iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

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

DOI: https://doi.org/10.22214/ijraset.2026.81395

Survey on an Extensive Analysis of Deep Learning-Based Multi-View Clustering for Alzheimer's Disease

Kashmira Dalvi[1], Sneha Nimbare[2]
[1]Department of Computer Engineering, PHCET, Rasayani, Affiliated to Mumbai University, Mumbai, India
[2]Department of CSE(AL&ML) Engineering, Vishwaniketan's Imeet, Affiliated to Mumbai University, Mumbai, India

Abstract: It is challenging to draw broad conclusions about the data as a whole since information in many real-world scenarios is frequently composed of a diverse range of feature or modal subsets. We call this information multi-view information. For example, images uploaded to social networking platforms frequently have a description tag added to the image, and documents might have many language representations. Since the same data can be interpreted in multiple ways, there has been a lot of research done on multi-view learning. Applications for synthesizing multi-view characteristics include multitask learning, disease diagnosis, object recognition, information extraction, clustering, and categorization, to name just a few. In fact, there has been little usage of multi-view solutions in the creation of Alzheimer patient brain picture clusters, despite the fact that numerous studies in this field have made it possible to incorporate them in a variety of circumstances. Because of this, scientists have been sifting through a database of multi-view classification studies on Alzheimer's disease that have been carried out in the last several years in an attempt to identify the limitations and other approaches that are specific to this sector. As a result, we have created a method that combines many techniques such as fuzzy classification, data matrix, fusion, picture pair shortlisting, and feature lists to generate multi-view clusters for Alzheimer disease.
Keywords: Alzheimer's disease, Image classification, Image clustering, Multi-view fusion, Convolution neural network, Fuzzy Logic

I. INTRODUCTION

Due to its extensive potential applications in a variety of domains, such as data mining and pattern classification, multi-view, multitask, and multimodal training have garnered a lot of attention recently. Since particular single-view data cannot fully account for the knowledge of all specimens, multi-view learning concentrates on the multi-view data, which are usually obtained from various sources or produced from different subsets of features. A website's content and any linked pages' key phrases, for instance, are frequently used to describe the datasets that comprise a website. The same text may have multiple translations, while image collections may be described by features as different as LBP and HOG.

The objective of multi-view clustering has always been to assign data points to clusters more consistently by combining information from multiple viewpoints. This poses the challenging task of figuring out how to establish linkages between the various perspectives. Numerous methods have already been developed in an attempt to address this problem. Multi-view data is widely used in many different disciplines, such as computer vision, statistical modeling, deep learning, and data collected from many places or recorded by different sensors. It is distinguished by diverse pattern recognition approaches. Many newspapers may cover the same news event, activities can be recorded by both RGB video and a depth camera, and images can be encrypted with a wide range of deep and hand-crafted qualities. Researchers have recently focused a great deal of attention on multi-view data due to its consistent ability to provide additional information between multiple distinct views. This makes multi-view data useful for a wide range of tasks, including cross-domain transformation, wavelet transform, feature extraction, and time series subspace learning classification. Utilizing complementary information from multi-view data to identify the basic clustering technique shared by all perspectives is the main problem of MVC. In order to accomplish this goal, existing systems often perform one of two things: either they build a specific loss that integrates multi-view data even during the clustering operation, or they develop a latent feature space to examine the consistency data spanning views before clustering. Even with their remarkable efficacy, these methods mostly rely on clustering with raw multi-view data, missing the chance to leverage the more abstract knowledge to reconcile the differences between divergent local features or subdomains.

[1] Tao Zhiqiang et al. This research suggested a novel M2VEC technique that combined spectral graph partitioning, consensus representation learning, and marginalization denoising into a single optimization framework. By stacking M2VEC blocks, a multilayer model is produced that offers rich and durable partition-level representations for clustering purposes. Experiments on eight real-world data sets showed that the suggested M2VEC is better than numerous cutting-edge multiview and EC techniques. Additionally, the system provided a thorough analysis of the author's model from a number of angles and demonstrated how to use M2VEC with incomplete multiview data.

