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SWIPE N’ BITE: Food Discovery and Social Matching Platform and AI-Driven Recommendations

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Abstract: Food discovery platforms today often overwhelm users with extensive listings, reviews, and manual filtering mechanisms, leading to decision fatigue and reduced engagement. Also, most food recommendation systems don't use social context or real-time user intent. This study introduces Swipe N' Bite, a smart food discovery and recommendation platform that features Food Cupid, a new food-interest-based social matching mechanism, along with swipe-based preference learning and machine learning-driven personalization. The system learns about users' unspoken preferences through swipe interactions, makes individualized food suggestions using a content-based similarity model, and allows for real-time social matching when several users show interest in the same food item within a short time frame. To make user interaction even better, an AI food assistant is added to help people find and ask about food in a conversational way. The platform is a web app built with modern frontend technologies and an architecture that can grow with it. Compared to traditional list-based food platforms, experimental testing and qualitative analysis show that more users are interested, it takes less time to find things, and the recommendations are more relevant.
Keywords: Food Discovery, Recommendation Systems, Swipe-Based Interaction, Social Matching, Food Cupid, Machine Learning, Conversational AI

I. INTRODUCTION

The quick rise of digital food platforms has changed how people discover new restaurants and types of food. Most food discovery apps that are popular use keyword searches, ratings, reviews, and list-based browsing to help users make decisions. These methods work well on a large scale, but they often cause choice overload, which means users have to deal with a lot of information before they make a choice. Because of this, users often get tired of making decisions, which makes them disengage or make bad choices.

New progress in human-centered design has shown that implicit feedback mechanisms like swipe-based interactions can greatly lower cognitive load while still getting useful information about user preferences. With swipe-driven interfaces, people can show that they do or do not want something easily. This lets systems learn what people like and don't like by tracking their actions instead of relying on ratings. Most current food platforms, on the other hand, don't use this interaction model enough and don't take advantage of the strong preference signals that come from these kinds of interactions. In parallel, social aspects of food discovery, such as shared interests, group exploration, and mutual recommendations remain largely unexplored in current systems. While social matching applications exist, they are typically profile-centric and not designed around shared contextual interests such as food. There is a notable absence of systems that enable users to connect based on real-time, mutual interest in specific food items, despite food being a highly social and experiential domain. To address these gaps, this research proposes Swipe N’ Bite, a food discovery platform that integrates swipe-based preference learning with Food Cupid, a novel social matching mechanism that connects users who express mutual interest in the same food item within a defined temporal window. Unlike traditional social or dating platforms, Food Cupid is interest-first rather than profile-first, emphasizing shared food preferences over demographic attributes. Additionally, the platform incorporates a machine learning-based recommendation engine that suggests similar food items based on saved preferences, as well as a Gemini-powered AI food assistant that enables conversational food exploration.

II. LITERATURE REVIEW

The issue of food discovery and recommendation has been extensively examined in various fields, including recommender systems, human-computer interaction, and social computing. Most traditional food recommendation platforms depend on clear user feedback methods like ratings, reviews, and search queries.

These methods have worked well for bringing together people's preferences, but they often have problems with not enough data, slow feedback, and users getting tired of having to enter the same information over and over. Because food choices are very personal and based on the situation, it is still hard to accurately capture what a user wants.

Early food recommendation systems were based on collaborative filtering, which means that recommendations were made based on how similar users or items were to each other. Collaborative filtering works well when there is a lot of historical data, but it has trouble with cold-start problems for new users and items. To get around these problems, content-based recommendation systems were made that used food characteristics like cuisine type, ingredients, dietary preferences, and meal categories. These methods showed better personalization, but they often couldn't change to fit changing user preferences and behavior in real time.

