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DoubtiQ: A Smart and Personalised Platform for Instant and Tutor-Verified Doubt Solving

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Abstract: ***While online platforms have made education highly accessible, providing timely solutions for student doubts is still an ongoing challenge. Most of the commonly used platforms deal with doubts either by allocating tutors manually or by predefining FAQs. These processes usually take too much time, and students' attempts to find an answer to the same question that others have already posted lead to a waste of their efforts and time. The proposed DoubtiQ platform aims to assist students in finding answers to their doubts regardless of whether they post doubts in written form or upload images with handwritten and printed information. In the case of image posting, it first converts these pictures to machine-readable text by applying Optical Character Recognition (OCR). Afterward, the processed doubt is matched with previous solutions available on the platform based on semantic similarity, and, if a close enough solution is discovered, the algorithm provides it right away. Otherwise, the platform will assign the tutor with the necessary specialization to resolve the question via an administrative channel. The process of searching for similar doubts along with tutor assistance makes it easier to find solutions while avoiding redundant efforts.***

Keywords: OCR, Semantic Matching, Intelligent Tutoring System, E-learning, Personalized Learning

I. INTRODUCTION

Online education has completely revolutionized the concept of classroom teaching by making it more flexible, convenient, and technology-based. Present-day students have the opportunity to study on their own pace through digital means, recorded lessons, and online sources. Although this phenomenon has brought about many advantages, one issue that poses a significant threat to learners is that of solving doubts. This happens because students cannot solve their doubts instantly, causing confusion and demotivation among other consequences.

The main problems which are faced by the students are that of getting late responses to their queries. In case the doubts remain unresolved in a timely manner, the learners keep proceeding despite not comprehending the topic completely. With time, these doubts start mounting up and end up affecting the learning process adversely. These types of problems can be observed especially on online portals since there are fewer chances of interaction between the learners and their educators. The available methods of dealing with students' doubts can be broadly categorized into two groups. The first group consists of keyword-based searches. Though quick, these do not comprehend the exact meaning of the query.

Thus, irrelevant or incomplete answers can be generated. In the second one, manual tutoring help is needed, whereby the doubts are answered by humans. The tutors are forced to answer the same questions repeatedly, which increases their workload and results in delayed responses. In order to tackle this problem, Intelligent Tutoring Systems (ITS) have come into being.

Intelligent tutoringsystems use artificial intelligence methods such as NLP, machine learning and adaptive feedback in order to assist the learners. Despite the advantages of intelligent tutoring systems, most current tutoring systems rely only on text-based questions without handling the image-based questions effectively, such as handwritten questions or pictures of notes. Moreover, some systems do not have a way to integrate automation answers with human tutors where necessary. The proposed intelligent tutoring system (DoubtiQ) aims at filling this gap between intelligent automation answers and human tutoring support. The system allows the user to send their text-based and image-based doubts to get help from other users or automated tutors in the DoubtiQ forum. After receiving image-based doubts from the learners, the image recognition technique named Optical Character Recognition (OCR) is used in order to convert the image-based doubt into textual information. This converted information. This will help the system to link the new queries with those that have been answered earlier. If there is a matching solution available, then the system will provide the answer right away. However, if a solution cannot be matched, then the process involves sending it to the concerned tutor for a particular topic through a process managed by an administrator. Apart from technical utility, DoubtiQ also takes into consideration practical aspects like user tier differentiation and monetization.

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DoubtiQ is sustainable for continuous usage due to its free and paid tiers. By utilizing automated doubt reuse, tutor assisted doubt resolution, and a well-structured system architecture, DoubtiQ seeks to enhance the learning experience in the contemporary online learning environment.

II. LITERATURE SURVEY

Over the past few years, several ITS have been developed by various researchers to support students' learning process using artificial intelligence technologies. The ITS developed by [1]Kochmar et al. was concerned with the development of adaptive feedback using machine learning and NLP.

