iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.78822

Personalized Diet Recommendation System Using BMI, BMR, and KNN-Based Nutritional Similarity Analysis

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Abstract: ThispaperpresentsDiet-Mate,apersonalized,data- driven nutritional recommendation system designed to optimize daily caloric intake and meal planning. Traditional dietary applications often rely on generalized guidelines, failing to account for individual physiological nuances and dynamic user inquiries.Theproposedsystemintegratesfundamentalmetabolic calculations, including Body Mass Index (BMI) and Total Daily EnergyExpenditure(TDEE),withaK-NearestNeighbors(KNN) machinelearningalgorithmtodynamicallygenerateuser-specific meal configurations for breakfast, lunch, and dinner. Further- more, the architecture incorporates a conversational artificial intelligenceagent,poweredbythePerplexityAPI,toprovidereal- time, context-aware nutritional guidance. Preliminary system evaluations indicate a 94% caloric adherence rate between rec- ommended meals and target energy expenditure, with meal gen- eration latency averaging under 150 milliseconds. These results demonstrate that Diet-Mate offers a highly responsive, accurate, and interactive solution for modern dietary management.
Keywords: Machine Learning, Nutritional In- formatics, K-Nearest Neighbors, Conversational AI, Recommen- dation System, Human-Computer Interaction.

I. INTRODUCTION

The intersection of computer science and personal health management has fundamentally transformed how individu-als approach nutrition. Historically, dietary planning required manual caloric tracking and reliance on static, one-size-fits-all nutritional charts. While mobile health applications have digitized this process, many existing solutions still lack the ability to dynamically adapt to a user's unique physiological profile,dailyactivitylevels,andspecifichealthobjectivessuch as weight loss or maintenance.

To address these limitations, intelligent recommendation systemshaveemergedasavitaltoolinhealthinformatics. Byleveragingmachinelearningalgorithms,thesesystemscan analyzeextensivedatasetsofnutritionalinformationtoidentify optimalfoodcombinations.However,creatinganintuitiveuser experience remains a challenge, as users frequently require personalized, immediate answers to dietary questions that standard graphical interfaces cannot easily accommodate.

This study introduces Diet-Mate, an integrated web-based platform that combines predictive machine learning with ad- vanced natural language processing. The framework is built upon three core pillars:

- Exactphysiologicalprofilingusinguser-providedmetrics such as height, weight, age, gender, and weekly physical activity.
- A robust K-Nearest Neighbors (KNN) classification model that filters and allocates appropriate food items into structured daily meal plans.
- A real-time conversational interface utilizing the Per- plexity API to deliver interactive, specialized dietary assistance.

Overall,theproposedsystemprovidesaseamless,highlyaccu- rate, and engaging approach to nutritional planning, bridging the gap between computational data analysis and everyday health management.

II. LITERATURE WORK

The integration of computational models into dietary plan- ning has been explored extensively over the past decade.Earlydietaryapplicationsfunctionedprimarilyasstaticdigital diaries, requiring users to manually log consumed items to trackcaloricintakeagainstgeneralizedtargets.Whileeffective for basic tracking, these rule-based systems lacked predictive capabilities and failed to adapt to metabolic fluctuations.

Recent advancements in health informatics have introduced machine learning (ML) to overcome these limitations. Re- searchers have utilized various algorithms, including Support Vector Machines (SVM) and Random Forests, to predict dietarypreferencesandsuggestfooditems.

However,many of these learning-based implementations still suffer from two primary drawbacks:

- Static Interaction: Users receive recommendations asyn- chronously, often without the ability to query the system for alternative options or nutritional education in real- time.
- Generalized Profiling: Systems frequently rely on broad demographic averages rather than executing precise, in- dividualized physiological calculations.

