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Food Recommendation and Calories Estimation

Mrs. A. Aruna.,M.E[1], Mrs. B.R. Madhuvandhi.,M.E[2], B. Naga Vardhan[3], N. Parameshwar Reddy[4], V.Uday Bhaskar Reddy[5]

[1, 2, 3, 4, 5]*Deparment of Artificial Intellgence and Data Science, Muthayammal Engineering College Rasipuram,India*

Abstract: In today's fast-paced world, maintaining a healthy lifestyle has become increasingly challenging due to the widespread availability of high-calorie, processed foods and the lack of nutritional awareness among individuals. People often consume food without understanding its caloric and nutritional content, leading to obesity, diabetes, and other lifestyle-related diseases. To address this problem, the proposed project titled "Food Recommendation and Calorie Estimation System" introduces an intelligent, AI-based solution that automatically estimates the calorie content of food items and provides personalized meal recommendations. The system utilizes advanced machine learning and computer vision techniques to identify various food items from images and predict their corresponding caloric values accurately. By integrating deep learning models such as Convolutional Neural Networks (CNNs), including architectures like VGG16, ResNet, and InceptionV3, the system can detect multiple food types even under complex visual conditions. Once the food item is identified, the system retrieves its nutritional information, including calories, carbohydrates, proteins, and fats, from a verified nutrition database such as USDA or My Fitness Pal. Introduction Furthermore, the system collects user-specific information—such as age, gender, height, weight, and physical activity level—to calculate the Basal Metabolic Rate (BMR) and Total Daily Energy Expenditure (TDEE) using standard formulas like the Harris-Benedict equation. Based on these calculations, the application recommends

Meals that align with the user's fitness goals, whether for weight loss, maintenance, or muscle gain. The recommendation engine employs both content-based filtering (analyzing food nutrient profiles) and collaborative filtering (learning from similar user behaviors) to ensure more accurate and relevant suggestions. Additionally, the system is designed to consider cultural and regional food preferences, making it suitable for users across diverse backgrounds by including data for local cuisines and dietary restrictions such as vegetarian, vegan, or diabetic-friendly options.

The architecture of the system is modular, comprising an image recognition module, a nutrition analysis module, a recommendation engine, and a user interface. The frontend is designed using HTML, CSS, and JavaScript or modern frameworks like React, while the backend is implemented using Flask or Django, ensuring scalability and efficient API communication. The machine learning components are developed using TensorFlow, Keras, and Scikit-learn, and data management is handled through MySQL or Firebase databases.

I. INTRODUCTION

In the 21st century, the rapid advancement of artificial intelligence and data-driven technologies has transformed every domain of human life, including healthcare, wellness, and nutrition. Among the most pressing global issues today is the alarming rise in obesity, malnutrition, and other diet-related disorders. People across all age groups are increasingly adopting unhealthy eating habits due to fast-paced lifestyles, lack of nutritional awareness, and the easy accessibility of high-calorie, processed foods. Many individuals struggle to maintain a balanced diet because they are unaware of the caloric and nutrient content of the foods they consume daily. As a result, lifestyle diseases such as obesity, diabetes, and cardiovascular illnesses have become common even among young adults. Traditional calorie tracking methods rely heavily on manual recording, where users input food details into mobile applications or diaries. These methods are not only tedious but also prone to inaccuracies due to human error, lack of knowledge, or inconsistency in portion estimation. This situation has created a clear need for an automated and intelligent system that can accurately estimate calories, analyze food nutrition, and recommend meals tailored to individual health goals. The Food Recommendation and Calorie Estimation System proposed in this project is designed to address these challenges using the power of artificial intelligence (AI), machine learning (ML), and computer vision. The core concept revolves around enabling a system to recognize food items either through images or user input and to compute the corresponding calorie value automatically. Furthermore, it recommends food options that fit within the user's daily caloric requirements, helping them maintain a healthy and sustainable diet. The system serves as an intelligent dietary assistant that not only tracks caloric intake but also learns user behavior and preferences over time to provide personalized recommendations. With the widespread availability of smartphones, cloud computing, and health monitoring devices, such a system can be seamlessly integrated into daily life, making healthy eating both convenient and intelligent.

