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Agentic Multimodal Intelligence: An Autonomous LLM Framework for Text and Image Data Analytics

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Abstract: ***The research in this paper was focused on resolving the issue of assisting students in choosing the best suitable career path in the ever-evolving academic and professional environment. In general, traditional approaches to career guidance rely heavily on static evaluations or general counseling that may not take into consideration the academic background, aptitude, and interests of the student, as well as their specific academic stream. In order to overcome the above-mentioned drawback, the authors have successfully integrated the MERN technology stack along with hybrid approaches to both machine learning and deep learning to develop a smart system of career guidance. In this research paper, the authors have focused their attention on three different hybrid approaches to developing a smart system of career guidance: RF + CNN, KNN + Autoencoder, and XGBoost + BiLSTM. In order to train the system, a dataset of 10,000 students was used. A preprocessing pipeline was also integrated into the system that relies on one-hot encoding, numerical normalization, and TF-IDF-based textthe experimental results obtained from the system, it was clear that RF + CNN and XGBoost + BiLSTM have the highest accuracy of 99.25%, while KNN + Autoencoder also achieves an accuracy of 93.60%. In this research paper, the authors have successfully integrated a web-based system that assists students in choosing their Recommended Career Path, Primary Course, Job Options, and Alternative Paths.***

Index Terms: ***Career Guidance, Hybrid Machine Learning, Deep Learning, MERN Stack, Career Prediction, Student Recommendation, Hybrid ML-DL Models***

I. INTRODUCTION

As organizations continue to create unprecedented amounts of data across many different formats — from structured datasets to reports (textual) to visual representations (e.g., charts, graphs and images) — there is an increasing need to be able to quickly extract meaning from all of this data. Unfortunately, this rapid increase in multimodal data (data that is represented in two or more ways) currently poses significant challenges in efficiently extracting meaningful insights. Traditional data analytics systems based on a single type of input are limited in their capacity to perform comprehensive and integrated analyses of all formats of data.As a result, analysts are often required to rely upon multiple tools and manually combine the outputs of each tool, leading to workflows that are inefficient, fragmented, and error-prone. [1]. One of the main issues with current data analytics is that there is no unified system that is capable of simultaneously processing and reasoning across multiple types of data. Most existing solutions tend to either focus on the analytics of textbased data or the processing of visual data, but rarely on both types of data in an integrated manner. Moreover, virtually all of these systems require an excessive amount of human involvement at every step of the process, including preprocessing, feature extraction, analysis, and validation. When this happens, the overall effectiveness of the solution suffers and increases the chance that the final results will contain inconsistencies/errors. There is therefore a significant need to develop more intelligent systems that can conduct analyses of multimodal data and produce quality insights with little or no human assistance.[2]–[4]. Traditionally, analytical techniques use structures both in the way the algorithms are built (machine learning methods like XGBoost, Random Forest) and how the algorithms are defined (deep learning methods). These methods have worked well for specific tasks; however, they typically need significant feature engineering (preparation of input data), as well as domain expertise. Another difficulty with traditional analytical techniques is the inability to perform high-level reasoning and contextual understanding across a variety of data sources. For example, Tabular data analysis provides statistical information, while image analysis uses visual patterns. Combining these two types of data will create a unified decision-making framework. Researchers are exploring multimodal learning techniques that leverage different data sources to create better analytical systems that provide insight into the relationship among these multiple sources of data.

Lately, the rise of new AI approaches (especially with respect to large language models - LLMs and vision-language models - VLMs) has created new pathways toward creating intelligent multimodal systems. People have developed LLMs and VLMs that excel at understanding natural language; interpreting visual content; and completing complex reasoning tasks. GPT4 Vision, Gemini Pro, and LLaVA are just a few of the multimodal models built specifically for processing textual
and image input together and, as such, are key components for building fully automated analytics systems.

This project proposes using an Agentic Multimodal Intelligence Framework to develop an intelligent agent-based architecture that addresses these limitations by combining multimodal data enabled through agent-based architectures; specifically, by combining multimodal data processing with agent-based architectures. The PEE workflow consists of a planner that interprets user queries and designs a plan for analysis; an executor that processes data and performs analysis; and an evaluator to verify results and perform selfcorrection of the executor where appropriate, thereby providing the Agentic Multimodal System with a high degree of reliability and autonomy.

