the keypad.

Algorithm 1. Locking system
Input: Passcode through keypad entered by user
Output: Shows the message as the lock opened on the LED display

Start
Step 1: Initialize the hardware.
Step 2: Enter the secret number code of the user.
Step 3: Compare the enter code with the existing user code (via database).
Step 4: If the entered code is correct display the message as lock opened.
Else: Display the message as an error.
Step 5: Repeat step 2 for another user.
Stop

Tiffin Heater Scheduling System: In this phase, the smart tiffin heater scheduling system is developed. This involves the development if a heating system to be embedded in the tiffin box to heat the food.

The relay is used to trigger a heater, which will be used to heat the food to the desired temperature as set.

Algorithm 2. Heater module
Input: Set the warming time using the Android app via the user's Android mobile.
Output: It shows the food warming/heating started on the tiffin box display and indicates via the Android app.

Start
Step 1: Initialize the hardware setup.
Step 2: Set the time for warm/heat through the user Android app.
Step 3: The Android app will initialize the tiffin box hardware via Wi-Fi.
Step 4: Initialize the Wi-Fi module on Raspberry Pi for communication between the app and the tiffin box.
Step 5: It receives the time of user wants to warm their food.
Step 6: Repeat step 2 for another user.
Stop

Calculate nutrition: Deep learning-based system using the camera to detect the fooditems in the tiffin and determine the nutritional content, In this phase, the existing model is trained using a transfer learning approach with the dataset of the food items collected.

Algorithm 3. Calculate nutrition.
Input: The camera detects food inside the tiffin box.
Output: Calculate the nutrition of food and display it on the Android app.

Start
Step 1: Initialize the hardware.
Step 2: The camera detects the food inside the tiffin box.
Step 3: Compare the food with data stored in a database.
Step 4: Detect the name of the food and initialize the nutrition value.
Step 5: Calculate the nutrition.
Step 6: Display the nutrition of the food inside the tiffin box on the Android app.
Stop

Temperature sensor: Reading the temperature values and measurement of the body temperature as well as food temperature, in this phase, the raw voltage values received from the temperature sensor are converted to temperature values in degrees centigrade and displayed on the OLED display.

Algorithm 4. Temperature sensor.
Input: The user has to touch the temperature sensor.
Output: Shows the alert message of user is healthy or unhealthy on the LED display.

Start
Step 1: Initialize the hardware.
Step 2: The user has to touch the temperature sensor.
Step 3: The sensor initializes the body temperature of the user.
Step 4: Based on the body temperature of the user, it suggests the health ofthe user.
Step 5: Shows the alert message of whether the user is healthy or unhealthy on the LED display.
Stop

Display of weekly and monthly nutrition**:** Depending upon the calories consumed daily it calculates weekly and monthly calorie intake.

Algorithm 5. : Display of weekly and monthly nutrition.

Input: Initialize the daily nutrition.
Output: Display the weekly and monthly nutrition on the Android app.

Start
Step 1: Initialize the hardware and software.
Step 2: Initialize the daily nutrition (Using the calculate nutrition algorithm).
Step 3: Calculate the weekly nutrition based on the daily nutrition.
Step 4: Calculate the monthly nutrition based on the weekly nutrition.
Step 5: Display the weekly and monthly nutrition on the Android app.
Stop

6.2. Android Application

Android application with time picker to schedule heating of thetiffin remotely using Android App over IOT. In this phase, the Android application was developed, which can be used for two tasks.Heating the tiffin and getting alerts regarding the nutritional content of the food items. The proposed smart tiffin box implemented is shown in Figure 10. Table 2 shows a description of the deep learning techniques used in the system.