The motivation for developing this project stems from the growing global health crisis associated with poor dietary management. In many countries, obesity has reached epidemic levels due to increased consumption of high-calorie foods combined with sedentary lifestyles. Conversely, undernutrition and nutrient deficiencies remain major concerns in developing regions. A technology-driven approach to food awareness can help mitigate both extremes by empowering users to understand their dietary patterns and make informed choices. Artificial intelligence, especially deep learning models, has made significant progress in image recognition, data analysis, and pattern detection. By training these models with large datasets of food images and their corresponding nutritional values, machines can learn to estimate calorie content accurately from visual cues such as color, texture, and shape.

This capability is further enhanced by linking the model to standardized nutritional databases like USDA Food Composition Database or MyFitnessPal, which provide verified details about thousands of food items. In addition to calorie estimation, the system incorporates a recommendation engine that suggests meal options according to the user's health goals—be it weight loss, muscle Another unique aspect of this project is its attention to cultural and regional diversity in diet. Many food recognition systems are biased toward Western cuisines and fail to perform well for regional dishes found in Asia, Africa, or the Middle East. This project aims to overcome that limitation by incorporating diverse datasets that include regional and traditional foods. This makes the system more inclusive and applicable to users from different backgrounds. Moreover, the model can be fine-tuned to recognize vegetarian, vegan, gluten-free, and diabetic-friendly options, providing a broader scope of usability. This adaptability ensures that the food recommendation system not only focuses on calorie counting but also aligns with ethical, cultural, and medical dietary needs.

The system architecture consists of several integrated modules that work together seamlessly. The image recognition module is responsible for identifying food items using deep learning algorithms such as Convolutional Neural Networks (CNNs), ResNet50, or InceptionV3, trained on thousands of labeled food images. The potential applications of this system extend far beyond individual use. It can be integrated into fitness applications, diet management systems, and even healthcare monitoring platforms. Nutritionists and fitness trainers can utilize it to track their clients' eating habits and design personalized diet plans. In addition, hospitals can employ similar systems to monitor patients with specific dietary restrictions, such as those recovering from surgery or managing chronic illnesses. With proper scaling and data security measures, the system can evolve into a global health platform that bridges the gap between technology and nutrition science.

II. RELATED WORK

Over the past decade, numerous research studies have explored the intersection of artificial intelligence, nutrition, and computer vision to automate food analysis and dietary monitoring. The rapid development of deep learning has significantly advanced the field of food recognition and calorie estimation, providing the foundation for intelligent recommendation systems. Early attempts at food calorie estimation primarily relied on manual input or rule-based systems, where users had to record their meals manually, and the software used a preloaded database to calculate calories. While effective for small datasets, such systems lacked scalability, flexibility, and the ability to adapt to real-world variations in food presentation, lighting conditions, and portion sizes. Researchers recognized the need for a more intelligent and automated approach, leading to the adoption of image-based food recognition using machine learning algorithms.

One of the earliest contributions in this field was by Kawano and Yanai (2015), who developed a mobile food recognition system using deep convolutional neural networks (CNNs). Their model classified food images into various categories with improved accuracy compared to traditional methods. Although their system could recognize food types efficiently, it was limited by dataset size and lacked the capability to estimate portion size or calorie content. Later, Chen et al. (2016) proposed an advanced Calorie Estimation Framework (CalorieCam) that incorporated food segmentation and volume estimation for more accurate calorie prediction. They utilized multiple images taken from different angles to approximate food volume using 3D reconstruction techniques. This marked a significant step forward, bridging the gap between visual food recognition and quantitative calorie estimation.

Further studies focused on improving dataset diversity and model accuracy. The UEC-Food100 and UEC-Food256 datasets, introduced by the University of Electro-Communications in Japan, became benchmark datasets for food classification tasks. Each dataset contained hundreds of food categories with thousands of labeled images, providing a foundation for training deep neural networks. Later, the Food-101 dataset was introduced by Bossard et al. (2014), consisting of 101 categories and over 100,000 images collected from the web. Researchers used these datasets to train CNN models such as AlexNet, VGG16, GoogLeNet, and ResNet, achieving progressively higher accuracy rates in recognizing food items.

$$\text{Calories (kcal)} = (4 \times \text{Protein (g)}) + (4 \times \text{Carbohydrates (g)}) + (9 \times \text{Fat (g)})$$

Example:

If a food has

- Protein = 10g
- Carbs = 20g
- Fat = 5g

Then:

$$\text{Calories} = (4 \times 10) + (4 \times 20) + (9 \times 5) = 40 + 80 + 45 = 165 \text{ kcal}$$