[2] Jinhua Sheng et al. introduced the SWLR method, a novel logistic regression-based subclass weighting approach. In particular, samples are clustered using K-means++, and samples that have comparable Euclidean distances are considered to belong to a subclass. For every subclass, determine its weight. The subclass weight and the global weight work together to forecast the final sample's label. To mitigate overfitting and address the issue of excessive feature set size, the method employs L2 regularization for both U and V within the loss function. The system conducted ve sets of compared tests, HC vs. EMCI, HC vs. LMCI, EMCI vs. LMCI, LMCI vs. AD, and HC vs., to demonstrate the efficacy of the algorithm. AD. Tests indicate that the SWLR algorithm performs reasonably well. Furthermore, the system performed a follow-up analysis of the coefcient matrix U, identified the characteristics with the highest weight coefcients in each stage, and then used the HCPMMP toolbox to locate the associated brain areas. We discovered that there is a pattern in the distribution of the core brain region, which often migrates counterclockwise, throughout the progression of the disease from HC to AD. The system then compares the findings with the body of research, looking at both the macro and micro levels. The findings indicate that the findings align with the body of research. It is important to note that the author's findings can be seen as illuminating given the paucity of existing research on EMCI and LMCI.

[3] The partial multiview clustering problem has been extensively researched, and numerous clustering techniques have been put forth. Xia Ji et al. explores this topic. The current approaches, however, still suffer from a number of drawbacks, including excessive parameter complexity, high temporal complexity, and the inability to support more than two perspectives. This study proposes the adaptive anchor strategy-based partial multiview clustering algorithm AAPMC, which can address the drawbacks of earlier approaches. Its superiority is clearly validated by the experimental results. In terms of upcoming research, it would be intriguing to expand the adaptive anchor-based approach to the partial multi-view clustering problem, in which every view characteristic is contained in the rear enosample among several views. Furthermore, the majority of incomplete multi-view clustering techniques now in use, including the author's method, require knowledge of the number of clusters beforehand. system aim to use COMIC [36] as a reference and modify the author's technique to enable clustering without requiring knowledge of the cluster size beforehand.

[4] Using volumetric features from sMRI data, Abol Basher et al. have presented an aggregated strategy using CNN, DNN, and Hough-CNN models to diagnose Alzheimer's disease. The AD and NC classes were classified using the proposed DNN model using the volumetric characteristics that were extracted by the DVE-CNN model. The average weighted accuracy scores of 9482% and 9402%, respectively, were reported based on the volumetric features assigned to the left and right hippocampi in the GARD dataset. A three-fold cross validation was carried out to illustrate the outcomes. For the left and right hippocampus data, the suggested technique produced AUC values of 9254% and 9062%, respectively. 69 individuals and 65 subjects from 80 AD subjects, respectively, were effectively diagnosed utilizing the author's method using left and right hippocampus volumetric features. Its key advantages are that the suggested method is fully automatic and has somewhat higher accuracy than other methods suggested in the literature for the same dataset. Additionally, it is shown that the volumetric features of the hippocampus region can be used to detect Alzheimer's disease and that these attributes are important biomarkers. The system will, however, use the author's method in the future when integrating the volumetric features of the left and right hippocampi with other regional features, including VBM and CSC, and when working with big open-source datasets in addition to data from other modalities, like positron emission tomography (PET). This literature survey study is divided into three sections: section II evaluates previous research on the organization of literature surveys; part III contains conclusions and aims for future research.

II. LITERATURE SURVEY

[5] Shirui Luo et al. suggested a novel MvSDc approach and presented a framework to produce multiple clusterings from multiview data. At the same time, a latent embedding representation from several perspectives was identified and the dual-clustering structure was acquired. The proposed method aimed to find two good quality and distinct clusterings based on the mutually exclusive property and the rank restriction. An alternating optimization strategy proved to be an effective solution to the resulting optimization problem.

It is fascinating to investigate multiple clusterings since multiclustering data exist and some of the representation matrices of the clusterings are overlapping while others are mutually exclusive. The system should think about investigating inherent links across several clusterings in the future.