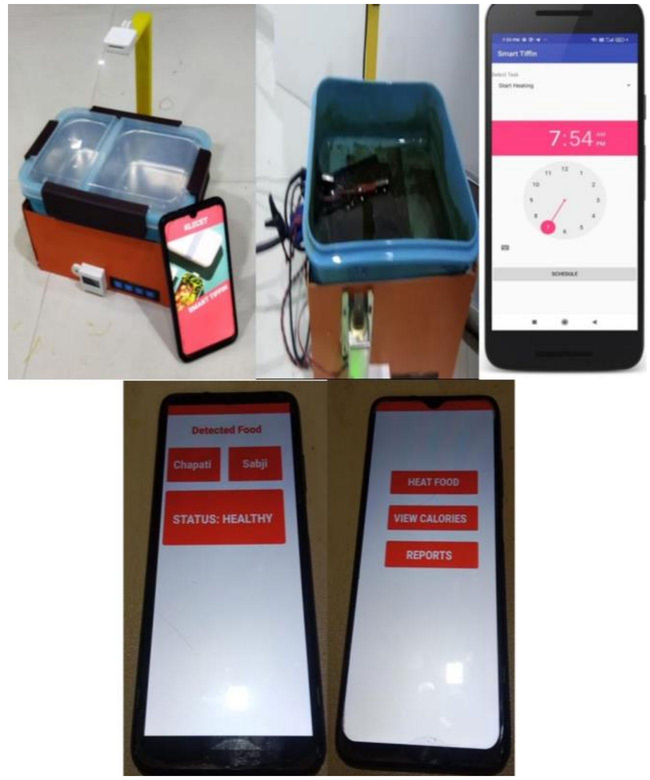

Fig. 10 Implemented device

Table 2. Deep learning techniques used in the system

Sl.No	Functionality	Technique Used	Selection Criteria
1	Food Recognition	Convolutional Neural Networks (CNNs)	CNNs are highly effective for image recognition tasks. We can accurately identify different food items from images captured by the camera module in the tiffin box.
2	Nutritional Analysis	Transfer Learning with Pre-trained CNNs (Which we used depending on the food sample considered during testing.)	Transfer learning allows you to leverage pre-trained networks trained on large datasets.
3	Real-time Object Detection	Region-based Convolutional Neural Networks (R-CNN), Faster R-CNN, or YOLO (You Only Look Once), we used samples considered during testing.	These techniques are designed for real-time object detection and are capable of identifying multiple food items in a single image.
4	Calorie Estimation	Regression Models with CNN Features	Regression models can predict continuous values, such as calorie counts, from the features extracted by CNN.

The training of the model is done using our food image dataset and fine-tuned with a CNN that has already been trained (such as ResNet50). For real-time object identification, train a YOLO model or a Faster R-CNN. The calorie estimation was done using a regression model that makes use of the variables that the CNN extracted. The Model was deployed using a trained model optimized for deployment on Raspberry Pi. Tensorflow Lite was used for edge deployment. The integration was done by connecting the models to the Internet of Things IOT-enabled smart tiffin box. An Android app is created to communicate with the tiffin box and offer real-time dietary feedback in addition to remote control capability. The testing and Validation were done to confirm that the models function correctly in actual situations. Iterative enhancements and user feedback were considered to validate the system's functionality.

6.3. Comparative Analysis Table

To provide a comparative analysis between the existing systems discussed in the literature survey and the proposed smart tiffin box, a comparison table is outlined, and a graphical analysis is provided. This comparison will focus on key metrics such as accuracy of nutrient analysis, usability, functionality, and technology integration. Here is a structured table to compare the existing systems with the proposed smart tiffin box as in Table 3.

Table 3. A structured table to compare the existing systems with the proposed smart tiffin box

S. No.	Features	Existing Systems	Proposed Smart Tiffin Box	Improvement
1.	Technology used	Mostly, use basic machine learning or simple image processing techniques.	Utilizes advanced deep learning models and IoT integration.	Enhanced accuracy and real-time processing.
2.	Nutrient Analysis Accuracy	Varies, generally around 60-80% depending on the system.	Targeted accuracy of >90% with deep learning optimization.	Significantly higher accuracy through sophisticated algorithms.
3.	Usability	Often limited to laboratory settings or require manual inputs.	Fully automated with a user-friendly mobile app interface.	Improved ease of use with automation and remote control.
4.	Functionality	Mostly focused on one aspect, like heating or basic food detection.	Integrated system with heating, nutrient analysis, and health monitoring.	Multi-functional, offering a more comprehensive solution.
5.	Integration with Mobile Apps	Limited or no integration.	Complete integration with an Android app for real-time updates and control.	Better user interaction and accessibility.