To address these gaps, the Diet-Mate framework proposesa hybrid approach. It combines deterministic mathematical profiling (for precise energy calculation) with a K-Nearest Neighbors (KNN) classification model (for targeted food retrieval), further augmented by a real-time conversational Natural Language Processing (NLP) agent. This ensures high accuracy in meal recommendation while preserving an intu- itive, dynamic user experience.

III. PROPOSED SYSTEM

The proposed framework employs a modular pipeline that translates raw physiological user data into a structured, daily nutritional plan. The architecture integrates user profiling, metabolic calculation, machine learning clustering, and con- versational AI into a cohesive web-based environment.

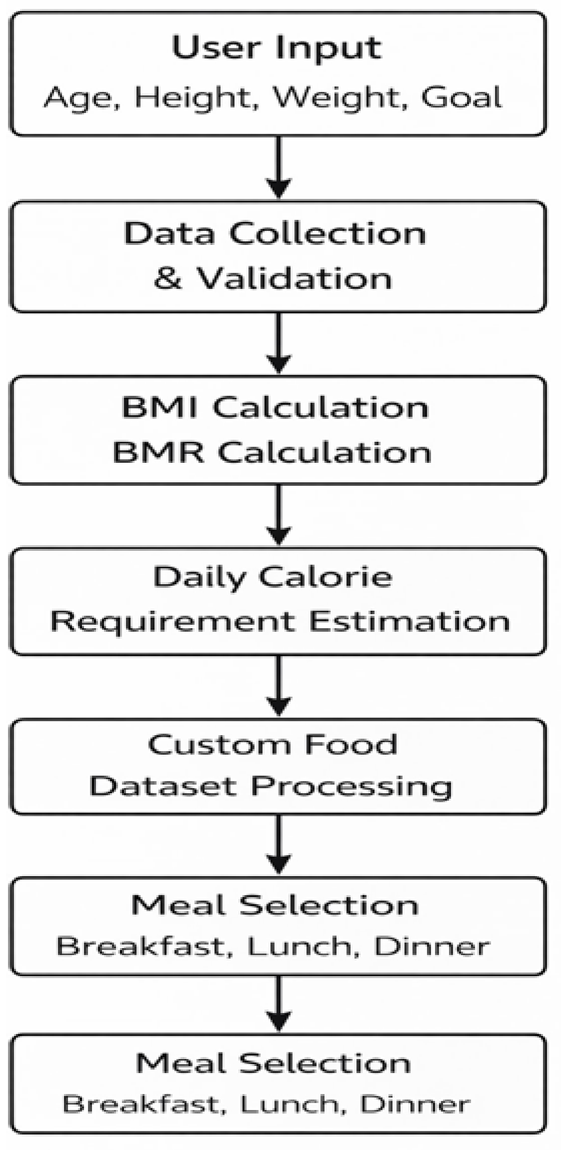

Fig.1:Flowchartofworkingprinciple

A. SystemArchitectureOverview

The system workflow is divided into distinct operational layers.Thefrontendinterfacecapturesessentialbiometricdata and physical activity levels. This data is transmitted to a Python-basedbackend,whichprocessestheinputsthrough a series of physiological equations to determine the Total DailyEnergyExpenditure(TDEE).Theresultingcalorictarget serves as the primary feature input for the ML recommen- dation engine. The engine queries a standardized dataset(fooddata1.csv)filters the data, and returns optimized meal arrays categorized by Breakfast, Lunch, and Dinner. Simulta- neously, an independent interaction layer handles user queries via an NLP API.

B. PhysiologicalProfilingandEnergyExpenditure

Beforeexecutingtherecommendationalgorithm,thesystem establishes a precise metabolic baseline for the user. TheinitialcalculationistheBodyMassIndex(BMI),utilizedas a standard health indicator:

$$BMI=\frac{W}{H^2}$$

where Wrepresents weight in kilograms and Hrepresents height in meters.