Recent research has underscored the significance of implicit feedback in recommendation systems. Clicks, dwell time, saves, and interaction patterns are all examples of implicit signals that show preferences in a way that is easy and low-effort. Swipe-based interaction models, which are popular on social and media discovery sites, have gotten a lot of attention because they can quickly capture binary preference signals. Studies in interaction design indicate that swipe gestures diminish cognitive load and decision friction, facilitating expedited preference expression while preserving high-quality behavioral data. Nonetheless, the utilization of swipe-based preference learning in food discovery systems is still constrained in the current literature. Most of the research that has been done so far is on preference modeling, recommendation accuracy, and user engagement. Nonetheless, the amalgamation of implicit preference learning, real-time social matching, and conversational AI in food discovery platforms is still constrained.

A. Systems for Recommending Food

Collaborative filtering techniques were a big part of early food recommendation systems. These techniques used similarities between users or items to guess what users would like [1]. These systems work well on large platforms, but they have problems with cold starts and sparse data, especially for new users and food items that have just been added [2]. To address these challenges, content-based recommendation methodologies were introduced, leveraging food attributes such as ingredients, cuisine type, dietary tags, and meal categories to produce tailored suggestions [3]. Recent research has investigated hybrid recommendation models that integrate collaborative and content-based filtering to enhance recommendation relevance [4]. Even though these models are more accurate, they usually rely on user ratings or reviews, which take a lot of work on the part of the user. Studies on user behavior modeling show that clear feedback systems can make people less likely to participate and slow down the process of capturing preferences [5]. Consequently, there is an increasing interest in utilizing implicit feedback signals such as clicks, saves, and interaction patterns for preference learning. There has been little research on using implicit feedback mechanisms in food discovery systems, though.

B. Interaction Based on Swiping and Implicit Preference Learning

People like swipe-based interaction models because they can quickly and easily capture binary user preferences with little mental effort. Research in human-computer interaction shows that swipe gestures make it easier to make decisions and get people more involved than traditional list-based interfaces [6]. Swipe-right and swipe-left interactions have been successfully used in binary feedback systems for media recommendation and social discovery platforms [7]. Studies indicate that swipe-based preference signals can be efficiently converted into user preference vectors for recommendation modeling [8]. These systems that are based on interactions let users change their preferences in real time without having to give explicit ratings. Even though these are good things, swipe-based interaction models aren't used very often on food discovery platforms. Most current food apps still use manual search, filters, and reviews, which means they miss out on the chance to use swipe-based implicit preference learning to make the app more personal.

C. Conversational AI and Social Matching in Recommendation Systems

Traditionally, social matching systems use demographic information, interests, or questionnaires to find profiles that are compatible with each other [9]. Such systems work well for dating and professional networking, but they often miss out on shared interests that are relevant to the situation and happening right now. Studies in social computing indicate that aligning users according to situational preferences can facilitate more significant interactions and increased engagement [10].

Nevertheless, food-oriented social matching systems remain significantly underexplored in the current literature, despite food being an inherently social endeavor. Conversational AI has also become an important part of modern recommendation systems. Users can naturally say what they like through dialogue with chatbot-based recommendation frameworks.

This makes the system easier to use and more engaging [11]. Recent improvements in large language models have made it even easier for conversational agents to give personalized and contextual recommendations [12].

However, the majority of conversational food assistants function independently of user behavioral data and do not incorporate implicit interaction signals, such as swipe preferences or saved items. In general, current research looks at food recommendations, swipe-based interactions, social matching, and conversational AI as separate issues. There are no single food discovery platforms that combine implicit preference learning, machine learning driven recommendations, and real-time interest-based social matching. The proposed Swipe N' Bite system fills this gap by adding Food Cupid, a temporary social matching system that connects users based on their shared, real-time food preferences.

Study	Key Findings
[1]	Reliance on explicit ratings
[3]	Limited real-time preference modeling
[6]	Swipe-based systems lack food domain integration
[9]	Absence of interest-based social matching

Table I. Table showing Key Findings

III. METHODOLOGY

The proposed system follows a multi-phase methodology that integrates swipe-based preference learning, machine learning-driven recommendation, and real-time interest-based social matching within a unified food discovery platform. The methodology is designed to capture implicit user preferences, generate personalized food recommendations, and facilitate social interaction based on shared food interests.