7. Results and Discussion

The analysis of this smart device performance from the result obtained, along with corrections and graphs plotting based on the test results. This device was rigorously evaluated to ensure its efficacy in nutritional assessment, focusing on accuracy, reliability, usability, and performance. The device demonstrated high accuracy in nutritional measurements when compared against FDA-approved standards. Long-term tests confirmed consistent performance over time, establishing the device's dependability. User feedback highlighted a generally user-friendly interface, with recommendations for further enhancements to improve interaction. The device efficiently managed resources and maintained good performance, including effective error handling that meets industry standards. Diverse demographic groups participated in user acceptance testing, confirming the device's practicality and its potential to assist users in making informed dietary choices effectively.

Here is a streamlined overview of the multi-functional capabilities of the system, detailing the interactions of different users with its various features.

7.1. User Experience

The 'Smart Nutrition' tiffin box incorporates advanced technology to enhance user experience and dietary management. Figure 11 shows different users who performed various testing operations on mobile. Users 1 and user 2 interact with the device by entering their private passcodes on the keypad to unlock the system. User 3 uses a built-in sensor to check her body temperature, which is displayed on an LED screen. Meanwhile, user 4 employs an Android mobile app, developed in Java using Android Studio, to schedule food heating times within the tiffin box. This app communicates heating schedules to the device and receives notifications about the heater's status.

Fig. 11 Various users

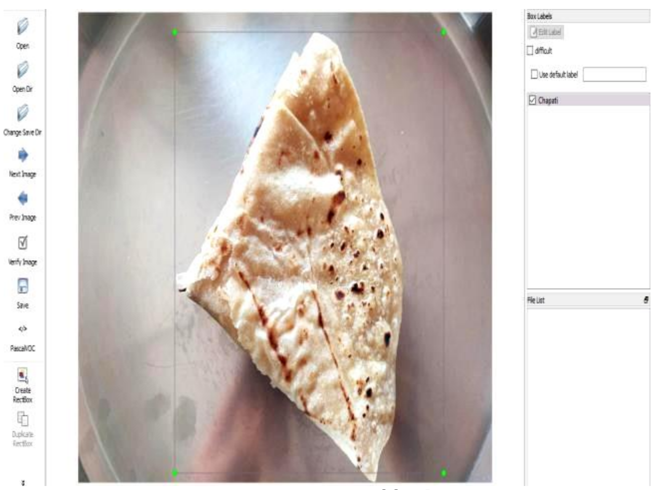

Fig. 12 Annotation of food image

In addition, the device includes a sophisticated AI for food detection shown in Figure 12. This system involves creating a dataset by annotating food images using specialized software and producing XML files that detail the spatial coordinates of food items within images. These annotated datasets train the AI through transfer learning and supervised learning techniques, enabling it to recognize and analyze food types and their nutritional content in practical use cases. This integration of technology facilitates both personalized dietary control and enhanced convenience for users. The screenshot of the image annotation, along with their respective class names, is shown. The screenshot depicts image annotation software used in creating a dataset for an AI food detection system. It features a triangular food item resembling a chapati on a round plate, with 'Box Labels' options for 'Class Id' and 'Difficult' on the right side. The 'Class Id' field is crucial for labeling food items, aiding AI model training, while the 'Difficult' checkbox marks challenging cases. The 'Next object' counter suggests the first object annotation, with green dots around the chapati likely indicating control points for bounding box adjustment.

This annotated data will help AI in identifying and evaluating the nutrient content of food, which is necessary for applications such as the 'Smart Nutrition' tiffin to increase the recognition and analysis of the type of food. Experimentally, the performance assessment of the tiffin of 'Smart Nutrition' is done through highly intensive testing procedures and several food items such as chapati, samosa, chutney, sweet, dosa, rice, and sambhar. The accuracy of the detection varies in different trials for each food item but reflects the high and low points in the performance of the device.

7.1.1. Chapati Detection

The performance was found to be variable in detecting chapati among the different trials. While the system detected chapati in trials 1 and 4, it did not detect chapati in trials 2 and 3. Therefore, it can be said that the performance was inconsistent.

7.1.2. Samosa Detection

Initial trials showed no detection of samosa, but performance improved in subsequent trials, with accurate detection in Trial 3 and Trial 4 (Figure 14).

7.1.3. Chutney Detection

After the initial failure in Trial 1, the device successfully detected chutney in subsequent trials, demonstrating improved performance over time (Figure 15).