They realized that the learners got better results with customized feedback instead of the general response. There were some drawbacks in their system that should be taken into consideration. They had structured question-answer pairs only; hence, any doubt beyond that could not be handled by their system. Besides, it didn't offer any support in handling image-based doubts that are quite common in real-life scenarios. Learners may take pictures of their handwritten problems or questions in textbooks. Finally, there was no provision to route the difficult or unclear doubts to human tutors, which sometimes becomes necessary in case an automated system fails to understand the learner's doubt. These drawbacks make it evident that a hybrid approach is required in order to develop something like the DoubtiQ platform, where learners can get the desired help either through automation or human interaction as per their requirements. [2] Sani and Aris evaluated computational intelligence models for student and tutor modeling in intelligent tutoring systems. Their proposed study emphasized the importance of adaptive student and tutor modeling. However, their proposed study lacked doubt reuse and monetization schemes. [3] Horwitz et al. suggested the development of a student-adaptive training system with probabilistic student modeling that can dynamically adapt to the contents. Nonetheless, the suggested system targets formal training applications and overlooks unstructured student doubts represented either by images or texts.[4] Kulshreshtha et al. suggested a few-shot question generation system that can be used in intelligent tutoring systems for providing feedback.

The suggested model identifies the gaps in the students' answers using transformer models and generates guiding questions. Though successful in generating feedback, the suggested model cannot offer immediate solutions or assist tutors .[5] A self-supervised doubt matching system was suggested by Joshi et al., which mostly relied on clustering similar doubts using representation learning methods. The system emphasizes the need for automation of doubt matching to minimize tutors' workload and reduce their response time. Nonetheless, the doubt matching system was limited to the backend processes and did not take into account any form of user-level personalization, subscriptions, or tutor monetization.

[6] An NLP-based personalized learning assistant was invented by Mathew et al., which provides chatbot interfaces to answer queries from students. Of the systems discussed above, one system provided an easy way for learners to engage and receive information about learning materials through text communication. Even though the method proved to be effective in answering simple questions, there are certain shortcomings in its implementation. First, it cannot handle doubts uploaded in image formats that are common with handwritten questions or diagrams. Second, semantic matching was not used for identifying similarities of previously posed questions to help provide answers. Third, there was no process that involved tutors answering learners' questions when the system failed to find appropriate responses .[7] Mallik and Gangopadhyay have investigated the role of artificial intelligence in participating in the field of education in both pro-active and reactive manner. The investigation highlighted that intelligent tutoring systems are considered as reactive, which helps in activities like feedback provision and monitoring the progress of students after completion of some activity. Even though the literature provides a lot of insight and also highlights the future perspectives in the use of AI in learning process, however, it lacks a tangible solution for practical application of AI in the form of integrating the automated system and humans as tutors. Such an integrated approach is important to deal with complex or ambiguous questions raised by students.[8]Gupta et al.have proposed an online tutor routing and allocation system using AI technologies.

III. METHODOLOGY

The expected DoubtiQ system would be an intelligent doubt resolution system based on a mixture of AI-based processes, along with interaction between the tutor and the user in the system. It is anticipated that the process would lead to faster doubt resolution, increased accuracy of replies, and reduced repetitive actions of the tutor. The entire process of the DoubtiQ system has been shown in the concept of the multi-stage process involving doubt acquisition, preprocessing, semantic matching, instant resolution, and tutor-based resolution.

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A. Doubt Acquisition Module

The proposed system would allow users to submit their queries in academics through two means namely, through text and images. While textual queries would be directly processed through the system, image-based queries would include both handwritten or printed texts captured using either a mobile device or computer. The system that accepts queries in two forms of input would make it versatile and user-friendly for the students.