The overall workflow of the system is divided into four primary phases: food discovery and preference capture, social matching through Food Cupid, personalized recommendation generation, and conversational assistance using an AI chatbot.

A. Swipe-Based Food Discovery and Preference Capture

The first phase of the system focuses on food discovery using a swipe-based interaction model. Each food item is shown to users as a separate card that has information like an image of the food, the name of the dish, the name of the restaurant, the location, and links to other sources. Users can interact with these cards by swiping left or right to show interest or disinterest.

Every swipe is seen as a sign of feedback. When a user swipes right, the food item goes into their Eat List. When they swipe left, it is recorded as a negative preference signal. As illustrated in Fig. 1, this interaction mechanism enables users to make quick decisions while minimizing cognitive effort. This method reduces the amount of work users have to do while still allowing them to learn about their preferences over time. All interaction data is logged and kept in the backend database. This is what makes recommendation and matching processes possible.

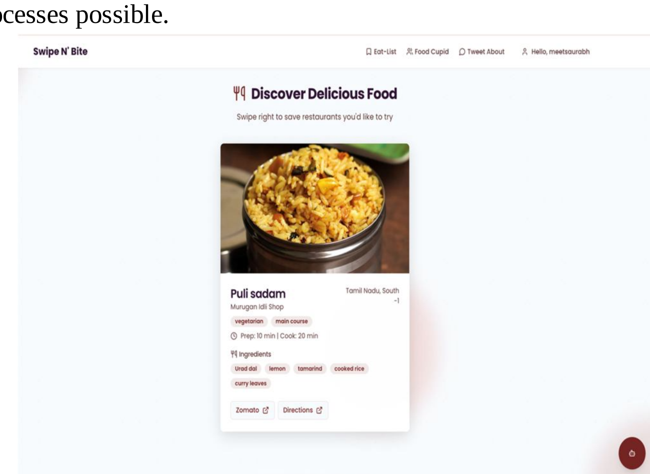

Fig. 1. Swipe-based food discovery interface

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B. Food Cupid: Temporal Food-Interest Social Matching Algorithm

The second phase introduces Food Cupid, a novel social matching mechanism based on temporal mutual food interest. Food Cupid is meant to connect people who are both interested in the same food item within a set amount of time, focusing on shared intent rather than profile similarity. The system saves the food identifier, user identifier, and timestamp when a user swipes right on a food item. A match condition happens when another user swipes right on the same food item within 5 to 10 minutes. When the system sees this condition, it makes a possible match and shows it to both users in the Food Cupid section. The match is only final if both users agree to it in writing.

When both parties agree, a chat interface is turned on so that users can talk to each other. If either user doesn't want to connect, the connection is dropped and no more communication happens. This acceptance-based system makes sure that users agree and cuts down on unwanted interactions. Food Cupid doesn't use demographic data; instead, it only looks at shared, real-time food preferences.

C. Machine Learning-Based Food Recommendation System

The third phase involves generating personalized food recommendations based on the user's saved preferences. A content-based recommendation method is used, which looks at things like cuisine type, ingredients, category, and dietary tags to find foods that are similar to each other. The recommendation engine uses the food items that the user has saved in their Eat List as input. We make feature vectors for each food item and then use similarity scores to find items that are very similar to what the user already likes. As shown in Fig. 2, the recommended food items are displayed in a dedicated "Recommended for You" section on the Eat List page, allowing users to discover similar dishes alongside their saved items. This recommendation system only uses implicit behavioral data, so there is no need for manual ratings or reviews. The model changes automatically as new food items are saved, which lets you keep customizing it over time.