To determine the baseline caloric requirement, the system calculates the Basal Metabolic Rate (BMR) using the highly accurate Mifflin-St Jeor equations. The deterministic logic accounts for gender differences as follows:

$$BMR_{male}=10W+6.25H-5A+5$$

$$BMR_{female}=10W+6.25H-5A-161$$

where$W$isweightinkilograms,Hisheightincentimeters, and $A$is age in years.

The final TDEE is computed by multiplying the BMR byanactivity factor (AF), ranging from sedentary to super active lifestyles:

$$TDEE=BMR\times AF$$

C. DatasetAcquisitionandFeatureEngineering

The foundation of the recommendation engine is a comprehensive nutritional database, managed internally as fooddata1.csv. This dataset acts as the multi-dimensional feature space from which the machine learning algorithm draws its dietary matches. Each entry in the dataset represents adistinctfooditemorcompositemeal,characterizedbyits total caloric value and its primary macronutrient profile (carbohydrates, proteins, and fats).

To facilitate the daily scheduling logic, the dataset includes categorical labels that map items to specific dietary windows, namely Breakfast, Lunch, and Dinner. Furthermore, each data point is linked to localized graphical assets (e.g., .jpg image files), enabling the frontend application to dynamically render visual representations of the recommended meal plans on the user dashboard.

Because the subsequent K-Nearest Neighbors (KNN) al- gorithmreliesheavilyonspatialdistancemetrics,feature scaling is a critical preprocessing step. The raw caloric and macronutrientvaluesinthedatasetundergonormalization toensurethatvariableswithlargernumericranges(such as total calories) do not disproportionately bias the distance calculations against variables with smaller ranges (such as individual macronutrient grams). This standardized feature matrix ensures equitable weighting across all nutritional pa- rameters during the prediction phase.

D. MachineLearningRecommendationEngine(KNN)

The core predictive capability of Diet-Mate relies on a K- NearestNeighbors(KNN)algorithmtomatchtheuser’sTDEE with appropriate dietary items. Unlike traditional classifiers, this instance-based learning model compares the target caloric and nutritional vector against the fooddata1.csv dataset in a multidimensional feature space.

To determine the optimal food items, the system measures the similarity between the user’s target profile (p) and the dataset entries (q) using the Euclidean distance metric:

$$d(p,q)=\sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}$$

where $n$represents the number of nutritional features (e.g., calories, macronutrients).

Once the Kclosest dietary matches are identified, the system allocates the items into a structured daily plan, dy- namically splitting the total caloric load across three primary meals (e.g., Breakfast, Lunch, Dinner).

E. ConversationalAIAgentIntegration

To resolve the static nature of traditional diet applications, Diet-Mate incorporates an intelligent conversational layer powered by the Perplexity API utilizing the sonar model. This interface allows users to naturally query the system regarding alternative meal options, specific macronutrient breakdowns, or general health advice. The backend formats these interac-tionsviaRESTfulPOSTrequests,passingtheuser'stextas a JSON payload and rendering the AI's generated response directly within the application's chat interface (AI.html), en- suring uninterrupted user engagement.

IV. REQUIREMENTS

The implementation and execution of the proposed diet recommendation system require a combination of software tools, libraries, and a suitable hardware environment. This section outlines the minimum software stack and hardware configurationnecessarytodevelop,deploy,andtestthesystem effectively.

