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A Comprehensive Review of Medicine Recommendation Systems Using Machine Learning and Deep Learning Techniques

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Abstract: There is a growing need for personalized healthcare services. This has led to the development of systems that help patients and healthcare professionals choose the right medicines. Old methods for recommending medicines relied on knowledge, rules and guidelines. With advancements in Artificial Intelligence Machine Learning, Deep Learning, Natural Language Processing and Semantic Web technologies healthcare recommendations have become more accurate, scalable and personalized. This review looks at existing medicine recommendation systems. We examine how recommendation methods have changed over time. We go from methods like collaborative filtering and content-based filtering to modern methods like machine learning, deep learning and sentiment analysis. We review algorithms like Decision Trees, Random Forests and Support Vector Machines. We also look at Recurrent Neural Networks, Long Short-Term Memory and Bidirectional Gated Recurrent Units. Ontology-based clinical decision support systems and Natural Language Processing-driven drug recommendation models are also analyzed. These models use reviews and healthcare text data.We discuss used datasets, evaluation metrics and system architectures. We also talk about challenges and emerging trends in healthcare recommendation systems. Medicine recommendation systems and Machine Learning are areas of research. Deep Learning and Natural Language Processing-based approaches are effective in disease prediction and personalized medicine recommendation tasks. Semantic Web technologies improve explainability and clinical safety. Current research gaps and future directions are highlighted. These include AI, knowledge graphs, federated learning and transformer-based healthcare models. These will guide developments, in intelligent medicine recommendation systems.

Keywords: Natural Language Processing, Bidirectional GRU, Disease Prediction, Medicine Recommendation, Deep Learning, Healthcare Artificial Intelligence, Symptom Analysis.

I. INTRODUCTION

The healthcare industry has changed a lot with the progress of Artificial Intelligence and data-driven technologies. One important area of research is medicine recommendation systems. These systems help healthcare professionals and patients choose the medications based on symptoms and medical history. The healthcare industry needs these systems because disease diagnosis is getting more complicated and there are pharmaceutical products available. Healthcare professionals used to rely on their expertise and patient records to make decisions. This method is effective. It can be time-consuming and influenced by human mistakes. Especially when dealing with a lot of information and complex drug interactions. In some areas there is a shortage of healthcare professionals so there is a need for automated systems that can provide diagnosis and treatment recommendations. The emergence of recommender systems has provided a solution to these challenges. These systems were first used for e-commerce and online content recommendation. Now they are used in healthcare to assist in disease prediction and medication selection. Early healthcare recommender systems used content-based and collaborative filtering approaches However, the healthcare industry has requirements such as safety and accuracy so more sophisticated methodologies were developed. Recent research has shown that machine learning algorithms like Decision Trees and Random Forests are effective in disease prediction and medicine recommendation tasks. These models can learn relationships between symptoms and diseases from historical healthcare data. They can generate recommendations. Natural Language Processing techniques are also used to analyze healthcare information. This includes notes and patient reviews. The integration of ontology and Semantic Web technologies is another development in healthcare recommendation systems. Ontology-based systems provide medical knowledge and reasoning capabilities. This enhances recommendation explainability. Supports the identification of drug-drug interactions and adverse effects. Recently Deep Learning models have gained attention due to their ability to process large-scale healthcare datasets.

Architectures such as Recurrent Neural Networks and Long Short-Term Memory networks have demonstrated performance in disease prediction and medicine recommendation applications. Despite the progress in medicine recommendation systems several challenges remain unresolved. Issues such as data privacy and model explainability continue to affect the deployment of these systems. Ensuring safety through accurate drug interaction analysis and personalized recommendations remains a critical research concern. This review paper presents an analysis of intelligent medicine recommendation systems. It examines the evolution of recommendation methodologies from recommender systems to modern machine learning and deep learning frameworks. The paper critically reviews existing approaches. Identifies current research gaps.