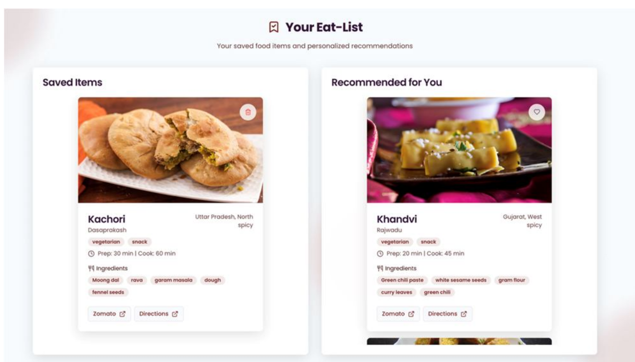

Fig. 2. Eat List with machine learning-based food recommendations

D. Conversational AI Integration Using Gemini API

The final phase integrates a conversational AI food assistant using the Gemini API. The chatbot gives people another way to find food by letting them ask questions in natural language about food, their tastes, dish suggestions, and restaurant suggestions. The AI assistant works with the platform's discovery and recommendation features. Swipe interactions show what people want without them saying it directly, but the chatbot lets users say what they want directly through conversation. This hybrid interaction model makes it easier to find new foods and makes the whole system easier to use. The conversational part is specific to the domain and designed for food discovery situations.

E. System Workflow Summary

The complete workflow begins with swipe-based interaction for food discovery, followed by implicit preference storage. These preferences are used to make personalized food recommendations and to find events that both people are interested in in Food Cupid. At the same time, users can talk to the AI chatbot to narrow down or look into their food options. This integrated approach makes sure that preference learning, recommendation generation, social matching, and conversational assistance all work together smoothly.

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IV. IMPLEMENTATION

The goal of the implementation phase is to create a platform for intelligent food discovery and social matching that works in real time. The system architecture is modular, with separate components for ingesting food data, processing user interactions, modeling preferences, making recommendations, and matching people with similar interests. Each component can be scaled and expanded on its own. The platform is a web-based app that brings together swipe-based interaction, machine learning-driven personalization, and conversational AI into one framework.

The food data ingestion module is in charge of organizing the structured food and restaurant information that the platform uses. A document-based database stores food items, including information about the type of cuisine, the ingredients, the category, dietary tags, the restaurant, and the location. When users interact with the app, swipe actions are recorded in real time along with the user's ID, the food's ID, and the time of the action. These interaction logs are the main source of information for learning preferences, making recommendations, and figuring out how to match people with Food Cupid. All interaction data is stored in a structured way so that it is easy to find and use across all system modules.

The processing module takes care of getting and checking user preferences from their interactions. When a user swipes right, it is seen as positive implicit feedback and the food items are added to their Eat List. When a user swipes left, it is seen as negative preference feedback. To stop duplicate entries and make sure that interaction logs are always the same, basic data validation methods are used. The processed preference data is used to change user-specific preference profiles, which change over time as more interactions happen. This method of using implicit feedback does away with the need for explicit ratings or reviews, making it possible to keep personalizing.

The recommendation module uses a machine learning-based content similarity model to make personalized food suggestions. Feature vectors based on things like cuisine, ingredients, and category are used to represent food items. The system can suggest dishes that are similar to the ones on the Eat List by comparing the similarity scores of the items on the list with other food items that are available. The Eat List page shows recommended items right away, so users can find related food options without having to click around. The recommendation engine changes automatically when new food items are saved, making sure that personalization is always up to date.

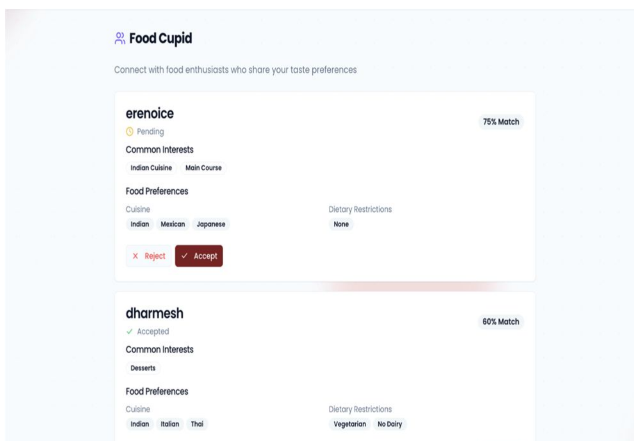

Fig. 3. Food Cupid interest-based social matching interface

Food Cupid is a temporary food-interest matching system that is part of the social matching module. When a user swipes right on a food item, the system looks for other users who have also shown interest in that item in the last 5 to 10 minutes. Upon detecting a valid condition, a potential match is generated and presented to both users, as illustrated in Fig. 3. A match is finalized only upon mutual acceptance, after which a chat interface is enabled. This system makes sure that users agree and cuts down on unwanted interactions while encouraging social connections based on shared food preferences.