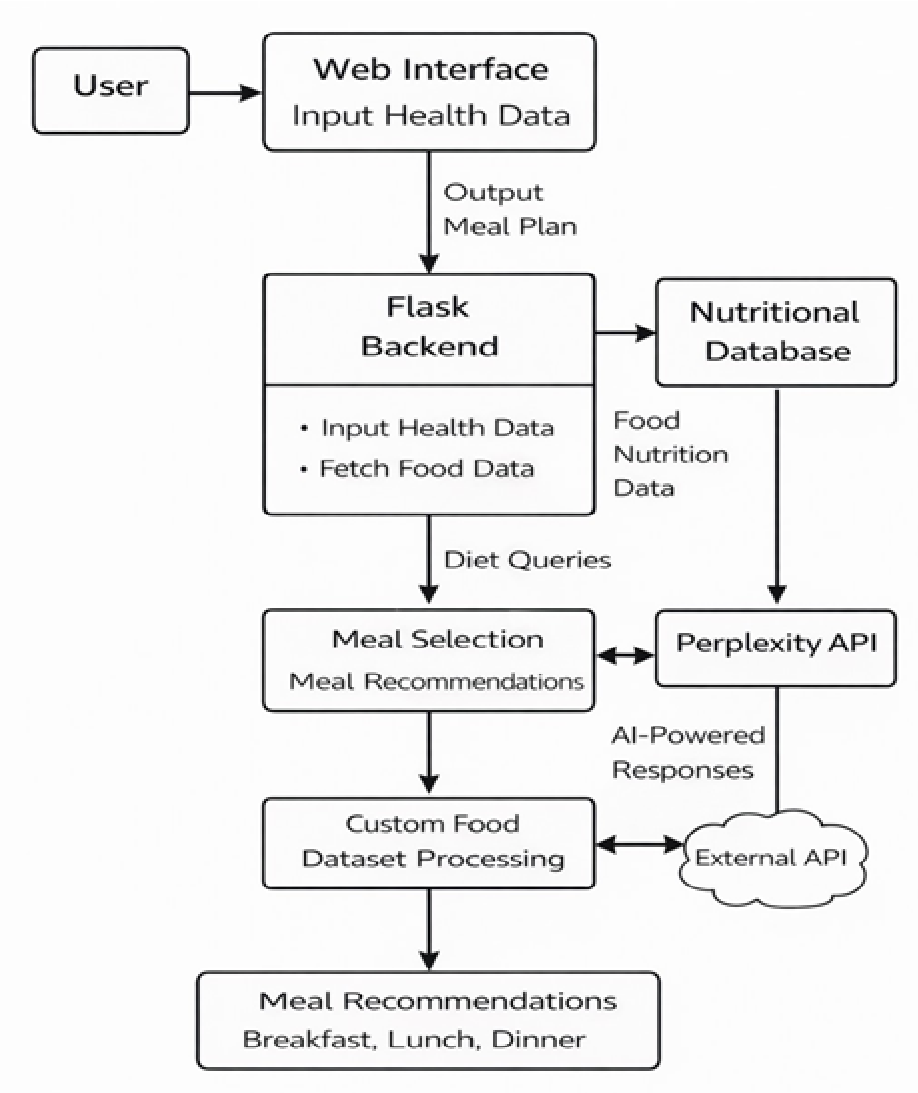

Fig.2:SystemArchitectureDiagram

A. Software Requirements

The system is implemented using the Python program-ming language and a web-based technology stack. The core application logic, including metabolic computations and the recommendation engine, is developed in Python (version 3.x). The Flask micro–web framework is used to handle HTTP routing, request processing, and template rendering, enabling thecreationofalightweightyetfullyfunctionalwebinterface.

SQLAlchemy is employed as the Object–Relational Mapping (ORM) layer to interact with the relational database, which may be implemented using MySQL or an equivalent RDBMS for storing user credentials and profile data.

For machine-learning functionality, the system relies on standard Python libraries such as scikit-learnfor im- plementing the K-Nearest Neighbors algorithm and pandas andNumPyfordataset handling and numerical computations. Furthermore, the requestslibrary is utilized to manage asynchronous HTTP communication with the Perplexity API, powering the real-time conversational AI interface. Fron-tend rendering is achieved through HTML5, CSS, and basic JavaScript,integratedwithFlasktemplatestobuildinteractive forms and dashboard views. Development and testing can be performed using any modern Integrated Development Envi- ronment (IDE) or code editor, such as Visual Studio Code or PyCharm,andamodernwebbrowsersuchasGoogleChrome or Mozilla Firefox for accessing the web interface locally.