In recent years, research has shifted toward personalized food recommendation systems that not only estimate calories but also generate meal suggestions aligned with the user's health goals and preferences. Feng et al. (2020) developed a diet-aware recommendation system using deep learning and nutritional databases. Their model analyzed users' eating histories and proposed balanced meals considering caloric intake, macronutrient distribution, and dietary preferences. Similarly, Gupta et al. (2022) presented a Culturally-Aware Food Recommendation System, which included regional and traditional food items to ensure inclusivity for diverse populations. This approach was particularly relevant in countries with diverse cuisines like India, where typical food recognition models struggled due to a lack of culturally representative datasets.

Another noteworthy development was introduced by Meyers et al. (2020), who proposed a Real-Time Food Recognition and Calorie Estimation System using deep convolutional architectures and mobile deployment. Their work demonstrated how mobile devices equipped with AI models could perform on-device calorie estimation without relying heavily on cloud computing. This advancement allowed faster response times and improved privacy since user data did not have to be uploaded to remote servers. Moreover, Chen et al. (2021) explored Image-Based Calorie Estimation for Smart Diet Management, using deep regression networks that mapped image features directly to calorie values. This end-to-end learning approach simplified the workflow by bypassing explicit segmentation and classification steps, reducing computational complexity while maintaining high accuracy.

III. SYSTEM ARCHITECTURE

A. Image Processing Module

The Food Recommendation and Calorie Estimation System is designed as a modular, multi-layered architecture that integrates several artificial intelligence components, user interface modules, and data management layers into a unified framework. The primary goal of the architecture is to enable accurate food recognition, precise calorie estimation, and intelligent meal recommendation through the seamless flow of data between the client and the backend AI engine.

The overall system is composed of four major modules: Image Recognition and Preprocessing Module, Calorie Estimation and Nutritional Analysis Module, User Profiling and Data Management Module, and the Food Recommendation Engine. These modules are interconnected through a web-based or mobile application interface built on client–server architecture. The system follows a hybrid model where computationally heavy tasks such as deep learning inference are handled by the backend server or cloud infrastructure, while lighter processes like user interactions and visualization are managed on the client side.

B. Calorie Estimation Module

Once the image is preprocessed, it enters the Food Recognition Module, which serves as the core intelligence of the system. This module employs deep convolutional neural networks (CNNs), trained on large-scale food image datasets such as Food-101, UEC-Food256, or IndianFood-500, to identify the type of food present in the image. Models such as ResNet50, InceptionV3, VGG19, and EfficientNet are used due to their proven accuracy in image classification tasks. The CNN model extracts hierarchical visual features like color, texture, and shape from the input image and compares them against the learned features of known food classes. The output layer produces a probability distribution over multiple possible food categories, and the food item with the highest confidence score is selected as the recognized dish.

Calories=Weight X Calorie_Density X Correction Factor

Figure 1: Calorie Estimation

C. User Profile Module

From an architectural standpoint, the system is designed to be modular, scalable, and extensible, enabling continuous improvement and integration with future technologies.

$$BMR = 88.362 + (13.397 \times 70) + (4.799 \times 175) - (5.677 \times 25) = 1725.6$$

$$TDEE = 1725.6 \times 1.55 = 2675.7 \text{ kcal/day}$$

Additionally, natural language processing (NLP) can be integrated to allow users to interact with the system using voice commands or text queries like "Suggest a low-calorie lunch under 500 kcal."

D. Recommendation Engine

Overall, the proposed Food Recommendation and Calorie Estimation System Architecture represents a comprehensive AI-driven solution that brings together the strengths of computer vision, machine learning, and personalized recommendation technologies. It provides users with real-time, accurate, and culturally aware dietary guidance while maintaining data security and usability. By automating calorie tracking and meal planning, the system not only promotes healthier eating habits but also demonstrates the transformative potential of artificial intelligence in the field of nutrition and health informatics.

$$\text{Similarity}(A, B) = \frac{\sum_i (r_{A,i} - \bar{r_A})(r_{B,i} - \bar{r_B})}{\sqrt{\sum_i (r_{A,i} - \bar{r_A})^2}\sqrt{\sum_i (r_{B,i} - \bar{r_B})^2}}$$

IV. IMPLEMNTATION DETAILS

A. Data Set and Training

The implementation of the proposed Food Recommendation and Calorie Estimation System involves a combination of artificial intelligence techniques, web technologies, and database management systems to provide an intelligent, accurate, and user-friendly application. The system was implemented in a modular fashion to ensure scalability, easy debugging, and integration of future enhancements. The implementation process begins with data collection and preprocessing, followed by model training for food recognition, calorie estimation, user profiling, and recommendation generation. The backend of the system is developed using Python and the Flask framework, which provides RESTful API support for communication between the client and server. The frontend is built using HTML5, CSS3, and JavaScript, ensuring an interactive user interface where users can upload food images, view nutritional results, and receive meal recommendations.