The frontend of the app is built with modern web technologies that make it easy to design and use. A card-based swipe interface lets you find food, and dedicated views let you see saved items, recommendations, Food Cupid matches, and chat features. A conversational AI assistant powered by the Gemini API is integrated to support natural language-based food discovery and recommendation queries, as shown in Fig. 4. The chatbot works with the swipe-based system, so users can switch between implicit and explicit conversation exploration.

The backend services handle the logic for storing data, processing interactions, making recommendations, and matching people up with others. The current prototype runs in a local development environment and uses fake datasets to mimic how it would work in the real world. The system architecture, on the other hand, is built to work with cloud platforms like the Google Cloud Platform (GCP) in the future. Cloud deployment will make it possible to scale, allow multiple users to interact in real time, and connect to external APIs.

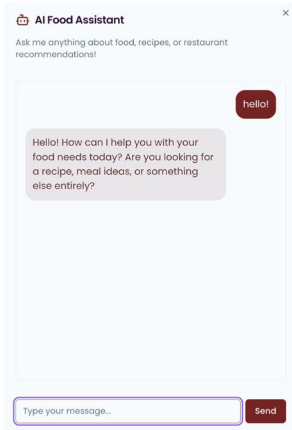

Fig. 4. AI-powered food assistant using Gemini API

During the implementation process, a lot of attention was paid to modular design, lightweight processing, and real-time responsiveness. This was done to make sure that the system stays strong, can be expanded, and can be changed to work with new features like advanced recommendation models and large-scale user deployment.

V. RESULTS AND DISCUSSION

The Swipe N' Bite prototype was successfully developed and evaluated in a controlled environment using simulated real-world food and restaurant data. The platform was tested on its main functional parts, such as swipe-based food discovery, the creation of an Eat List, Food Cupid social matching, machine learning-based recommendations, and conversational interaction with the AI chatbot. We watched how users interacted with the system to see how well it captured their preferences, how relevant its recommendations were, and how it matched people up with others. During the test, users could look through food items using the swipe-based interface and show their preferences by swiping right or left. When you swiped right, food items were added to the Eat List. This was the basis for creating recommendations and modeling preferences. The system always picked up on implicit preferences without needing explicit ratings or reviews. The Eat List changed over time as people used the platform more, showing their individual food preferences across different types of food and cuisines. The recommendation engine was able to find similar food items that matched the user's saved preferences, showing that it was able to adapt to changes in user behavior.

We tested the Food Cupid module by watching how many people were interested in the same thing at the same time. If two users swiped right on the same food item within the 5–10 minute time frame, potential matches were made and shown in the Food Cupid section. The chat interface was only turned on after both people agreed to the match. This mechanism made sure that social interactions only happened when users agreed and had a common interest in food. The matching process worked well and didn't create duplicate or unwanted matches, which proved that the temporal interest-based matching logic worked.

In addition, the conversational AI assistant let people look at food options by asking questions in a natural way. Along with the swipe-based discovery process, users could ask for suggestions for cuisines, dishes, and new foods to try. Users could easily switch between different discovery modes thanks to the coexistence of swipe-based implicit interaction and chatbot-based explicit interaction.

The results show that combining swipe-based preference learning with machine learning-driven recommendations and interest-based social matching is better than traditional list-based food platforms in many ways. The system can change in real time because recommendations and matches change based on how users interact with them. The card-based swipe interface makes it easier for people to think and make decisions faster. The Food Cupid mechanism adds a social element based on shared, real-time food interests instead of static profiles.