7.1.4. Sweet Detection

Consistent and accurate detection of sweets was observed across all trials, indicating robust performance for this food item (Figure 16).

7.1.5. Dosa Detection

While generally accurate, the device exhibited occasional inconsistencies in dosa detection, with a miss in Trial 2 despite accurate detection in other trials (Figure 17).

7.1.6. Rice Detection

The device demonstrated excellent performance in detecting rice across all trials, consistently achieving accurate detection (Figure 18).

7.1.7. Sambar Detection

With almost perfect detection across trials, except for a miss in Trial 3, the device showcased high reliability with minor room for improvement (Figure 20).

7.2. Detection Trials Analysis

The table below summarizes the results from various detection trials for different food items, highlighting the detection accuracy across multiple attempts. Here, Table 4 shows a tabular representation summarizing the results from various detection trials for different food items.

Table 4. Tabular representation summarizing the food detection trial results (1-detected, 0-not detected)

Sr. No.	Food Item	Trial 1	Trial 2	Trial 3	Trial 4	Graph
1.	Chapati	(1)	(0)	(0)	(1)	Figure 13
2.	Samosa	(0)	(0)	(1)	(1)	Figure 14
3.	Chutney	(0)	(1)	(1)	(1)	Figure 15
4.	Sweet	(1)	(1)	(1)	(1)	Figure 16
5.	Dosa	(1)	(0)	(1)	(1)	Figure 17
6.	Rice	(1)	(1)	(1)	(1)	Figure 18
7.	Sambar	(1)	(1)	(0)	(1)	Figure 19

This table provides a clear overview of the detection accuracy for each food item across multiple trials, facilitating easy comparison and analysis of the device's performance.