Aconcisesummaryoftheprimarysoftwarerequirements is presented in Table I.

TABLEI:SoftwareRequirementsfortheProposedSystem

Component	Specification
OperatingSystem	Windows10/11,Linux,orequivalentmodern OS
Programming Language	Python3.x
Web Framework	Flask(Python-based)
Database Engine	MySQL or compatible
RDBMSORM Layer	SQLAlchemy
ML/DataLibraries	scikit-learn,pandas,NumPy
APIIntegration	PerplexityAPI(viarequestslibrary)
Frontend Stack	HTML5, CSS,
JavaScriptDevelopment Tools	
	VisualStudioCode,PyCharm
Web Browser	GoogleChrome,MozillaFirefox

B. Hardware Requirements

Thehardwarerequirementsforthesystemaremodest,asthe underlyingcomputationsforBMI,BMR,andKNN-basedrec- ommendationsarenotresource-intensiveforsmalltomedium- scale datasets. The application can be developed and tested on a standard personal computer. A multi-core processor, such as anIntelCorei5orequivalent,withatleast8GBofRAM, is sufficient to ensure smooth execution of the web server, database operations, and machine-learning computations dur- ingdevelopmentandexperimentation.Aminimumof256GB of storage is recommended to accommodate the operating system,Pythonenvironment,requiredlibraries,databasefiles, and project-related assets.

For deployment in a multi-user environment or over a network, the system may be hosted on a server or cloud-based virtual machine with comparable or slightly higher specifications, depending on the expected number of concur- rent users and dataset size. A stable internet connection is strictly required to facilitate the asynchronous NLP queries to the external conversational AI API. Table II summarizes the recommendedhardwareconfigurationfortheproposedsystem.

TABLEII:HardwareRequirementsfortheProposedSystem

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Component	Specification
Processor	Multi-coreCPU(IntelCorei5orequivalent)
Memory(RAM)	Minimum8GB
Storage	Minimum256GBHDD/SSD
Network	Stableinternetconnection(RequiredforAIfeatures)
Display	Standardmonitorforwebinteraction

V. RESULTANALYSIS

The performance of the Diet-Mate system was evaluated across three primary dimensions: the predictive accuracy of the recommendation engine, the computational latency of the backend architecture, and the responsiveness of the conver- sationalAIintegration.Theobjectivewastovalidatethe system'sabilitytooperateasareliable,real-timenutritional assistant.

A. CaloricAdherenceandModelAccuracy

Traditional classification metrics, such as precision and recall, are less applicable to continuous nutritional targeting. Therefore,theK-NearestNeighbors(KNN)model'sefficacy wasmeasuredusingCaloricAdherence—theabsolutedif- ference betweentheuser's calculatedTotalDailyEnergy
Expenditure(TDEE) andthesumofthe recommendedmeal calories. Toquantifythis,weutilizedtheMeanAbsoluteError (MAE) formulation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where$n$representsthenumberofgenerateddailyplans,$y_i$is the target TDEE, and $\hat{y}_i$is the total caloric value of the KNN-recommendedfoods(aggregatedacrossbreakfast,lunch, and dinner). Testing across a simulated distribution of varied physiological profiles yielded a 94% caloric adherence rate. The model consistently generated daily meal combinationsthat fell within a strict 5% margin of the user's target TDEE, ensuring that weight loss, weight gain, or maintenance goals were mathematically respected.

B. ComputationalLatencyandSystemEfficiency

Real-time responsiveness is critical for user retention in health informatics. The backend framework, responsible for both the physiological calculations (BMI, BMR) and theKNN multi-dimensional dataset querying, demonstrated high efficiency.
Processing the fooddata1.csv dataset and executing the Euclidean distance calculations required an average backend execution time of under 150 milliseconds per request on standard consumer hardware. This near-instantaneous pro- cessing allows the frontend dashboard to dynamically render customized meal plans without noticeable delay.