A comparative summary of Swipe N’ Bite and traditional food discovery platforms is presented in Table II, highlighting differences in preference capture, recommendation behavior, social matching, and interaction design.

Feature Comparison

Feature	Traditional Apps	Swipe N’Bite
Preference Capture	Explicit Rating	Implicit Swipes
Social Matching	Profile-based	Food-interest based
Recommendations	Static	Dynamic ML-based
Interactions	List Based	Swipe + Chat

Table II. Feature comparison with traditional food discovery platforms

However, some problems were found during the evaluation. The current recommendation model is based on content-based similarity and does not use collaborative filtering. This could make recommendations less diverse on a larger scale. The Food Cupid mechanism works within a set time frame and doesn't take into account things like how close the location is or when it's available. The chatbot also works on its own and doesn't yet use historical preference data to improve how it talks to people.

Even with these problems, the prototype proves the main idea that using implicit interaction modeling, personalized recommendation systems, and interest-driven social matching can greatly improve the experience of finding new foods. Swipe N' Bite shows a scalable and human-centered way to find new foods and meet new people by combining behavioral data, machine learning, and conversational AI on one platform.

VI. CONCLUSION

This research introduced Swipe N’ Bite, an intelligent food discovery and social matching platform that incorporates swipe-based preference learning, machine learning-driven recommendations, and an innovative interest-based social matching system known as Food Cupid. The system was made to fix some of the main problems with traditional food discovery platforms, such as decision fatigue, the need for clear feedback, and the lack of socially contextual discovery mechanisms.

The platform effectively captures changing food preferences with little effort from users by using implicit user interactions like swipe gestures. The content-based recommendation engine lets users get personalized food suggestions based on their saved preferences. The Food Cupid mechanism adds a social aspect by connecting users who are both interested in the same food items at the same time. The addition of a conversational AI assistant also makes exploratory discovery better by allowing natural language interaction and modeling behavioral preferences.

The current prototype makes some real-world factors easier to understand, like a wide range of users and restaurants that are open at the time, but it does prove the main idea: using implicit interaction modeling, machine learning-based personalization, and interest-driven social matching can greatly enhance food discovery experiences. The long-term goal of this project is to turn Swipe N' Bite into a smart, scalable platform that helps people find food in a way that is socially enriching and focused on people.

Swipe N' Bite's long-term goal is to become a smart, scalable platform that helps people find food in a way that is good for society and the environment. The platform is in line with the broader Sustainable Development Goals (SDGs) like SDG 11 (Sustainable Cities and Communities) by helping people make smarter food choices in cities and communities, and SDG 12 (Responsible Consumption and Production) by letting people make food choices based on their preferences and needs within their own ecosystems.

VII. FUTURE SCOPE

The current platform is a good start for smart food discovery and social matching, but it does have some problems. The recommendation engine now uses a content-based similarity model. It doesn't use collaborative filtering or cross-user preference learning, which could make recommendations less diverse at scale. The Food Cupid mechanism works within a set time frame and does not take into account other factors that could affect the situation, such as how close the user is to the restaurant or how many tables are available. Also, the platform is tested in a controlled setting with simulated datasets, which makes it hard to do large-scale performance and usability tests.

There are plans for several future improvements to make the system work better and have a bigger effect. Using hybrid recommendation methods that mix content based and collaborative filtering could make personalization more accurate and easier to scale. Adding contextual factors like geographic distance, time availability, and group-based matching to the Food Cupid system could make it even more socially relevant. Also, a better connection between the conversational AI assistant and the user's preference history could lead to more personalized and flexible conversational recommendations.

From a deployment point of view, moving the platform to a cloud-based infrastructure is planned to make it possible for many users to interact with it at the same time, to grow, and to connect with live food and restaurant data sources. Future work will also include making an app that works well on mobile devices, doing user studies in the real world, and testing the system's performance when a lot of people use it. With these improvements, Swipe N' Bite could go from being a test system to a fully functional smart food discovery platform.