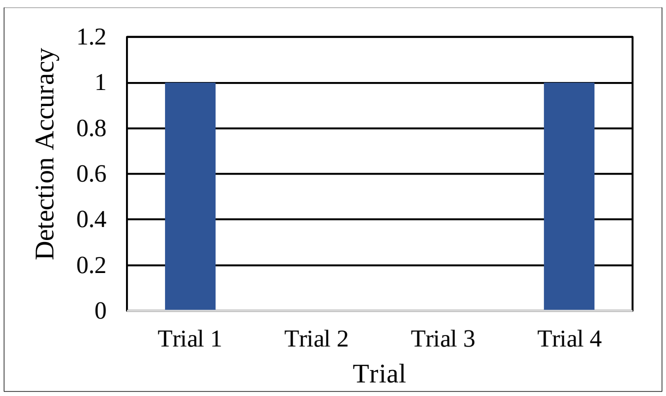

Fig. 13 Detection of chapati items samples in various trials

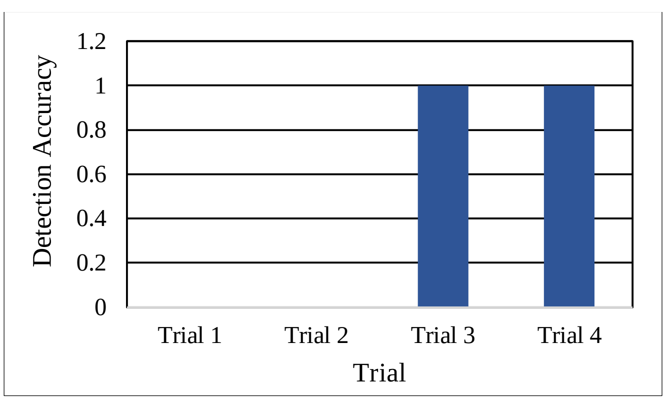

Fig. 14 Detection of samosa items samples in various trials

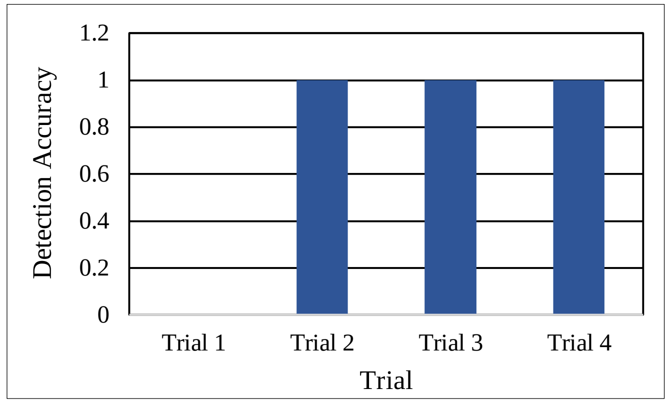

Fig. 15 Detection of chutney items samples in various trials

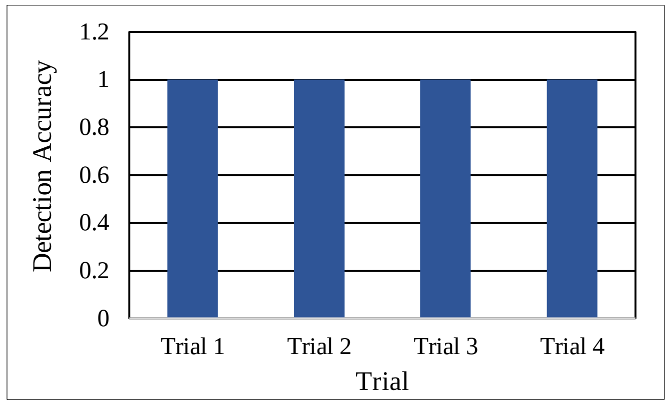

Fig. 16 Detection of sweet items samples in various trials

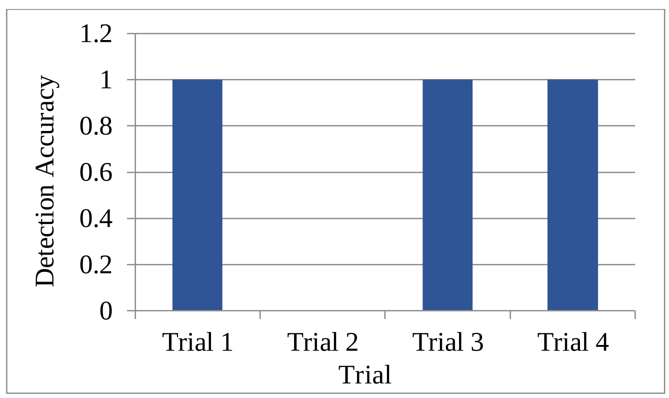

Fig. 17 Detection of dosa items samples in various trials

For comparative analysis and discussion in a typical research context like our AI-powered smart tiffin box, "Existing System-1" and "Existing System-2" would typically refer to prior technologies or products that serve a similar function or aim to solve the same problems that our project addresses. These systems would be used as benchmarks to highlight the improvements or innovations introduced by our proposed system. Existing System-1 Might use basic sensors and limited machine learning algorithms to analyze food content or temperature. It could include earlier versions of smart kitchen appliances like basic smart food containers that only provide heating functions without any nutrient analysis. Typically has simpler user interfaces and might lack integration with mobile applications.