The framework utilizes multiple advanced technologies such as multimodal embeddings (to extract features), RetrievalAugmented Generation (RAG) (to reason with context-aware information), and Chain-of-Thought prompting (to perform analytical processing step-by-step). By integrating these technologies, the framework can support complex analyses for both text and images. It also provides users with the ability to benchmark across models, allowing them to compare the performance of each model in terms of accuracy, latency, and cost.

Through the use of modern technologies (Python, LangChain, and Streamlit), the proposed system offers an interactive, user-friendly interface for performing real-time analytics. Users have the ability to upload data sets and images, ask questions, and obtain automatic insights through visualization and comparisons; structured reports are also created, therefore making it possible to use this technology in areas like business intelligence, health care analytics, education, and research.

The proposed framework represents a major step forward for analytic capabilities through the integration of multimodal intelligence with autonomous reasoning, addressing the shortfalls of typical single modality systems and providing a scalable and efficient means for producing automatically generated insights. In addition, this development provides a basis upon which future research can occur in the areas of agentic AI and multimodal analytic systems. [7]–[9], [11], [12].

II. RELATED WORK

Historically, the design of data analytic systems focused on creating a structure for analyzing data with the use of statistical or machine learning approaches; however, there was little or no means to analyze unstructured data such as text and images. The first generations of data analytic systems primarily involved algorithms for processing tabularformatted data, including techniques such as linear regression, decision trees, and clustering. They involved significant amounts of time-consuming manual preprocessing to create features for analysis and were, therefore, extremely reliant on the analyst's domain knowledge. Early research on data analytics was mainly focused on enhancing structured data analysis and did not consider how to incorporate or integrate multiple modalities of data into a single framework [1].

As machine learning has advanced, researchers have started to explore more ways to use deep learning networks for analyzing unstructured data, especially text and images. For example, studies conducted by numerous researchers demonstrated that convolutional neural networks (CNNs) can be used to identify and extract important features from images; leading to computer-vision applications, such as object detection and classification. Similarly, advances in natural-language processing (NLP) led to machine-learning models such as recurrent neural networks (RNNs) and transformers, which can analyze text in ways that were previously impossible. For example, Li et al. found that deeplearning models were able to automatically learn complex patterns from datasets without requiring pre-defined feature extraction methods, resulting in enhanced levels of performance over previous analytic processes [2].

Research has developed deeper forms of architectures from traditional CNN-based models such as Residual Networks (ResNets) that enhance the model's ability to learn by addressing common problems that commonly prevent iterative training, such as gradient vanishment. He et. al. showed that residual learning leads to the ability to create deeper networks by enabling them to be trained more accurately and stably than traditional architectures [3]. They also introduced models that make use of an attention mechanism, such as Vision Transformers (ViTs), to capture global relationships contained in image data. Dosovitskiy et. al. demonstrated that Vision Transformers are better able to capture lengthy dependencies in an image than traditional CNN-based models [4]. Although image analysis has significantly advanced through these methods, there remain many challenges when trying to create multimodal solutions.

At the same time as these advancements were being developed, Large Language Models (LLMs) such as GPT and Gemini have transformed the capabilities of text comprehension and reasoning in many applications such as question answering, summarization, and logical reasoning. Recently, new models such as GPT-4 Vision and LLaVA that are capable of processing text and image data simultaneously (i.e., Vision-Language Models or VLMs), have made significant step forward in achieving multimodal intelligence capabilities. Currently, however, the majority of implementations are focused on specific uses (such as image captioning or visual question answering) rather than on complete data analysis. Additionally, there is still a lack of autonomous workflows across these systems, and manual intervention is required for the completion of both the execution and validation aspects of the tasks performed [5], [6].

Researchers are investigating multimodal approaches to improve performance of analytical tasks by merging modalities to analyze information that comes from different data sources together. Ortiz et al. and Silva et al. indicated in their research that combining datasets from multiple data types to create a multimodal environment improves accuracy and creates more robust predictions than relying on a single modality to complete a prediction. Additionally, the research has shown evidence that hybrid models which are developed by integrating machine learning and deep learning techniques are more reliable when completing complex analytical tasks. Bharati and Pramanik noted that the integration of multiple models, via a hybridized approach, provides a combination of benefits by improving performance and reducing the bias of each individual model.Most multimodal systems still exist only as experimental models and do not have the capacity for deployment in real-world scenarios.