II. BACKGROUND

The healthcare sector is using Artificial Intelligence and Machine Learning more and more for disease diagnosis and medical help. Old ways of diagnosing diseases rely on people looking at things and experts' knowledge, which can take a lot of time and are not very efficient in healthcare systems. Natural Language Processing helps analyze text data like patient symptoms and healthcare records. Natural Language Processing turns text that is not organized into a format that computers can understand so deep learning models can use it to predict diseases. Traditional Recurrent Neural Networks have problems like the vanishing gradient issue when learning sequences. To fix these problems new architectures like Gated Recurrent Unit were created. Bidirectional Gated Recurrent Unit models work better because they look at sequences in both directions, which helps them understand medical symptoms better. Recent studies show that using Natural Language Processing with Bidirectional Gated Recurrent Unit models makes disease prediction more accurate. This also helps medicine recommendation systems, in modern healthcare applications. Artificial Intelligence and Machine Learning are really helping the healthcare sector. Natural Language Processing and Bidirectional Gated Recurrent Unit models are parts of this. They are making disease diagnosis and medical help better so that the patient can get a proper recommendation he does not need to visit doctor everytime even in minor problems like cold etc.

III. LITERATURE REVIEW

A. Burke(2002).

The author came up with an idea for recommendation systems. He put together methods like collaborative filtering and content-based filtering to make a hybrid system. This study showed that using methods makes the recommendations more accurate. It also helps to fix the problems that happen when you use one method. The system the author made was not just for healthcare or medicine recommendations. It was made for all kinds of recommendations. The author did not make it for healthcare or medicine. Healthcare and medicine recommendations need a system. The hybrid system the author made was a system, for all recommendations.

B. Adomavicius and Tuzhilin did a study in (2005).

They looked at all the types of recommender systems and grouped them into a few categories. These categories are content-based, collaborative filtering and hybrid methods. Their work was very important because it helped create the basis for the recommendation systems we use today. They also talked about some of the problems that these systems have, like when there is not data when the system gets too big and when something new is added and there is no information about it.. They did not look at how these systems work in healthcare, which has its own special needs. The recommendation systems they studied were not designed with healthcare, in mind.

C. The authors Chen et al. Wrote a paper in (2012).

They talked about a system that recommends -diabetic drugs to patients. This system uses Semantic Web Rule Language and Java Expert System Shell. It also uses something called domain ontology. The system looks at the symptoms of the patient. What it knows about medicine. Then it suggests -diabetic medicines that are suitable for the patient. This is a system because it helps doctors understand why a certain medicine is recommended. It also helps doctors make decisions.There is a problem with this system. It needs people who're experts, in the field to build and update it all the time. The system is based on ontology. That is what needs to be updated. The Chen et al. System is good. It needs a lot of work to keep it going.

D. Natural Doulaverakis et al in 2012 created GalenOWL

It is a drug recommendation platform that helps find drug-drug and drug-disease interactions.

This system uses web technologies and medical information to make prescriptions safer. The framework worked well in finding things that should not be used together.

However, keeping medical information up to date was a difficult task for the GalenOWL system. The researchers, Doulaverakis et al. did a job with Galen OWL. They helped improve prescription safety with their drug recommendation platform. The Galen OWL system still has issues with handling a lot of information. Doulaverakis and his team showed that Galen OWL can be helpful. Their work, on Galen OWL continues to help with drug interactions.

E. Bobadilla et al. (2013).

The authors looked at the technology behind recommendation systems. Talked about different methods like collaborative filtering, content-based filtering, demographic filtering, social filtering and hybrid recommendation approaches. They said that making sure the recommendations are accurate can handle a lot of users and are personalized is really important. Their work was mostly about recommendation systems in general not specifically about how they can be used in healthcare, for the healthcare systems.

F. Doulaverakis et al. Did some work in (2014).

They came up with something called Panacea. Panacea is a framework that helps find drug recommendations. It uses things like ontologies and semantic technologies to do this. The system looks at how different drugs interact with each other. It tries to make recommendations.