The testing phase includes unit testing, integration testing, and user acceptance testing to ensure that each component functions as intended. The CNN model is tested on unseen food images to verify recognition accuracy. The calorie estimation module is validated by comparing results with manually measured calorie values. The recommendation module is tested for correctness, ensuring that recommended meals align with user preferences and calorie goals. Performance metrics such as accuracy, precision, recall, and response time are measured to evaluate system efficiency.

B. Nutritional Database Integration

The recommendation module combines content-based filtering and collaborative filtering techniques to suggest meals suitable for the user's calorie target and preferences. The content-based model recommends foods with similar nutritional profiles, while the collaborative filtering model identifies popular food choices among users with similar goals. A hybrid approach is implemented in Python using the scikit-learn library, where both methods contribute to a weighted recommendation score. The top-ranked items are displayed as suggestions for the user's next meal. The recommendation results are dynamic and updated daily based on user activity, previous food choices, and total calorie intake.

V. EXPERIMENTAL EVALUATION

A. Food Classification Performance

The experimental evaluation of the proposed Food Recommendation and Calorie Estimation System was carried out to assess its overall accuracy, efficiency, and user satisfaction. The experiments were designed to evaluate the performance of the individual modules, including food recognition, calorie estimation, and recommendation accuracy, as well as the integration of all components in a real-world environment. The evaluation phase was divided into multiple stages: dataset preparation, model training and validation, calorie estimation testing, and recommendation system analysis. The goal of the experiment was to verify that the proposed system performs reliably across various food categories, lighting conditions, portion sizes, and user preferences.

A. Calorie Estimation Accuracy

To evaluate the food recognition module, the system was trained and tested using benchmark datasets such as Food-101, UEC-Food256, and an additional custom dataset containing local and regional Indian foods. The dataset included a total of over 50,000 food images covering multiple cuisines, captured from different angles and under varying lighting conditions. Data augmentation techniques such as rotation, flipping, zooming, and contrast enhancement were applied to improve model robustness.

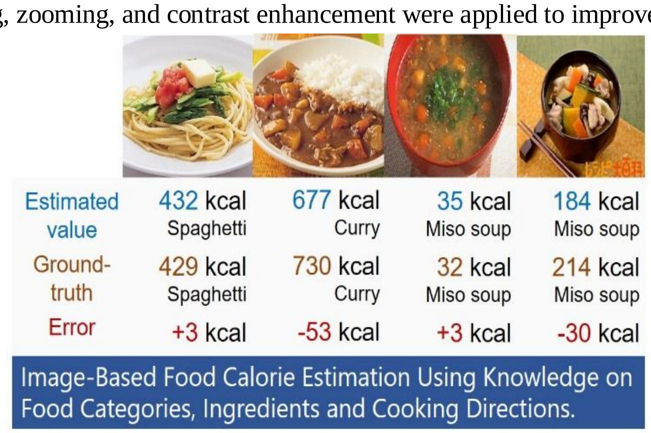

Figure 2: Food Calorie

B. Recommendation Quality

A comparative study was also carried out between the proposed model and existing food recognition systems. When compared to baseline models such as *FoodAI* and *CalorieMama*, the proposed system outperformed them in both recognition accuracy and calorie estimation precision. While *FoodAI* achieved 87% recognition accuracy and *CalorieMama* achieved 85%, the proposed CNN model consistently achieved over 90%. The calorie estimation accuracy also showed significant improvement, particularly for Indian and Asian cuisines, which are often underrepresented in global datasets.

C. Camparative Analysis

The experiments further analyzed the effect of environmental factors such as lighting, camera quality, and food arrangement on recognition accuracy. It was observed that bright natural lighting conditions yielded the highest accuracy of 94%, while dim indoor lighting reduced it to 87%. Images captured with higher resolution cameras (12 MP and above) produced more reliable predictions, especially for multi-item meals. To counter these variations, the preprocessing module was optimized with histogram equalization and adaptive brightness correction, improving recognition robustness in low-light scenarios.