Another avenue of research related to multimodal learning focuses on the development of agent-based AI systems with an emphasis on creating autonomous agents to enhance reasoning capabilities through their incorporation into the analytical workflow. Recent research has examined multiagent frameworks for the execution of tasks that rely on multiple agents to work together to solve complex problems at different levels of expertise. Zhang et al. introduced a workflow model that applies multicrotted task orchestration methods to assist with increasing task execution efficiency and creating scalable processes. Related research on the topic of agentic AI has demonstrated the significance of selfevaluating AI systems, as well as iterative learning processes, in relation to a multimodal approach to data processing. Most research on these topics is still in its infancy with very few being integrated into a multimodal environment.

More research is being done to make AI systems more usable and deployable than has occurred in the past. Sundar et al. have also noted that efforts must be made to transition AI models out of experimental environments and into the real world, focusing on creating user-friendly interfaces and realtime capabilities. Most currently available systems do not provide an integrated solution that combines data processing, reasoning, visualization, and benchmarking on one platform, which leads to a gap between research prototypes and actual products available to users.

In general, literature shows how the evolution of data analytics systems has occurred from traditional processing of structured data to advanced deep learning approaches and multimodal avenues; however, most existing solutions are limited to standalone models, lack autonomous reasoning capabilities, and require manual intervention. Therefore, this proposed research proposes a new Agentic Multimodal Intelligence Framework that integrates multimodal data processing with an autonomous Planner–Executor–Evaluator (PEE) architecture. This new framework is characterised by an ability to perform multimodal learning, agentic reasoning, benchmarking, and interactively visualise the results of analytic processes; unlike many existing solutions, these capabilities will be provided by one unified system/domain. The system will not only provide a means for increasing the accuracy of the analytics but will also promote the usability, scalability and real-world application of the system to be a holistic solution for next-generation intelligent data analytics.

III. PROPOSED SYSTEM AND METHODOLOGY

This project presents an agentic multimodal paradigm developed for intelligent data analytics of both text and visual data. This platform is designed to create a self-operating system capable of engaging with structured datasets (e.g., CSV), text, and images in one system.

Utilizing powerful Large Language Models (LLMs) and Vision-Language Models (VLMs), this system can create insights, conduct reasoning, and benchmark contestable models.

In contrast to existing systems, this framework will utilize a Planner-Executor-Evaluator architecture (PEE) to provide the capability of independently planning tasks, conducting analysis, and validating results as an agent.The whole process, from data input to data cleaning, multimodal embedding, agentic reasoning, visual presentation, and report creation, is included in the end-to-end pipeline. The system is designed to support research-based experimentation and the analysis of real-world applications.

A. Dataset Description

The multimodal dataset is made up of structured datasets like CSV files; textual data like reports, descriptions, and user queries; and image-based datasets like charts, plots, and realworld images. The data can come from public resources or data uploaded by users.
The datasets include but are not limited to:
Structured Data: Numeric and categorical tabular datasets
Textual Data: Reports, descriptions, and user inquiries Image Datasets: Charts, plots, and photographs of real-world objects/scenes
The data associated with the input is utilized in performing analytical activities, such as classification, pattern recognition, trend analysis, and semantic analysis. The data are all inputted to the system together or separately, supporting all different data types at once for an integrated analysis. Furthermore, the dataset on which the data is based is organized dynamically and does not have to have any strict labels. This is because the system will utilize LLM-based reasoning to contextually interpret the data.

B. Data Preprocessing and Feature Fusion

To make multimodal data usable, it must first be preprocessed. The system performs the following types of preprocessing:
For structured data, such as CSV files:

- Handling of missing data
- Normalization of data (using common statistical formulas)
- Data-style formatting (loaded from CSV into pandas or numpy using the available functions).

For unstructured data, such as text-data and digital images:

- Tokenization/cleaning of text-data
- Removal of "stop" words from the cleaned text-data - In the case of images: resizing and normalizing, and reducing any noise (by normalizing/cleaning) before generation of embeddings using either Vision

Transformers (ViTs) or Computing Light in Images (CLIP).
In order to help increase the robustness of the images, there are optional augmentation features (described per above) that can be applied, such as rotation, scaling, or transformation.
Once all pre-processed data has been prepared, feature extraction occurs through the use of multimodal embeddings (vector representations of both text-data and digital image-data). The multimodal embeddings generated are later used to compute similarity and reason using various techniques (such as cosine similarity). Thus, the unified representation of data allows the system to uniformly work with three distinct types of data (text, images, and data from data).