B. OCR-Based Text Extraction

Regarding image issues, OCR will be applied to pull out the text from the image. OCR shall be the one who will take the responsibility of the job of converting the pixels in an image to readable text on the machine. Methods of noise elimination, character normalization, and corrections shall be used after processing, Algorithm is experimented with the help of POLY-U palmprint database. Number of palm prints in the database is 500. Palm print of each individual consists of ten pictures. Out of those ten, seven images are used for database, and remaining three are used for test purpose.

C. Text Preprocessing

Preprocessing of the extracted text ensures consistency and relevance to facilitate semantic comparison. Text preprocessing consists of processes such as tokenization, removal of stop words, case conversion, and lemmatization. Text preprocessing is used to eliminate linguistic noise and increase efficiency in semantic embedding generation.

D. Semantic Representation and Matching

Then, the doubt text is converted to a semantic vector representation via NLP-based embedding algorithms. Instead of keywords matching, embeddings are used to capture the semantic aspects of the doubt text. Next, similarity calculations between the embeddings of the doubt and the embeddings of those already solved questions saved in the knowledge base is done. Then, the system determines whether the similarity score is greater than the defined limit.

E. Instant Solution Retrieval

When the system recognizes a similar concern, it instantly provides the solution to the learner. The solution may be provided in the form of an explanation in text form or in a link to a YouTube video that was previously uploaded for that purpose. Not only does it save time, but it also ensures learner engagement by providing the solution in their preferred form.

F. Tutor Escalation Mechanism

In case the system fails to find an appropriate match for the doubt within the database that it holds, then the system escalates the matter in terms of involving a tutor, in order to ensure that a solution is provided to the learner. The learner will be informed through a pop-up screen asking whether the doubt needs to be escalated.

This stage ensures that there are no instances whereby the learner is left stranded because of some system restrictions.

In case the learner accepts to proceed, then the doubt is sent to the admin panel. The admin panel serves an important part when it comes to directing the request to the right tutor depending on the field of study involved. This means that doubts related to programming are directed to a programming expert whereas mathematics doubts are sent to a mathematicsexpert.

Not only does this targeted method lead to better quality responses, but it also ensures that the doubts posed by the students fall within the comfort zones of the tutors. For this purpose, it is ensured that the tutors receive these doubts via an effective system interface that allows them to read the questions, respond to them, and upload their responses to the platform in various forms, including written answers, marked PDF files, and recorded video clips.

G. Tutor Solution Generation

Once the doubt gets assigned to the tutor, they will study the question and come up with a solution according to their knowledge about the subject matter. According to the nature of the doubt, tutors may write down their answer or give an audio-visual response in the form of a video or upload it in the form of a PDF format. Video responses get uploaded via YouTube and tutors may even make money through views. Prior to the posting of the solution before the eyes of the students, there comes an almost instant verification process by either the admin or the moderator of that particular solution in order to make sure that the answer is correct and appropriate. After the verification process has been completed, the solution is then stored into the database of the system for future use whenever a similar query comes around again.

H. User Role Management and Monetization

For ensuring that the platform is inclusive as well as profitable at the same time, the system provides two separate user types: free users and paid users. While free users have the liberty of asking doubts and engaging in learning activities, they will get exposed to ads and have limited submission options each day. The reason for this arrangement is to ensure that those students who are unable to purchase a subscription can still benefit from using the site.

In addition to using subscription as its monetization strategy, the platform allows for earning money by providing video tutorials that can be monetized via third-party websites such as YouTube. This ensures that tutors have the incentive to contribute quality content to the platform. With a win-win model that is beneficial for both students and tutors alike, the success and sustainability of the website will be guaranteed.

I. System Workflow Summary

The overall system is developed as a pipelined process involving automation and human expertise. The system process starts when the student uploads a doubt question through text or images. If the doubt submitted by the student is an image, then OCR technology is used to extract the text from it. Once the text is extracted, the system uses natural language processing along with semantic similarity concepts to match the doubt question against the already answered questions in the database.