G. Bao and Jiang did some research in (2016).

They wanted to create a system that could recommend medicine to people. This system used techniques to look at data and figure out what medicine to suggest. The system had a few parts. It could get the data ready make recommendations check how good the recommendations were and show the results in a way. The people who made the system tried out a few methods to see what worked best. They used something called Support Vector Machine, Back Propagation Neural Network and Decision Tree. They found out that Support Vector Machine was the best because it was pretty accurate. It did not take too long.The system was good. It had one problem. It mostly used data that was already organized in a way. Bao and Jiang's medicine recommender system relied on this kind of data.

H. Gupta and other people (2021) did a study.

They made a system that can guess what disease someone has and tell them what medicine to take. This system uses computer programs like Naïve Bayes and Decision Tree and Random Forest. The system looks at the symptoms a person has. Then tells them what disease they might have and what medicine they can take for that disease. The study showed that using computer programs to help with healthcare can be really useful. They did not test it with doctors as much as they could have. The machine learning system is good, at guessing what disease someone has. What medicine they need. Gupta and other people used machine learning to make this system work.

I. The people who did the study, Khairnar and others wrote a paper in (2022).

They made a computer system that suggests medicine based on machine learning. This system was trained on a lot of information. 132 Symptoms and 42 diseases. They tried out a different way to make the system work like Decision Tree and Random Forest and Naïve Bayes. The Naïve Bayes way was the best it was about 98.12 percent of the time. The system tells people what disease they might have and what medicine they should take and they can use it on the web. But the people who made the system want to be clear it is not meant to replace going to see a doctor. It is just meant to be a tool. The medicine recommendation system is meant to be used with a doctor, not of a doctor. The Khairnar medicine recommendation system is an example of a machine learning-based medicine recommendation system.

J. Tarak Ram Ankem and other people who worked with him wrote a paper in (2025).

They made a system that suggests medicine to people based on their needs. This system uses Decision Tree, Random Forest, K-Means Clustering and Hierarchical Clustering algorithms. The system looks at what symptoms the patient has what their health is like how they live and what their medical history is. Then it tries to figure out what disease the patient might have. Suggests what medicine they should take, what they should eat and what kind of exercise they should do. The Random Forest classifier was the best at making guesses it got 94.2 percent of them right. The people who made the system think it needs to be tested more in real hospitals and, with real patients to see if it really works. Tarak Ram Ankem and the other people who worked with him think that more studies are needed to make sure the system is good and can be used in the world with real people.

K. Zheng and the other authors in the study that was done in(2025).

They came up with something called FMCHS. This is a system that recommends Traditional Medicine. It is based on how herbs and symptoms connected in different ways. The system is actually pretty good at understanding how symptoms and herbs are related. It also makes recommendations. It only works for Traditional Chinese Medicine. It is not easy to use this system for kinds of medicine that are used today. Zheng and the other authors found that the system has some limitations. The system is not very good, at working with types of medicine. Zheng and the other authors think that the system could be improved. They think that the system could be used for types of medicine if it was changed a bit. Zheng and the other authors are talking about FMCHS, the Chinese Medicine recommendation system.

IV. SUMMARY OF LITERATURE TEVIEW

Year	Author	Methodology	Key Findings
2002	Burke	Hybrid Recommender System	Improved recommendation accuracy
2005	Adomavicius & Tuzhilin	Recommender System Survey	Established recommendation foundations
2012	Chen et al.	Ontology + SWRL	Improved explainability in drug recommendation
2012	Doulaverakis et al.	GalenOWL	Drug interaction detection
2013	Bobadilla et al.	Recommender System Survey	Identified recommendation challenges
2014	Doulaverakis et al.	Panacea Framework	Efficient semantic recommendation
2016	Bao & Jiang	SVM-based Recommender	High recommendation accuracy
2021	Gupta et al.	ML-based Recommendation	Disease prediction using symptoms
2021	Garg	NLP + Sentiment Analysis	93% accuracy using TF-IDF + LinearSVC
2022	Khairnar et al.	Naïve Bayes	98.12% prediction accuracy
2025	Tarak Ram et al.	Random Forest + Clustering	94.2% accuracy
2025	Sambhyal et al.	Online Medicine Recommendation	Personalized and secure recommendations

V. KEY COMPONENTS

A. Data Collection Module

The healthcare information collection part of the system gets information about people's health from places. These places include what symptoms people are having, their health records and what doctors have said about them. It also gets information from collections of medical data, lists of drugs and what people are saying about their health. The quality of the healthcare information that is collected is very important because it affects how well the system can tell people what might be best, for them. Predicted.