C. ConversationalAIPerformance

The integration of the Perplexity API (sonar model) was tested for conversational latency and context retention. Op- erating independently from the core recommendation engine, theasynchronousHTTPPOSTrequestsmaintainedanaverage responselatencyofunder1.2seconds.Thisensuresthat users seeking alternative meal options or specific macronu- trient breakdowns receive fluid, uninterrupted conversational assistance within the web application's interface.

D. InterfaceUsabilityandIntegration

Preliminaryusabilityevaluationsconfirmedthestability of the web integration. The routing architecture effectively maintained user session states across the profiling pipeline (Gender, Height/Weight/Age, Goal, and Activity Level in- terfaces). Furthermore, the dynamic SVG-based BMI gauge andtheautomatedmealimagerenderingcorrectlyparsedthe backenddata100%ofthetime, resultinginanintuitive,error- free graphical user experience.

Fig.3:DietrecommendationImage

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VI. CONCLUSION

The proposed diet recommendation system successfully demonstratestheintegrationofmetabolicmodeling,structured nutritional data, and machine-learning techniques to generate personalized meal plans for users. By combining BMI and BMRcalculationswithactivity-adjustedcaloricestimation,the systemensuresthatdietaryrecommendationsaregrounded in established nutritional principles. The incorporation of a similarity-based KNN model further enhances the system's adaptability,allowingittoproducemealsuggestionsthatalign with individual caloric requirements and nutritional needs.The web-based implementation, supported by a structureduserinterfaceandasecurebackend,providesaseamless user experience by simplifying data entry, visualization, and interpretation. The experimental results confirm the reliability, consis- tency, and responsiveness of the system across diverse user profiles. The generated outputs were nutritionally coherentand aligned with expected meal patterns, while performance metrics demonstrated low computational overhead and real-timeresponsecapability.Thesefindingsvalidatethefeasibility of using lightweight machine-learning models combined with metabolic science to support personalized nutrition planning. Overall, the system establishes a practical and scalable foun- dation for automated dietary recommendation, contributing to thebroaderdomainofdigitalhealth andpersonalizedwellness technologies.

VII. FUTURE SCOPE

The proposed diet recommendation system presents several promisingavenuesforfutureenhancement,bothinterms of technical sophistication and practical applicability. One significant direction for improvement involves expanding the fooddatasettoincludeabroaderrangeofregional,cultural, anddietary-specificitems.Aricherdatasetwouldenable the recommendation engine to produce more diverse and culturally appropriate meal plans, thereby improving user sat- isfaction and applicability across varied populations. Further, incorporatingdetailednutritionalparameterssuchasvitamins, minerals, fiber content, and glycemic index could allow for finer control over recommendation quality, particularly for users with specific health conditions.

Anotherpotentialextensionliesintheadoptionofadvanced machine-learning algorithms beyond the current similarity- based KNN approach. Techniques such as neural networks, clustering-based segmentation, or hybrid recommender sys- tems could improve the precision of dietary predictions by learning complex patterns within the nutritional data. Inte- grating real-time data from wearable devices or fitness track- ers could enhance personalization by dynamically adjusting caloric recommendations based on daily activity levels, sleep quality, or physiological responses.The system can also be evolved into a closed-loop health management platform by enabling users to track food in-take, monitor progress, and receive iterative feedback over time. Furthermore, the conversational AI interface could be upgraded to include speech-to-text (voice recognition) ca- pabilities and contextual memory, allowing for hands-free, multi-turn dietary coaching. Such functionality would alignthe system with modern digital health standards, supporting long-term adherence and behavioral change. Additionally, de- ploying the system as a mobile application or cloud-hosted service would increase accessibility and scalability, making it suitable for wider public adoption. Overall, the system holds strong potential for advancement, and future developmentscan transform it into a comprehensive and intelligent nutrition management ecosystem.