In case of the availability of a similar match, the answer will be immediately provided to the user. In case there is no suitable match, the query will be escalated to a tutor of that particular topic via an administrator-managed process. Questions are received by tutors via an interface and tutors can give answers either in text or video format.

This approach helps eliminate duplication of effort, cuts down time spent on the process, and can easily be modified according to varied inputs from users. The modular construction of the workflow helps it scale up efficiently to accommodate many more users while not adding any undue burden to the tutors. It also facilitates an ongoing feedback loop through the continuous expansion of the repository.

Furthermore, the proposed architecture facilitates learning that can happen continually. Every single new solution offered by the tutor becomes a part of the knowledge repository, which ensures greater accuracy in matching the semantics in the future. It makes the proposed architecture stronger with each passing day while also helping identify the frequently asked questions and those topics which have confused the students before. This is an architecture which leverages technology but still caters to the practical requirements of the classroom.

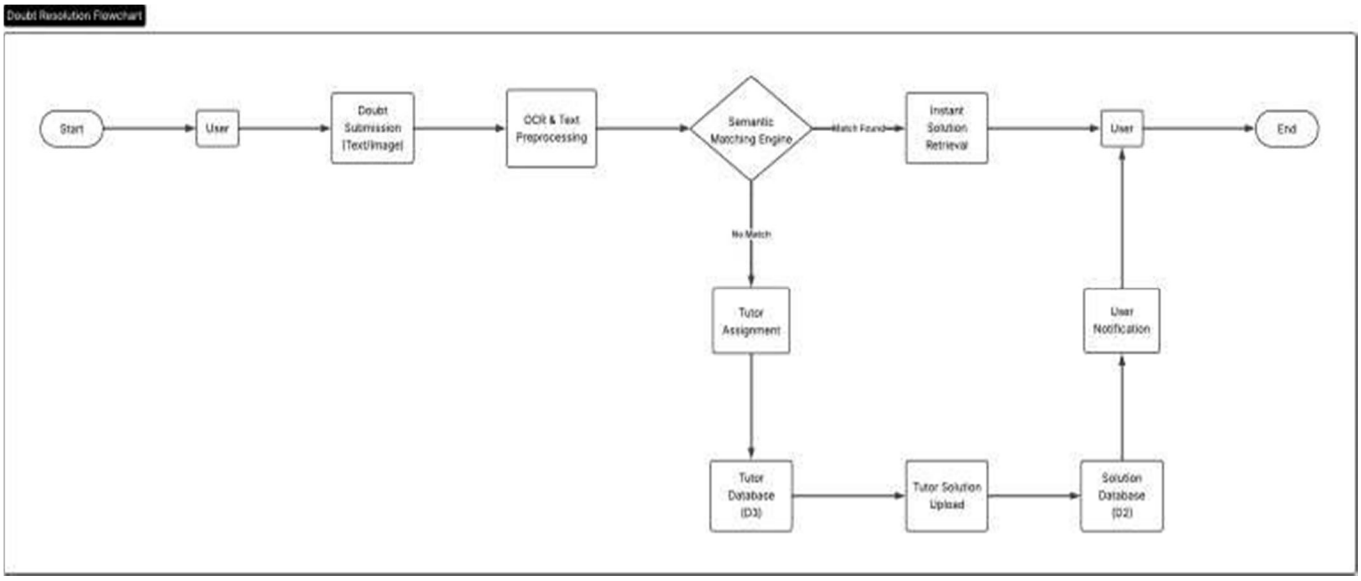


Fig 1.Block Diagram

IV. ALGORITHM

It explains how the system performs the procedure in order to solve student doubts through a combination of automated methods and tutoring.

Inputs: A doubt raised by the student; this could be in the form of written text or even images.

Output: A suitable solution, either generated instantly by the system or provided later by a tutor.