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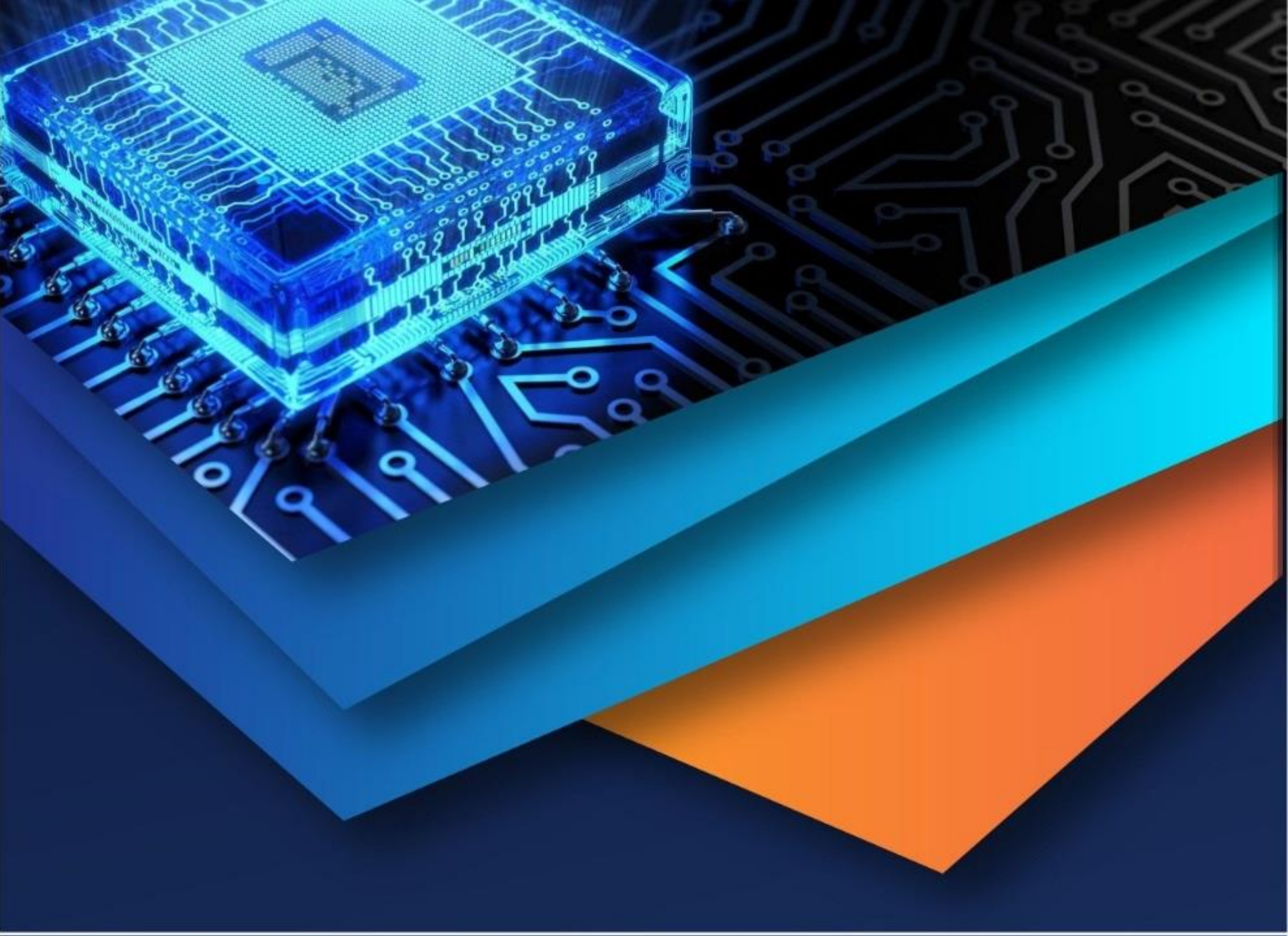

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