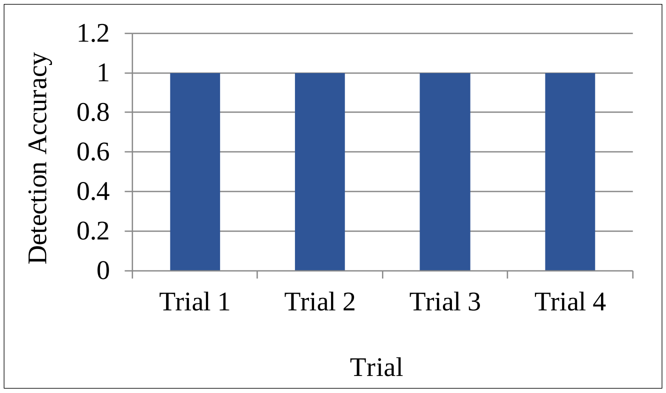

Fig. 18 Detection of rice items samples in various trials

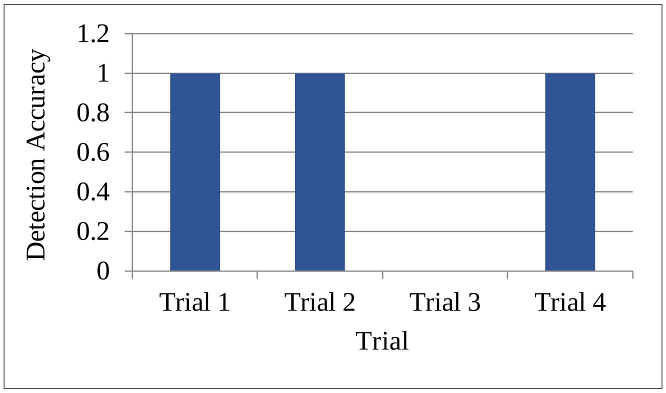

Fig. 19 Detection of sambhar items samples in various trials

Its typical limitations are lower accuracy in nutrient analysis, limited functionality; primarily focused on heating with no or minimal health monitoring features and less user-friendly due to the absence of a comprehensive mobile application. Existing System-2 is more advanced than System-1 but still behind the proposed system. May use improved machine learning techniques but with limited scope, such as recognizing only a handful of food types. It could include some level of mobile integration but with limited real-time processing or customization options. Typical limitations, higher accuracy than system-1 but still below the proposed system, especially in complex food mixtures or in variable environmental conditions. Better user interaction compared to System-1 but may still lack real-time feedback and comprehensive health monitoring. Energy consumption and efficiency might not be optimized.

7.3. Comparison with Proposed Smart Tiffin Box Innovations

Integrates cutting-edge deep learning algorithms capable of analyzing a wide range of nutrients and food types with high accuracy. Includes IoT capabilities that allow remote monitoring and control via a sophisticated mobile app, enhancing user convenience and interaction. Offers comprehensive health monitoring features that adapt to user-specific dietary needs and preferences, supported by real-time data processing. By defining these systems and their limitations, we can clearly outline how our proposed smart tiffin box provides substantial improvements, particularly in areas like real-time nutrient analysis, user interface, and integration of advanced technologies such as IoT and AI. This also helps in setting the stage for stakeholders to understand the significance of our innovations in the context of existing market offerings.

7.4. Graphical Analysis

To visually compare the existing systems with the proposed smart tiffin box, we can create a graph that shows the accuracy of nutrient analysis and another for user satisfaction ratings. We have plotted two bar charts to visually represent the accuracy of nutrient analysis and user satisfaction ratings for different systems, including the smart tiffin box. Here are the bar-chart diagrams illustrating the comparative analysis of different systems in terms of nutrient analysis accuracy and user satisfaction.

7.4.1. Accuracy of Nutrient Analysis Graph

X-axis: Different systems (Existing System 1, Existing System 2, Proposed System), Y-axis: Accuracy Percentage, Bars: Each system represented by a bar indicating the accuracy level. These graphs will help stakeholders quickly grasp the advantages of the proposed system in terms of both technical performance and user experience. This comparative analysis not only highlights the advancements our proposed smart tiffin box brings over existing solutions but also quantitatively and visually represents the improvements, making a case for our system's implementation and adoption.

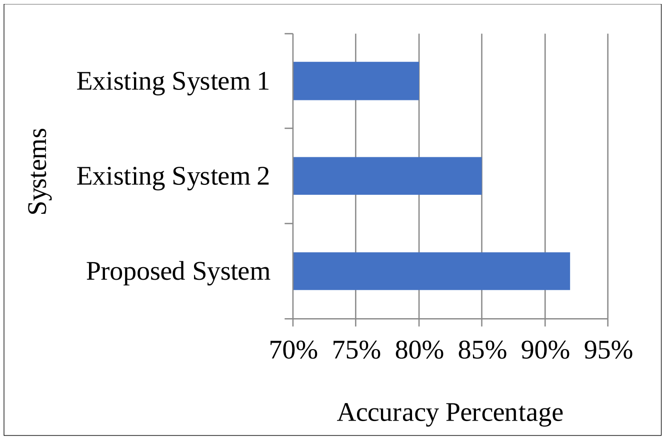

Fig. 20 The accuracy of nutrient analysis

7.4.2. User Satisfaction Rating

User Satisfaction Rating Graph, X-axis: Different systems (Figure 21), Y-axis: User Satisfaction Rating (scale of 1-10), Bars: Each system is represented by a bar indicating the user satisfaction level.