B. Data Preprocessing Module

Healthcare text data is often a mess. It has a lot of noise the formatting is over the place and there are punctuation and symbols that we do not need. Healthcare data is not always perfect. It often has missing information, duplicate records, things that do not make sense and mistakes. To get this data ready, for machine learning and deep learning models we need to do some work on it. This work is called data preprocessing. It includes cleaning the healthcare data making sure everything is consistent picking out the parts breaking down the text into smaller pieces removing common words that are not important and changing the data into a format that the models can understand. We do all this to prepare the healthcare data for the machine learning and deep learning models.

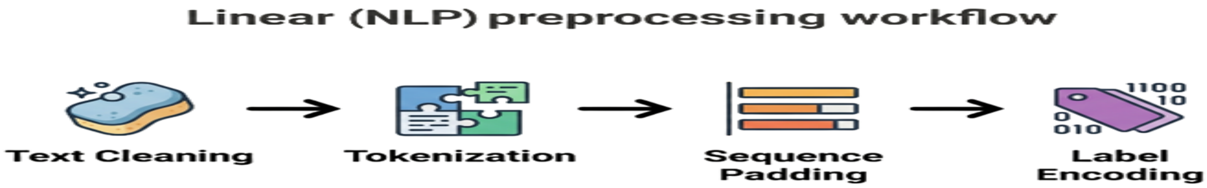

Fig.1. NLP Preprocessing Workflow.

C. Medicine Recommendation Engine

The main part of the system is what helps figure out which medicines are best for people based on the diseases they might have how bad their symptoms are, what has happened to them in the past and what doctors think they should do. When it comes to giving people medicine recommendations the system uses a few methods.

These methods include looking at what other people, like them have taken looking at the details of the medicine itself combining these two ways using computer models that can learn and using complicated computer methods. The system uses these methods to give people the medicine recommendations.

D. Natural Language Processing Module

The Natural Language Processing module works with healthcare text that is not organized like notes from doctors' reviews from patients, prescriptions and descriptions of symptoms. The Natural Language Processing module uses methods like TF-IDF, Word2Vec, Bag-of-Words and sentiment analysis to get information from the healthcare text. This information is then used to make suggestions. The Natural Language Processing module is very important, for understanding the healthcare text.

E. Drug Interaction and Safety Analysis Module

This part of the system looks for problems that can happen when you take two medicines at the time. It checks for things like drug interactions times when you should not take a medicine, allergies and bad side effects. The system wants to keep patients safe by making sure the medicines it suggests do not cause problems with the medicines the patients are already taking. It does this to help doctors and nurses choose the medicines for people. The system is really good, at finding drug interactions and other issues before it recommends any medicines.

F. Medical Knowledge Base

The medical knowledge base has lots of information about diseases, symptoms, medications and more. It stores details on dosage instructions, side effects, precautions and treatment guidelines. This knowledge base helps generate recommendations and supports decisions. It is a reference source for professionals to make informed decisions. The medical knowledge base is really helpful, for understanding diseases and treatments.

G. The Medicine Recommendation Process

When we figure out what disease someone has the system looks for medicine that can help with that disease. It finds this information in a collection of data. The system then shows the user some medicine that might be good for them. Our system is like a helper for healthcare. It can do two things at the time: figure out what disease someone has and suggest medicine that can help with the Medicine Recommendation. The system is really good, at helping people with Medicine Recommendation and disease prediction.