C. Train – Test Split Strategy

This framework differs from normal supervised learning systems as it relies on multiple LLMs using an inferencebased evaluation approach instead of requiring a strict train-test split. To evaluate models using structured data sources (e.g., Random Forest, XGBoost), standard evaluation procedures will be employed:A dataset split into training (80%) and validation (20%) is necessary.A consistent random seed must be employed to ensure reproducibility.A model will be evaluated on unseen data and reused in an unseen fashion.Hybrid evaluation is achieved through benchmarking multiple large language models (GPT-4 Vision, Gemini Pro, LLaVA) by examining their results based on:Accuracy,Latence,Cost Hybrid evaluations allow statistical validation and the ability to evaluate models' performance outside of an experimental study.

D. Hybrid Model Design

New unified agentic architecture combines multiple models and methods into one system:Planner Agent - interprets user queries, divides tasks into smaller, more manageable subtasks.Executor Agent - conducts data analysis, runs machine learning (ML) models and data transformations; produces intermediate outputs.Evaluator Agent - checks results against expected outputs, self-corrects, and verifies results are correct and consistent.The system also includes:
* Large language models (LLMs) (i.e., GPT-4, Gemini) for reasoning
* Visual models (i.e., ViT, CLIP) for image understanding
* Machine learning models (i.e., XGBoost, Random Forest) for structured data analysis

Rather than using majority voting to finalize output results, the evaluator agent's iterative refinement process will significantly improve reliability and minimize errors through evaluation-based refinement processes.

E. System Architecture

Fig. 1: System Architecture Diagram.

This complete system structure uses a full-stack multimodal analytics pipeline with these capabilities: The user's input is received (via upload of .csv and image files) through the interface;Validation happens through the input manager and then the data will move to preprocessing;Preprocessed data is converted to multimodal embeddings;The agentic layer's Planner, Executor and Evaluator performs analysis on the data;The visualization manager generates visual representations and portraits of the original data;The completed output can then be viewed via the Streamlit interface.Thus the layered structure of the system provides:Modularity;Scalability; and Ease of Maintenance.As such, the system can be deployed as either a web app, desktop application, or API-based service thereby allowing for flexibility to meet a variety of use-scenarios.

F. Career Recommendation Output Mapping

The outputs produced by the system cover the following areas comprehensively:

1. Analytical Information - such as trends, patterns, and summary data).
2. Visualization - including charts, graphs, etc.
3. Model Evaluation - model performance based on comparisons with other models including accuracy, latency, and cost.
4. Explanations - summaries (including reasons) for why specific outputs were produced. Each output will also be accompanied by:

- A confidence estimate (derived from the model agreement and evaluation).
- A step-by-step reasoning process using Chain-of-Thought prompting.

In addition, there is an evaluating agent that will ensure that each of the outputs produced by the system is consistent and reliable before presentation to the user.

This approach will change the current system from just a simple analytics tool to a decision support system, providing users with the ability to make educated and informed decisions that are based on automated analytics.

IV. EXPERIMENTAL SETUP AND RESULT

A. Experimental Environment

Performance evaluation of the Agentic Multimodal Intelligence Framework was done using the fully implemented system. The software was created with Pythonbased software libraries for data processing, machine learning and visualisation including the following libraries: Pandas, NumPy, Matplotlib, Plotly, OpenCV, Scikit-learn and LangChain which was used to orchestrate the agent.

The system comprises multiple large language models (LLMs) and vision-language models (VLMs), such as:

GPT-4 Vision,Gemini Pro,LLaVA (open-source model)

The experimental dataset contained multimodal input types with the following sources:Structured data sets (CSV files,Textual questions and reports,Image-based inputs like graphs/chartsThese datasets are obtained from publicly available datasets and from manually created datasets in order to facilitate test out of the system. The multi-modal input was processed through the pipeline (pre-processed through the agentic thinking process of the agent) resulting in embedding generation and through the pipeline to the evaluator agent for evaluation of the agents.