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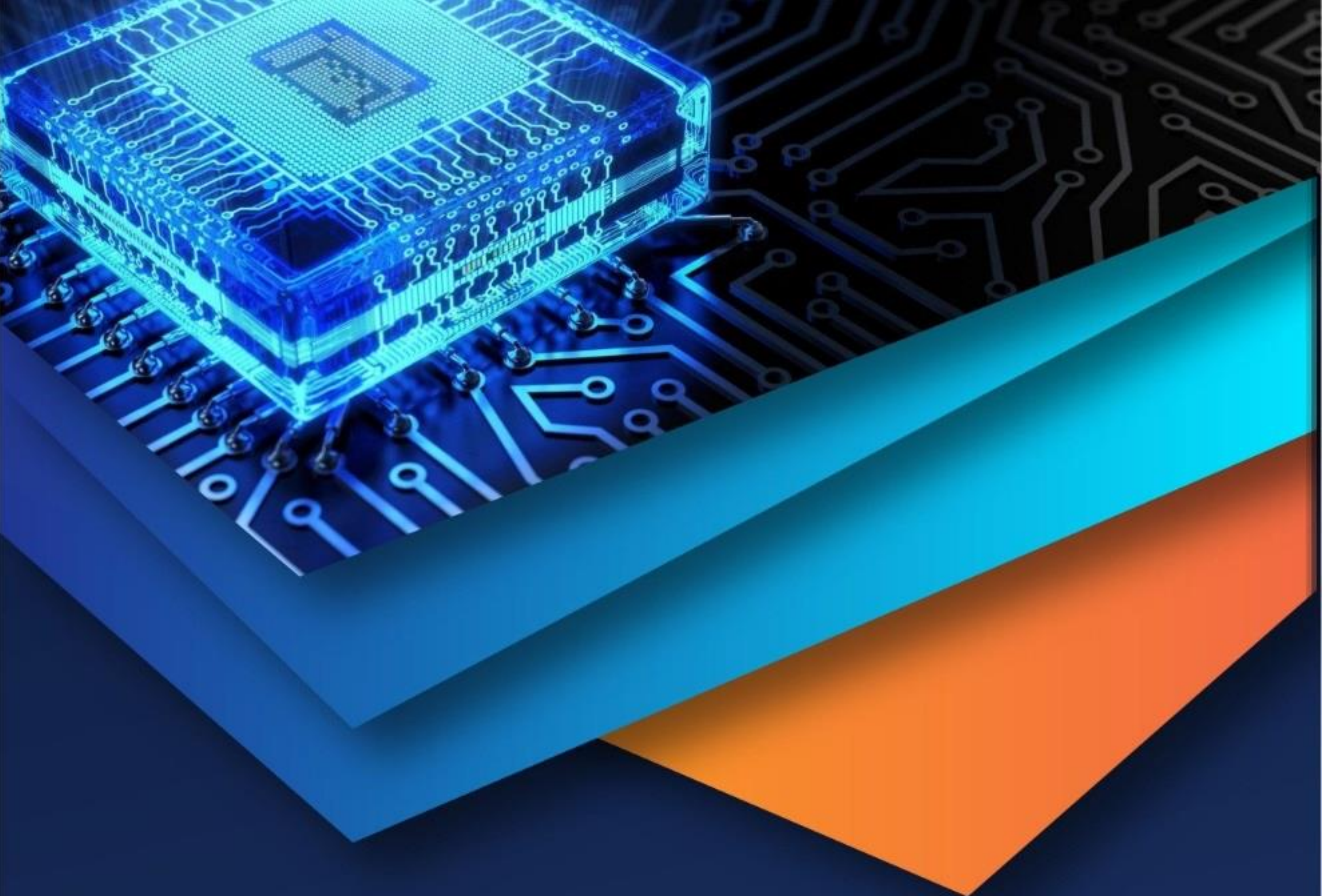

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