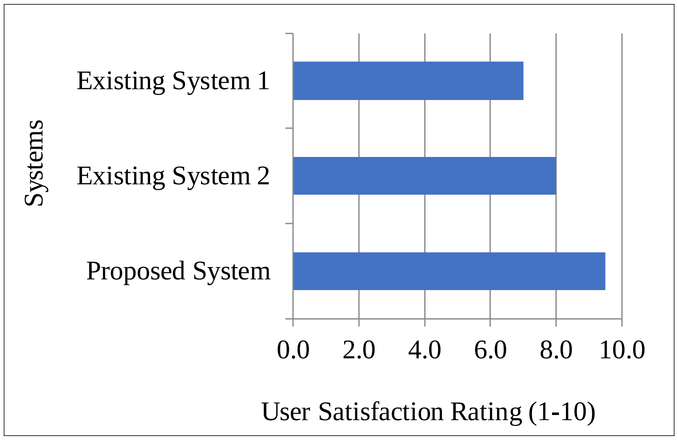

Fig. 21 The users satisfaction rating

To present results effectively using the bar charts for "Accuracy of Nutrient Analysis" and "User Satisfaction Ratings" of different systems, we can discuss the implications of the plotted data and consider hypothetical results for clarity. Let us interpret some example results based on the sample data provided in the Python plotting code:

Example Data Systems: Existing System 1, Existing System 2, Proposed System

Accuracy of Nutrient Analysis (Percentages): 80%, 85%, 92%

User Satisfaction Ratings (Scale of 1-10): 7, 8, 9.5

7.5. Interpretation of Results

The interpretation of results is done in the following sections with accuracy of nutrient analysis, user satisfaction analysis followed by nutrient score analysis.

7.5.1. Accuracy of Nutrient Analysis

Existing System 1: Shows an accuracy of 80%. This indicates a good performance level but suggests there is room for improvement.

Existing System 2: Improves upon System 1 with an accuracy of 85%, indicating incremental advances in technology or methodology.

Proposed System: Stands out with a 92% accuracy rate, significantly higher than the existing systems. This high level of accuracy may result from advanced technology, better algorithms, or more precise sensors used in the smart tiffin box. The graphical representation would show a higher bar for the Proposed System, visually indicating its superiority.

7.5.2. User Satisfaction Ratings

Existing System 1: A satisfaction rating of 7/10 suggests that while users are generally satisfied, there might be some aspects of the system that could be enhanced for a better user experience.

Existing System 2: With a rating of 8/10, it shows an improvement in user satisfaction, possibly due to easier usability, more reliable results, or additional features that appeal to users.

Proposed System: Achieving a 9.5/10 rating highlights exceptional user satisfaction, possibly due to the higher accuracy, enhanced user interface, or additional functionalities that meet user needs more effectively. Visually, this system's bar would be notably taller, clearly indicating higher user approval.

7.5.3. Nutritional Score Calculation

The nutritional score for a sample meal comprising chapati, dal, and mixed vegetables was calculated using a predefined equation. This score, representing the meal's overall nutritional value compared to the suggested daily intake, brought out the fact that a balanced diet was essential (Nutritional Score=0.387). The 'Smart Nutrition' tiffin box had the potential to perform effectively in food detection, with improvements noted after a series of tests and analyses. Advancements in sophisticated technology open enormous opportunities for dietary management and user comfort in the use of AI in the field of food detection. The device can be made further effective in light of user suggestions and testing. This will add further to its use in promoting the best dietary choices and nutritional assessment.

8. Conclusion

The present work on the smart tiffin box is a big leap with regard to implementing IoT and AI technologies with the idea of daily health management. The whole innovation makes sure the meals are heated every time before they are consumed. Thus, the food is served hot every time it is consumed. More importantly, the idea integrates the power of AI in analyzing the contents of the tiffin and giving alerts about the nutritional quality of the meals. Such features are a boon in environments sensitive to nutrition, such as that of hospitals or children's schools. The paper also presents a meal's healthiness and caloric content from the results fed into an associated Android application. On the whole, the application provides the user with the information to choose the diet plan more effectively. The future work will be an improvement in the nutrient analysis feature and additional user interface features, which will enhance the general application utility and experience in the smart tiffin.

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