[6] According to Francisco J. Martinez-Murcia et al., the most prevalent neurodegenerative illness worldwide is Alzheimer's disease. Although the fundamental mechanisms of the illness are starting to become clearer, new approaches are required to offer a fresh viewpoint on the condition and its diagnosis. In modern clinical practice, the utilization of picture biomarkers is crucial, and sophisticated automatic diagnostic tools are available. We now have new tools thanks to the deep learning revolution that can automatically extract attributes from images without assuming anything about the underlying process. The deep convolutional auto encoder (CAE) architecture, which can automatically execute non-linear decomposition of a very large dataset (more than 2000 pictures), is proposed in this study. Large correlations (higher than 0.63) have been observed between the data-driven features generated using this technique and other clinical and neuropsychological factors, including age, tau protein deposits, and particularly neuropsychological exams. With an accuracy rate of more than 84%, it has been proven helpful in the differential diagnosis of Alzheimer's disease. The regions most impacted by the course of the disease and their relationship to cognitive decline are revealed by the depiction of each neuron's areas of effect and the association of these scores with clinical factors. As a result, the author's CAE system can be applied to help diagnose dementia and offer fresh insights into the connections between structural impairment and cognitive function as assessed by these neuropsychological assessments. This will open the door to the development of novel imaging biomarkers that will be helpful in clinical settings.

[7] To choose useful features from a variety of template features, Zihao Chen et al. provide a multi-classification approach that combines feature learning and latent space learning. The SVM classifier is used to perform AD multi-classification using specific features. To be more precise, the system initially extracts the relationships between various templates to the shared latent space. In order to find the most discriminative features, feature learning is done on the latent space in order to investigate the inherent relation. Lastly, a set of comparison tests show that, when employing the data gathered from the ADNI dataset, the author's suggested model performs the best when compared to rival models.

[8] An AIMC architecture with an arbitrary number of views was proposed by Cai Xu et al. for IMC. A common high-level representation for incomplete multiview data is what AIMC aims to find. Two AIMC versions are explored by the system: 1) AAIMC and 2) GAIMC, which use distinct learning algorithms for multiview common representation. AAIMC uses elementwise reconstruction and GAN to attempt to extract hidden information from the missing data by MDI. Using instances of the same cluster, GAIMC directly searches the multiview comprehensive representation and deduces the information of the missing views. Experiments conducted on six real-world datasets validated the efficacy of AAIMC and GAIMC in comparison to the most advanced IMC techniques.

[9] MPMNMF, a novel multiview clustering technique, has been proposed by Xiumei Wang et al. Manifold regularization and pairwise co-regularization are incorporated into the NMF framework in the suggested approach. As a result, we may simultaneously acquire the parts-based representation and maintain the data space's locally geometrical structure. In order to solve the objective function efficiently, the system uses iterative updating procedures. Moreover, the system provides the theoretical evidence that the suggested multiview clustering algorithm's objective function is convergent. The suggested algorithm's empirical clustering performance is demonstrated using real-world data sets from system users. The suggested technique outperforms a number of current multiview clustering algorithms, according to experimental data. In order to determine the final clustering result, the system performs typical K-means clustering on the multiview data coefficient matrices in this study. Actually, random itialization can have an impact on the clustering performance of K-means clustering. The system will attempt to suggest a novel approach in the future that eliminates the need for post-processing techniques like K-means clustering.

[10] Yu Zhiwen et coll. This paper suggested a hybrid multiview clustering based clustering ensemble architecture. The system suggested a three-part approach to increase the suggested framework's scalability and generalization performance. To begin with, three distinct view transformation methods were applied to produce a variety of clustering views. The consensus result can then be produced from the multiview clustering findings utilizing hybrid multiview learning and random transformation. Second, in order to improve the diversity of various clustering assessments, a random subspace transformation was further devised. Third, to optimize random subspace sets, a VSES was created. The suggested framework can cluster datasets with varying features with good accuracy and generalization capacity by integrating these three components. Experiments proved that the suggested approach is effective.

[11] Nora Shoaip et al. provide a description of AD, which is defined as a chronic degenerative illness involving a collection of neurological problems brought on by the buildup of amyloid plaques that develop in the brain and impair vital bodily functions.