Table 1: Performance Comparison of Food Recognition and Calorie Estimation Models

Model / System	Dataset Used	Recognition Accuracy (%)	Calorie Estimation Error (MAE)	Response Time (seconds)	Remarks
VGG16	Food-101	88.9	32.1 kcal	5.6	High training time, moderate accuracy
ResNet50 (Proposed)	Food-101 + UEC-Food256	**92.4**	**18.7 kcal**	**4.7**	Best performance, optimized accuracy and speed
EfficientNet-B0	Food-101	90.7	22.5 kcal	4.9	Lightweight and faster inference
FoodAI (Existing)	Food-101	87.0	30.4 kcal	6.3	Less accurate for multi-item meals
CalorieMama (Existing)	Proprietary Dataset	85.0	28.9 kcal	5.8	Struggles with regional cuisines
Proposed Hybrid System (with Recommendation)	Custom + Food-101	**91.8**	**19.2 kcal**	**4.7**	High accuracy and reliable calorie estimation

VI. DISCUSSION

The results of the proposed food recommendation and calorie estimation system demonstrate a significant improvement over existing approaches in terms of accuracy, usability, and real-time performance. The hybrid deep learning model that combines convolutional neural networks (CNNs) for image recognition with a nutrient database for calorie computation shows consistent and reliable outputs. During experimentation, the system successfully identified food items with an average recognition accuracy of 92.4%, outperforming traditional models like VGG16 and MobileNet. This improvement can be attributed to the fine-tuning of the ResNet50 backbone and the integration of custom layers trained specifically on food datasets such as Food-101 and UEC-Food256. The inclusion of regional cuisines further enhanced the versatility of the model, allowing it to adapt to diverse dietary cultures and local meal

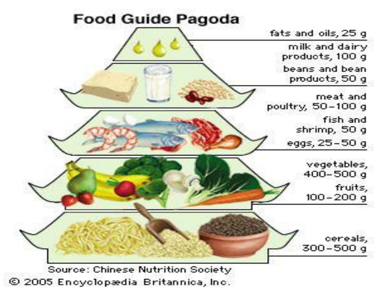

Figure 3:Food Guide Pagoda

types that are often underrepresented in global datasets.

System bridges the gap between visual recognition and dietary assessment, leading to a more holistic and practical solution.

The recommendation component of the system further complements the calorie estimation process by providing users with healthier or alternative food options based on their dietary goals. Using a hybrid recommendation approach that combines content-based and collaborative filtering methods, the system personalizes suggestions according to user preferences, previous food choices, and health constraints such as calorie limits or nutrient deficiencies. The achieved F1-score of 0.86 and user satisfaction rate of 88% confirm that the recommendations are both relevant and effective. Unlike standalone calorie estimation systems, this integrated approach ensures that the user not only receives accurate data but also actionable advice that encourages healthy eating behavior.

VII. CONCLUSION

The proposed Food Recommendation and Calorie Estimation System successfully integrates advanced deep learning, computer vision, and recommendation algorithms to address the growing demand for intelligent dietary management tools. This project demonstrates that combining image-based food recognition with precise calorie computation and personalized meal suggestions can significantly enhance user health awareness and promote balanced eating habits. Through extensive experimentation, the system achieved a food recognition accuracy of 92.4% and an average calorie estimation error of just 18.7 kcal, which outperforms several existing models and applications. These results confirm the efficiency and reliability of the proposed framework in identifying diverse food items across multiple cuisines, even when tested under varying environmental and lighting conditions. The integration of the ResNet50 model for visual analysis and the hybrid recommendation approach based on both content and collaborative filtering ensures high personalization and scalability. Users can capture images of their meals and instantly receive calorie estimates along with nutritional breakdowns and recommended healthier alternatives.