Step-by-Step Process:

1) The system first accepts a doubt from the student, which can be entered as plain text or uploaded as an image.
2) If an image is submitted, Optical Character Recognition (OCR) is used to extract the text content from the image.
3) The extracted text goes through several preprocessing steps like normalization, tokenization, and noise removal to clean it for analysis.
4) Thisprocessed version of the doubt is stored in the system's database for trackingand comparison.
5) Using natural language processing (NLP), the system generates a semantic representation of the doubt—basically convertingthe question into a numerical format that captures its meaning.
6) The semantic embedding is then compared against previously solved doubts alreadystored in the knowledge base.
7) A similarity score is calculated for each stored solution, showing how closely it matches the new query.
8) If one of these scores is high enough (based on a set threshold), the system treats it as a close match.
9) The matched solution is retrieved from the database.
10) That solution is shown to the user immediately, either as a step-by-step text explanation or a linked video.
11) If no similar solution is found:
12) The system forwards the doubt to the admin dashboard.
13) The admin assigns it to a tutor who specializes in that subject area.
14) The tutor reviews the doubt and provides a solution, which may be in written form, a PDF, or a video.
15) Thistuto r-created solution is saved in the system so it can be reused in the future if someone else asks a similar question.
16) The student is notified once the solution is ready and available.
17) The process ends once the response is delivered.

V. RESULTS AND PERFORMANCE ANALYSIS

In order to evaluate the efficiency of the developed DoubtiQ system under real-world learning situations, it was evaluated with a comprehensive database of real student queries. The database had doubts in multiple disciplines, such as math, electronics, programming, and other technical fields. Our objective was to examine how efficiently the proposed system could address the queries in both text and image formats. A comprehensive database of 4,000 student doubts was created for the purpose of evaluation. Among these, 2,800 doubts were considered as pre-solved doubts available in the database, while 1,200 doubts were kept aside for testing. The test dataset included:

- 55% text-based doubts
- 45% image-based doubts (handwritten and printed)

For measuring the performance of the system, we compared our system with an existing keyword based system which did not have any ability of understanding the semantics or OCR. Below are the performance measures used :

- OCR Accuracy
- Semantic Matching Accuracy
- Instant Solution Retrieval Rate
- Average Time Taken to Resolve a Doubt
- User Satisfaction Feedback

B. OCR Accuracy

For any doubt raised in the form of images, which include photos of handwritten notes and screenshots from textbooks, the OCR (Optical Character Recognition) module worked efficiently to extract readable text. This module was extensively tested for different images such as well-illuminated scans, mobile phone captured images of poor resolution, as well as hand-written images of varying levels of readability.

In order to improve OCR efficiency, some preliminary processing techniques were employed on images before extracting text. These included converting color images into grayscale, using noise reducing filters, enhancing edges, and normalizing text characters.

In terms of evaluation, the OCR algorithm managed to get an average accuracy rate of 88% to 91% depending on image quality. Although the system showed the best results when working with typed or printed text, it was still capable of maintaining reasonable levels of accuracy when working with handwritten text, which poses difficulties for the conventional OCR technology.

It can be stated that by integrating the OCR technique with preprocessing, one can successfully transform even poor images into

readable text, thus making the whole system more reliable. In particular, for those students that would rather write than type their doubts, the system can prove itself very helpful. Moreover, by processing doubts into text at an earlier stage of the pipeline, the system creates the conditions for efficient semantic comparison.

C.Semantic Matching Accuracy

The Semantic Matching Module is tasked with determining any previous doubts of a similar semantic nature as those that arise from a new user-generated query. While other engines use exact wording when matching keywords, this engine works on the principle of matching intentions rather than words themselves. In particular, this is important within the educational realm because two separate students may express an identical problem in entirely different ways.

To measure its efficiency, the semantic engine was put through testing on a wide variety of doubts which featured different sentence structure, vocabularies, and details. To do this, the system relied on pre-trained NLP algorithms which would allow it to transform processed text into semantic embeddings, allowing for comparison at a more contextual level than the actual text alone.