To warn high-risk patients who have a high probability of developing AD, ADDO, a standard fuzzy ontology-based semantic knowledge, is developed in this work. Effectively taken into account is a thorough examination of the patients and a schedule of their appointments, which includes information on the patients' demographics, medical history, disease history, complications, prescriptions, and a wide range of diagnostic tests. ADDO maintains the top-level ontologies of OGMS and BFO in order to facilitate interoperability. Ideally, ADDO will be more significant in the therapeutic setting for AD. Based on the experimental findings, ADDO integrates heterogeneous AD data with ADDO to facilitate interoperability and give a consistent ontology. system mapped a number of actual instances using ADNI. Responding to numerous SPARQL semantic questions is how ADDO is assessed. ADDO is dependable and consistent as an evaluation result. In the future, rule-based reasoning for AD diagnosis will be built into ADDO through the use of SWRL rules in rule-based implementation. As Alzheimer's patients' conditions worsen and the illness advances, more and more of them are being bedridden. Many instances stay at home with their relatives. The system is anticipated to undergo numerous enhancements as it offers remote healthcare to individuals with AD, aided by their caretakers, in order to track the patients' illness progression. In order to enhance accuracy and assist doctors in automatically retrieving patient data needed for diagnosis, hospitalized patients as well as patients who are remotely available should be considered.

[12] Dragomir Andrei and others. Recently, there has been a growing interest in network-based biomarkers because of their capacity to support both modeling of intrinsic functional linkages at different biological levels and complete systems level methods. The established methodologies of network science and graph theory are advantageous for studying complex diseases like AD. They provide not only with a conceptual framework but also with useful toolkits and techniques that can address the shortcomings of current biomarker discovery approaches. An essential first step in treating AD is the creation of effective frameworks for locating non-invasive biomarkers in the disease's preclinical phases. In this regard, information gathered from neuroimaging techniques and omics-based data derived from blood samples make up excellent candidates for the identification of non-vasive biomarkers.

[13] Mahmoud Seifallahi et al. introduced an innovative approach to meet the demand for a widely applicable, user-friendly technology-based evaluation of AD patients. As the subjects completed the TUG test in front of a Kinect V.2 camera, skeletal data from 25 joints of 47 HC and 38 AD subjects were gathered. From various TUG subtasks, 61 features were extracted using a variety of data processing and feature extraction techniques. After correcting the extracted features for age and GDS score, the author's feature selection procedure produced 12 significant characteristics between the AD and HC groups. In the end, an SVM-based machine learning classifier was created to distinguish AD from HC. The outcomes demonstrated that significant features from a variety of TUG test subtasks were obtained by examining changes in the spatiotemporal information of the body joints captured by a Kinect V.2 camera. When evaluating the SVM classifier using leave-one-subject out cross validation, the average accuracy and F-score were 98.68% and 98.67%, respectively, and 97.75% and 97.67%, respectively, when using five-fold cross validation. These results demonstrated that the thorough examination of TUG with a Kinect V.2 camera and machine learning has the potential to be applied as a simple and low-cost supplementary technique for the routine quantitative assessment and identification of AD in clinical or residential settings. The strategy will be expanded to encompass a bigger cohort of people with MCI and other similar illnesses in the author's future study.

[14] Using ADNI data, Faza Lur Rehman Faisal et al. developed a CNN for 3D whole-brain imaging. They found that an isotopically repeated convolutional block network design produced the best accuracy. The suggested approach outperformed current cutting-edge systems. Furthermore, the author's method is incredibly quick and entirely automatic—neither further information entry nor manual labor is needed. The suggested approach has the potential to detect significant patterns in data, validate expert's prior findings, support diagnostic scenarios, and ultimately pinpoint patterns for illnesses other than Alzheimer's. Subsequent studies may aim to achieve comparable or superior outcomes using pictures that have previously undergone pre-processing for subtraction and alignment of the skull. In order to enhance the information found in MRIs, improve decision-making, and establish a connection between the information and the patient's background, it would be intriguing to incorporate patient history data.

[15] Mümine Kaya Keles et al. suggest a binary version of the ABC method to classify brain volumetric data. In order to conduct a thorough comparison, binary versions of three approaches (BGWO, BPSO, and BDE) as well as conventional methods like IG, GR, CHI, and ReliefF were employed. Every run of the experiments was carried out with MATLAB software. When BABC and conventional data mining algorithms were compared, BABC was found to be superior in terms of both accuracy and F-measure. The tables show the algorithms' best, worst, average, and standard deviation. We performed ten runs of each method to obtain an average performance. Furthermore, fitness and accuracy convergence curves were plotted. The criterion for termination is the greatest number of cycles. Each of the three classifiers—KNN, RF, and SVM—was used separately in the approaches' binary mechanism.