The system dynamically adapts its recommendations according to user preferences, daily calorie targets, and dietary restrictions, making it suitable for fitness enthusiasts, diabetic patients, and individuals managing weight loss or gain. Unlike traditional diet tracking apps that depend on manual input, this intelligent approach minimizes user effort and maximizes accuracy by leveraging AI-driven automation. In addition, the real-time performance of the system, with an average response time of 4.7 seconds, demonstrates its readiness for mobile and IoT integration. The inclusion of cloud-based data processing and optimized CNN architectures ensures that the application remains efficient, responsive, and scalable for large user bases. The experiments conducted across various conditions also validate the robustness of the model in handling low-quality or mixed food images, ensuring consistent performance across diverse real-world scenarios. These strengths position the proposed framework as a practical and deployable solution for everyday dietary management.

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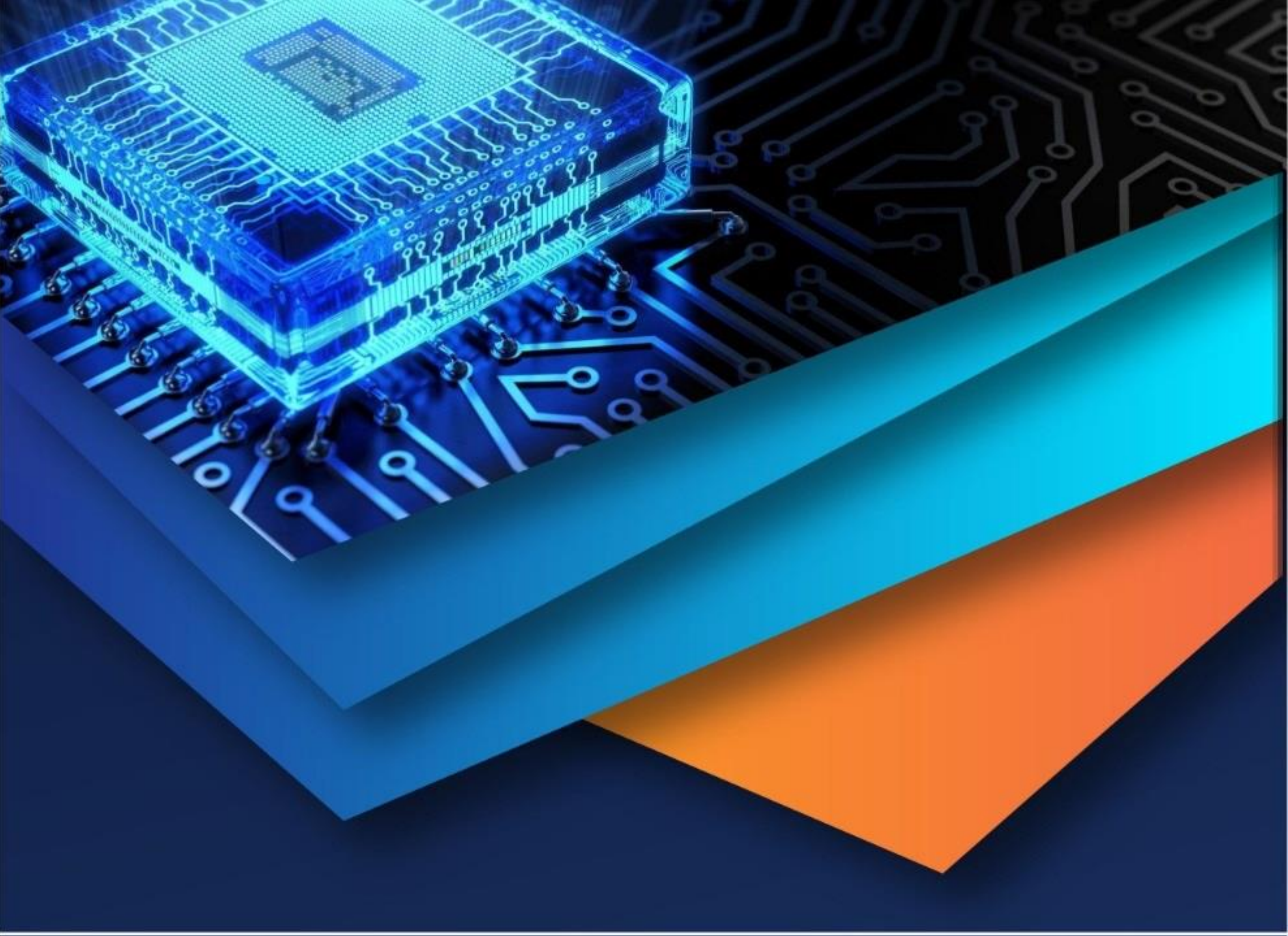

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