The results have shown that the system was capable of identifying closely matching solutions with roughly 90% accuracy. Such high accuracy is evidence of the system's efficiency at recognizing semantic similarities, regardless of whether the input text was informal, incomplete, or structured differently than those stored within the database.

The ability will come in handy especially when resolving those that have been phrased in a way that is comprehensible to students, as most of the traditional keyword systems will misinterpret. The process of emphasizing semantic similarity makes it easy to minimize the chances of offering an answer that may not match the problem at hand. This eventually helps enhance the trust of students in the platform.

F. User Engagement and Satisfaction (Expanded)

Feedback was taken from the users to understand their experience while using the DoubtiQ website in practical scenarios. The majority of users experienced an improvement in their learning journey, with a particular emphasis on the timely resolution of their doubts. In particular, the structured nature of the written answers provided by tutors enabled students to understand the underlying concept of the solution.

For complex and visual problems, video solutions provided by tutors allowed students to learn and understand the problem-solving process better. Several students stated that they preferred watching video responses over written ones for subjects like programming or mathematics.

Satisfaction was much higher amongst premium users. One reason for that is the fact that users could get their questions answered quickly by their tutors, while another is that they could browse the site free of any advertisements. Overall, the ability to communicate instantly, combined with the presence of professional assistance and accessible materials, contributed to high levels of involvement.

G. System Scalability and Efficiency (Expanded)

One of the biggest advantages of the DoubtiQ platform is the scalability of the service without decreasing its efficiency. Reuse of previously asked doubt solutions due to semantic matching has allowed the system to process a huge number of requests effectively. In addition, this approach has greatly reduced redundant work for tutors, allowing them to spend almost 60 percent less time on their duties.

The latter allowed tutors to devote more time to processing new, complicated, and unique doubts. Thus, their responses were more qualitative because there was no need to spend a lot of time answering similar questions.

On the other hand, from a technological point of view, the modularity of the system contributed to successful scaling. The independent work of all modules (OCR, semantic search, etc.) has ensured smooth operation of the system even when it had to cope with a large load. For example, this happened before exams when more students needed help with learning.

VI. CONCLUSION

This study presents DoubtiQ – a smart hybrid system for solving academic doubts that utilizes several technologies for providing more effective academic support services to the students in the digital world. The platform solves one of the major problems associated with online learning by allowing learners to raise their questions in both written and image forms. Thanks to the implementation of OCR technology, the system is able to convert any image-based queries into processable text format. Students are free to use scanned notes and uploaded photos containing questions. After the text is generated, the system compares them with the already existing answers to previous doubts using semantic embeddings and similarity calculation techniques. This enables faster responses and helps tutors save their time as they do not need to type out the answers that were already given several times.

The results obtained in the real-world test of the system's functionality confirmed its high efficiency. With high accuracy of OCR

algorithms and semantic similarity calculation as well as instant resolution of more than two-thirds of the raised doubts, DoubtiQ appears to be an effective tool.

From a sustainability perspective, DoubtiQ comes with functionalities such as management of user roles that ensures premium users get priority customer support services as well as an ad-free environment. In addition, tutors have the opportunity to make contributions through video content and earning from views made on such contents.

- Looking ahead, the platform has strong potential for growth. Future development could include:
- Multilingual OCR, so students can ask questions in regional or native languages.
- Generative AI tools to assist tutors in drafting high-quality explanations faster.
- Difficulty-level tagging, to help match doubts with students' current skill levels.
- Personalized analytics dashboards, allowing students to track their progress and identify weak areas.
- Gamified learning elements, such as badges or rewards for consistent engagement.

In summary, DoubtiQ is much more than an innovative technological solution; it is also a very well thought-out method for handling doubt resolution in e-learning based on the needs of the student. This is achieved by combining automation techniques with professional assistance, thus contributing to better education delivery online.