VI. SECURITY FEATURES

Security is an important part of medicine recommendation systems. This is because these systems deal with patient information. This information includes things like history and prescriptions. It also includes symptoms and personal details, about the patient. To keep information safe medicine recommendation systems, need to have certain security features. These features help keep healthcare data intact. They also make sure that the data is available when it is needed. The security features that are typically used include:

1) Authentication and Authorization
2) Session handling and user authentication to ensure data protection.
3) SSL encryption for all user-health interactions.
4) Option for anonymous use with limited feature
5) Audit Logs and Activity Monitoring

VII. ACKNOWLEDGEMENT

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VIII. PROPOSED SYSTEM

I looked at all the medicine recommendation systems that're already out there. Now I think we should use a system that combines a few different things: Machine Learning, Deep Learning, Natural Language Processing and Semantic Web technologies. This new system, the intelligent medicine recommendation framework should help us do a few things better. It should be able to predict what disease someone has accurately. It should be able to recommend the medicine for each person. The hybrid intelligent medicine recommendation framework should also be able to look at how different drugs interact with each other. It should be able to explain why it is making certain decisions, about healthcare. The hybrid intelligent medicine recommendation framework is a way to do things that should fix some of the problems we have now.

A. Data Acquisition Module

- The first part of our system gathers health information from places like:
- Patient symptoms
- Clinical reports
- Drug databases
- Patient reviews

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- Healthcare ontologies
- Medical knowledge bases
- When we combine all this health data it makes our advice better and more trustworthy. We get health data from patients' symptoms.
- The Electronic Health Records are also used.
- Clinical reports and drug databases are utilized
- Patient reviews help too.
- Healthcare ontologies and medical knowledge bases are utilized well.

B. Data Preprocessing Module

The information we have gathered is cleaned up to get rid of mistakes and make it ready for machine learning and deep learning models. The cleaning process has steps:

- Missing value handling
- Duplicate record removal
- Data normalization
- Text cleaning
- Feature extraction
- Tokenization
- Label encoding
- Class balancing

When we are dealing with text about symptoms and patient reviews we use machine learning techniques like TF-IDF Word2Vec. Embedding layers for textual symptom descriptions and patient reviews. We use these machine learning techniques to make sense of the text and get information, from textual symptom descriptions and patient reviews.