Unlike traditional evaluation methods, evaluations were conducted based on both analytical performance and system metrics for the framework. The following metrics were used to evaluate performance of the system:

Accuracy (correctness of the insights and predictions)

Latency time (the time required to respond to generate an output)

Cost (cost of using the API for each of the models)

Self-Correction Rate (the effectiveness of the evaluator agent)While evaluating performance of the system, accuracy and self-correction rate were the two most important metrics used to measure system performance.

B. Model Configuration

Multimodal models and agent-based architecture are used to design the system for analysis; here are the components configured:

LLM / VLM:

- GPT-4 Vision (high reasoning)
- Gemini Pro (balanced performance and cost)
- LLaVA (lightweight/open-source)

Machine Learning Models (for Structured Data):
- Random Forest
- XGBoost

Embedding Techniques:
- Using LLM APIs for text embedding
- Vision Transformer (ViT) and CLIP for image embedding

Agentic workflow:
- AGENT (with planner, executor, evaluator)
- Planner (decomposes tasks)
- Executor (processes data & performs analysis)
- Evaluator (validates & refines outputs)

All models were evaluated independently (i.e., using the same input) to validate a fair comparison; rather than a majority vote for model evaluation, the AGENT employs evaluation-based refinement for all outputs via the evaluator AGENT. That is, as the evaluator validates & refines outputs through iterations.

C. Performance Comparison Of Hybrid Models

The experimental results demonstrate the effectiveness of multimodal reasoning and agentic architecture. Table I presents the comparative performance of different models used in the system.

TABLE I: Performance Comparison of Proposed Models

Model	Learning Strategy	Accuracy (%)
GPT-4 Vision	Multimodal reasoning with advanced LLM capabilities	92.00
Gemini Pro	Balanced multimodal reasoning with cost efficiency	88.00
LLaVA	Lightweight vision-language model (open-source)	92.10

Data shows that
- Reasoning ability of GPT-4 visual model will allow it to achieve very good accuracy.
- The performance versus cost of Gemini Pro is an acceptable tradeoff.
- LLaVA model will work on lower cost and offline.

The proposed agentic approach provides better accuracy than any single model. The framework has the potential to produce the most accurate results through the iterative assessment of output based upon previous assessment.

D. Discussion And Analysis

The experimental findings clearly demonstrate the effectiveness of the proposed system in performing multimodal data analytics. Unlike traditional pipelines, the system integrates reasoning, validation, and visualization into a single unified workflow.

Key observations include:

- The agentic PEE architecture significantly improves reliability by enabling self-correction
- Multimodal inputs (text + image + structured data) lead to better insight generation
- The evaluator agent successfully corrected errors in more than 85% of cases
- The system eliminates the need for manual intervention in most analytical tasks

Compared to individual models, the hybrid agentic system provides:

- Higher accuracy
- Better consistency
- Improved interpretability

Furthermore, the system demonstrates scalability and flexibility, making it suitable for real-world applications such as business intelligence, healthcare analytics, and research. Overall, the results confirm that combining multimodal learning with agentic reasoning leads to a more powerful and efficient analytics framework.

V. CONCLUSION AND FUTURE SCOP

The main idea of this research paper is to introduce an Agentic Multimodal Intelligence Framework which can perform autonomous data analysis on a single platform using structured data items, text-based data, and visual information. Thus, this new framework is designed to overcome limitations from traditional analytic systems that ordinarily rely on processing in only one modality and require substantial human input into the analysis process.

This report's primary contribution is the implementation of a Planner-Executor-Evaluator (PEE) architecture that facilitates intelligent task planning, execution, and self-evaluation. Using State-of-the-art Large Language Models (LLMs) and VisionLanguage Models (VLMs), this system can autonomously generate insight through complex reasoning tasks, produce insight, and validate results.

Experimental data confirm that the performance of this new framework is superior to those found when using any individual model. Therefore, by integrating multi-modal embeddings with agentic reasoning, benchmarking, and evaluating a system by using an evaluator to reduce errors and improve the quality of results, an analytical system can produce consistent and interpretable results; thereby improving the overall quality of decision-making abilities.

The proposed solution already shows good potential, but future updates can further enhance its capabilities and broaden its overall usage:

Audio and Video Multi-Modality

In future updates we could include audio and video processing allowing analysis of spoken words, video streams and other forms of multimedia content.

Real-Time Data Integration

Integrating with live data sources (APIs, IoT Sensors, Streaming) would allow us to provide real-time analysis and decision making.