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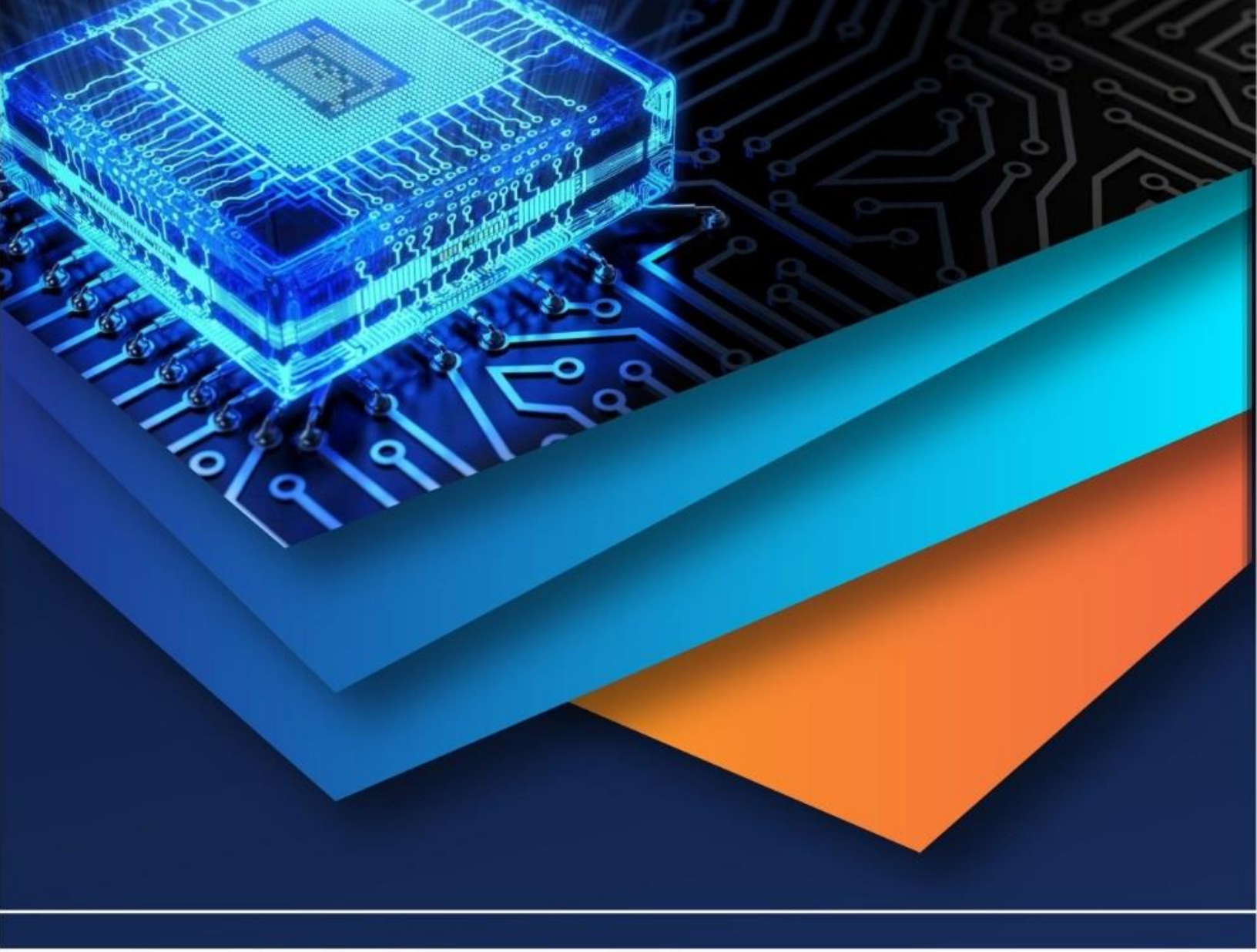
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