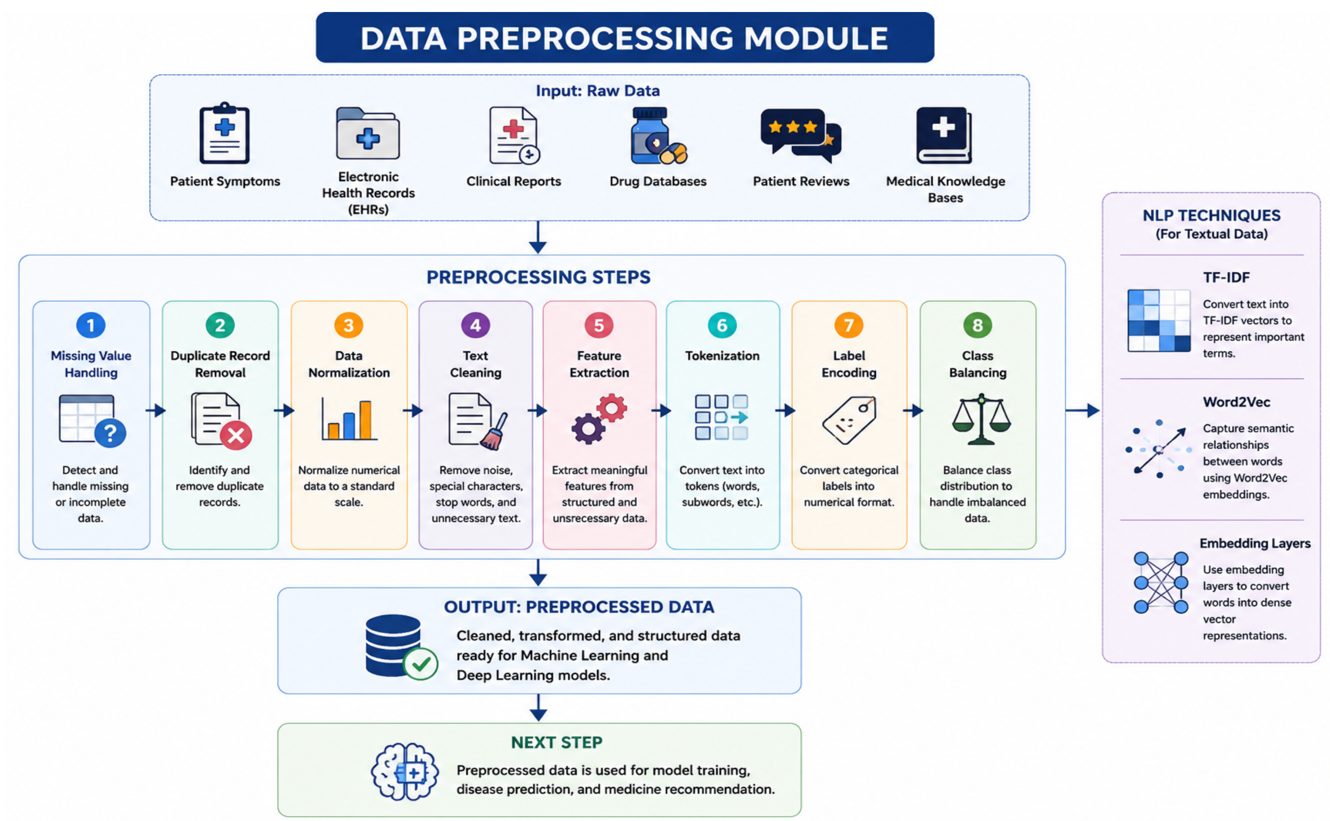

Fig. 2. Data Preprocessing Module for Medicine Recommendation Systems

C. *Disease Prediction Engine*

The Disease Prediction Engine looks at the symptoms a patient has. Tries to figure out what disease is most likely to be the cause. We use some ways of teaching computers to make predictions, such as:

- Decision Tree
- Random Forest
- Support Vector Machine (SVM)
- XGBoost

These methods help us make a guess about what disease a patient might have. To really understand how symptoms are connected to each other we also use some more advanced computer methods, like:

- LSTM
- GRU
- Bidirectional GRU (Bi-GRU)

The Disease Prediction Engine uses the Bi-GRU method because it is the best at understanding how symptoms are related to each other. The Bi-GRU method can look at the symptoms in both the backward directions, which helps the Disease Prediction Engine make more accurate predictions about what disease a patient has. The Disease Prediction Engine and the Bi-GRU method work together to make the Disease Prediction Engine better, at predicting diseases.

D. Medicine Recommendation Engine

After the doctors figure out what disease you have the computer program that helps with suggestions will tell you what medicine to take. It does this by using a way of combining ideas. The computer program looks at a thing:

What the medicine is supposed to do

It matches the medicine with what's wrong, with you and how you are feeling.

What has worked for people

It looks at what medicine people took before and what happened to them.

What the experts know

It uses the rules that doctors follow and what they know about taking care of people.

This way of combining ideas helps make sure you get the medicine for you. The disease prediction and medicine recommendation are connected to give you the result. The computer program uses disease prediction to suggest the medicine for your disease.

E. Personalized Healthcare Recommendation Module

The system looks at a lot of things to make it personal for each person. It considers things like

- Age
- Gender
- Medical history
- Lifestyle factors
- Treatments
- Patient feedback

The system does more than just tell people what medicine to take. It also gives them

- Diet recommendations
- Workout suggestions
- healthcare measures
- Lifestyle improvement guidance

This part of the system is meant to help people with their overall healthcare management not just give them medicine recommendations. The system is about healthcare management, which is a lot more than just giving people medicine recommendations. The healthcare management system is what makes it really useful, for people.

F.Security and Privacy Layer

Healthcare information is very personal so we make sure that our system is secure.

The security part of our system has important features:

- User authentication
- Role-based access control
- Data encryption
- Secure cloud storage
- Privacy-preserving data processing

All these things work together to keep information safe and private. We want to make sure that patient information is only seen by people who are supposed to see it and that it does not get lost or damaged. Healthcare information is kept confidential, intact and available when it is needed.