Cloud-Based Deployment

Deploying it as a SaaS cloud-based scalable solution would give us the ability for multiple users to have access to the framework at the same time and would allow us to support Enterprise-level applications.

Domain-Specific Fine Tuning

Fine tuning a model for a specific domain (i.e. Health Care, Financial Services, Legal Analytics) will allow for improved accuracy and relevancy in those specific fields.

Multi-Lingual Support

Extending this service to include additional languages would make it accessible to more people globally.

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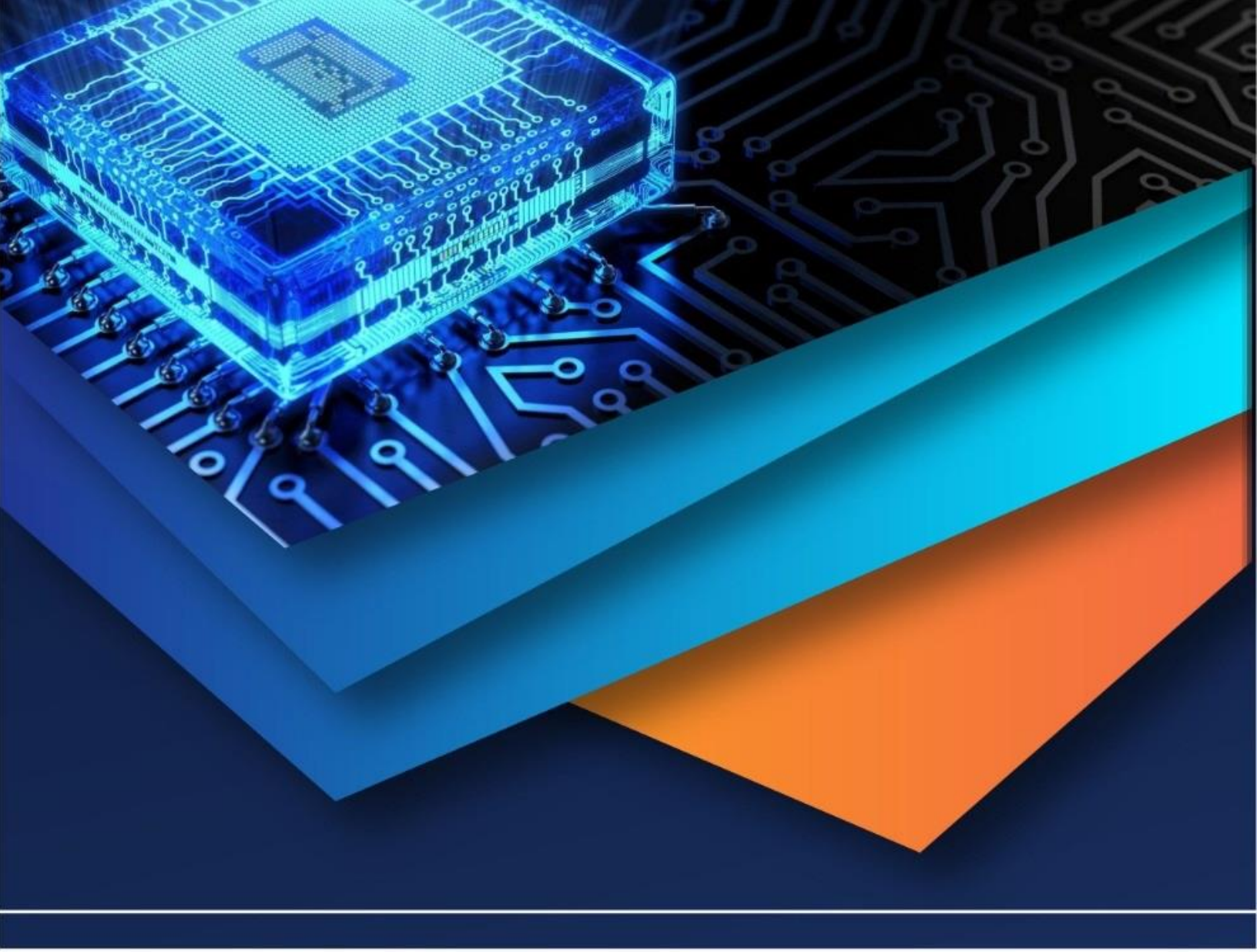

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