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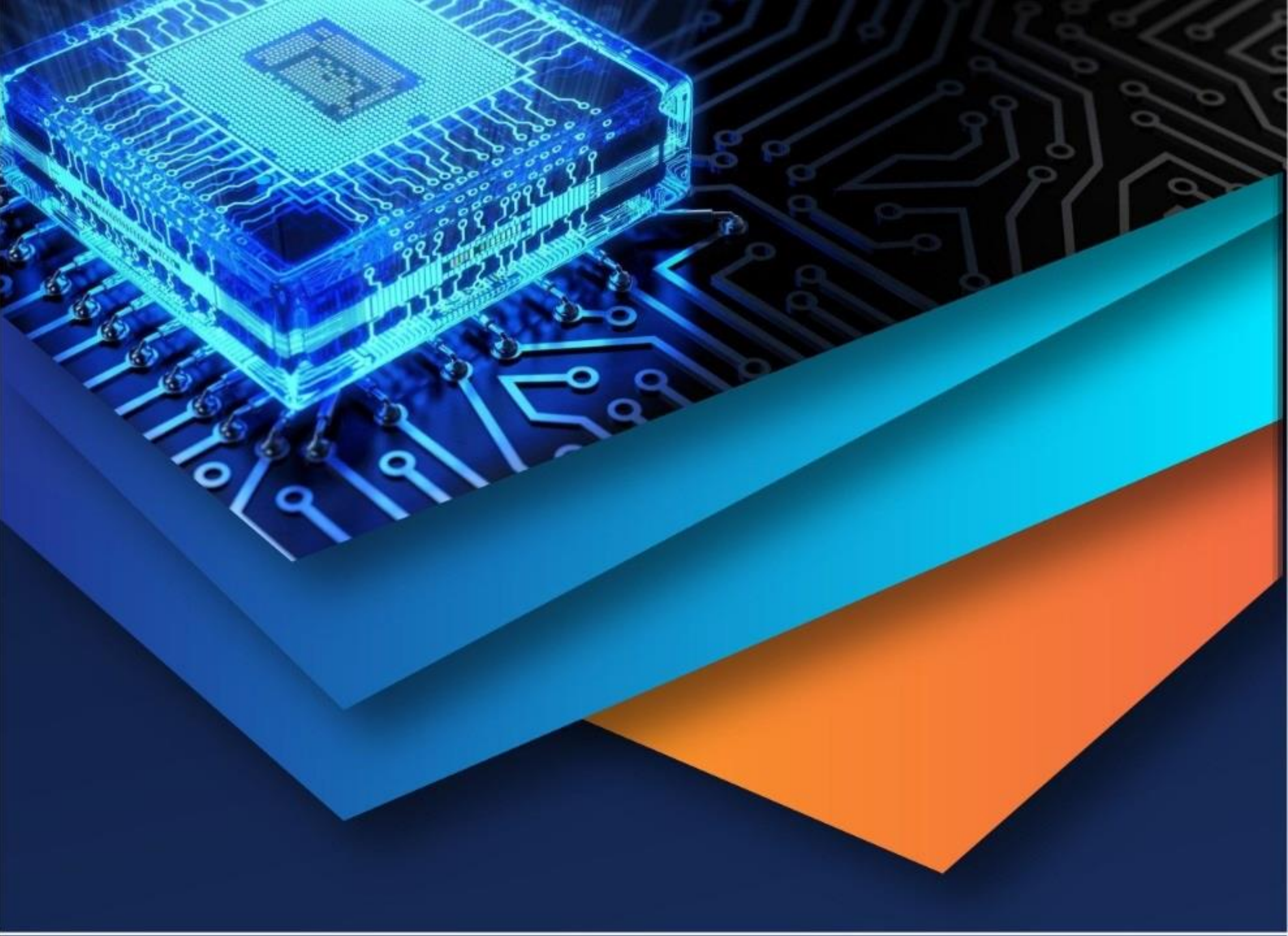

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