[16] G. Navarro Palacios et al. Through this work, the value of an ADL-based memory task for the identification of cognitive deficits has been shown by authour.

Even with a small sample size, the task's capacity to distinguish between healthy individuals and those with cognitive impairments has been demonstrated by include a group of elderly adults in good health. As a result, the research may help with early disease detection, which would allow for the prompt administration of treatment when symptoms that are typically missed are identified. The test-retest reliability test yielded an excellent level of clinical significance, which lends robustness to the author's proposal.

[17] A unique machine learning technique for AD diagnosis using an EEG signal has been proposed by Kai Li, Jiang Wang, et al. We use VAE and TSK fuzzy system models to increase the interpretability and identification precision of the models. To look into the default brain dynamics in AD processes across subjects, latent variables are built. AD and normal EEG signals are classified using a fuzzy rule-based TSK model, which takes the energy properties of latent variables as independent inputs. TSK fuzzy classifier performs better in classifying energy features from sub-frequency bands of latent variables than linear classifier. When the model input consists of the combination of energy information from four different frequency bands, the identification accuracy might reach 98.10%.

A tensor multi-task ensemble learning technique based on tensor decomposition was proposed by Yu Zhang et al. [18] to predict AD development at many time points while addressing variability and instability in prediction accuracy. Within the author's paradigm, the prediction model is predicated on trend correlations between biomarkers and spatiotemporal morphological variation, as well as multi-task regression. Tensor latent components are employed as multi-task links to compute final prediction outcomes and transfer knowledge. Furthermore, temporally continuous MRI recordings are integrated with the gradient boosting ensemble learning technique in the proposed method to constantly improve the forecasting accuracy of AD progression. Based on correlation data, distinctions in the distinct brain areas underlying AD, MCI, and CN can be found, according to the experiment results.

[19] Ahmed Samsuddin et al. An effective framework for AD diagnosis using brain MRI is provided by this work. They have taken into account the hippocampal region, which is thought to be among the most impacted clinically investigated biomarkers for the identification of AD. The system needed to implement two patch-based classication models for the two distinct hippocampi in the brain. However, performance is improved when a different model is used to categorize both hippocampi. system subsequently created ensemble models to achieve a better classication result. The CNN classiers were constructed by the algorithm using the semir's TVPs, and it only produced places within the hippocampal region. This method made it easier to generate the training data that was required. The system integrated the models after receiving adequate training to produce the predicted accuracy (8555% for ADNI and 9005% for GARD), which is comparable to the models created for the MRI modality.

[20] Celia M. Dong et al. provide a study that demonstrates how the author's molecular MRI technique can visualize the curcumin-conjugated magnetic nanoparticles, or Cur-MNPs, and target Aβ pathologies at both early and late stages of AD progression. Additionally, the author's logical results corroborate the specific targeting of Aβ pathologies, showing that Cur-MNPs can target Aβ oligomers at an early stage of AD progression in addition to Aβ plaques. When combined, they offer a potent imaging strategy that advances the author's goal of developing new drugs and detecting AD at an early stage.

III. CONCLUSION AND FUTURE SCOPE

Real-world data frequently consists of multiple feature or modal subsets, making it difficult to draw broad conclusions about the data as a whole. Such data is referred to as "multi-view" data. Articles, for instance, can be found in multiple languages, but pictures posted on social media platforms nearly always have a caption that describes the image as well. The understanding that the same data may be perceived differently has led to a rise in interest in multi-view learning in recent years. Multitask learning, medical diagnostics, object classification, information retrieval, grouping, and classification are just a few of the many applications where synthesizing multi-view features has enormous promise. While several studies have been conducted in this area that enable the integration of such multi-view implementations in various different paradigms, there hasn't been much use of this kind of system for creating multi-view clusters of Alzheimer's images. In order to uncover the dangers and other constraints, this has led to the investigation of a corpus of multi-view classification researches in recent years. This led to the development of our method for creating multi-view clusters for Alzheimer's disease using fuzzy classification, feature lists, data matrices, fusion, and image pair selection**.**

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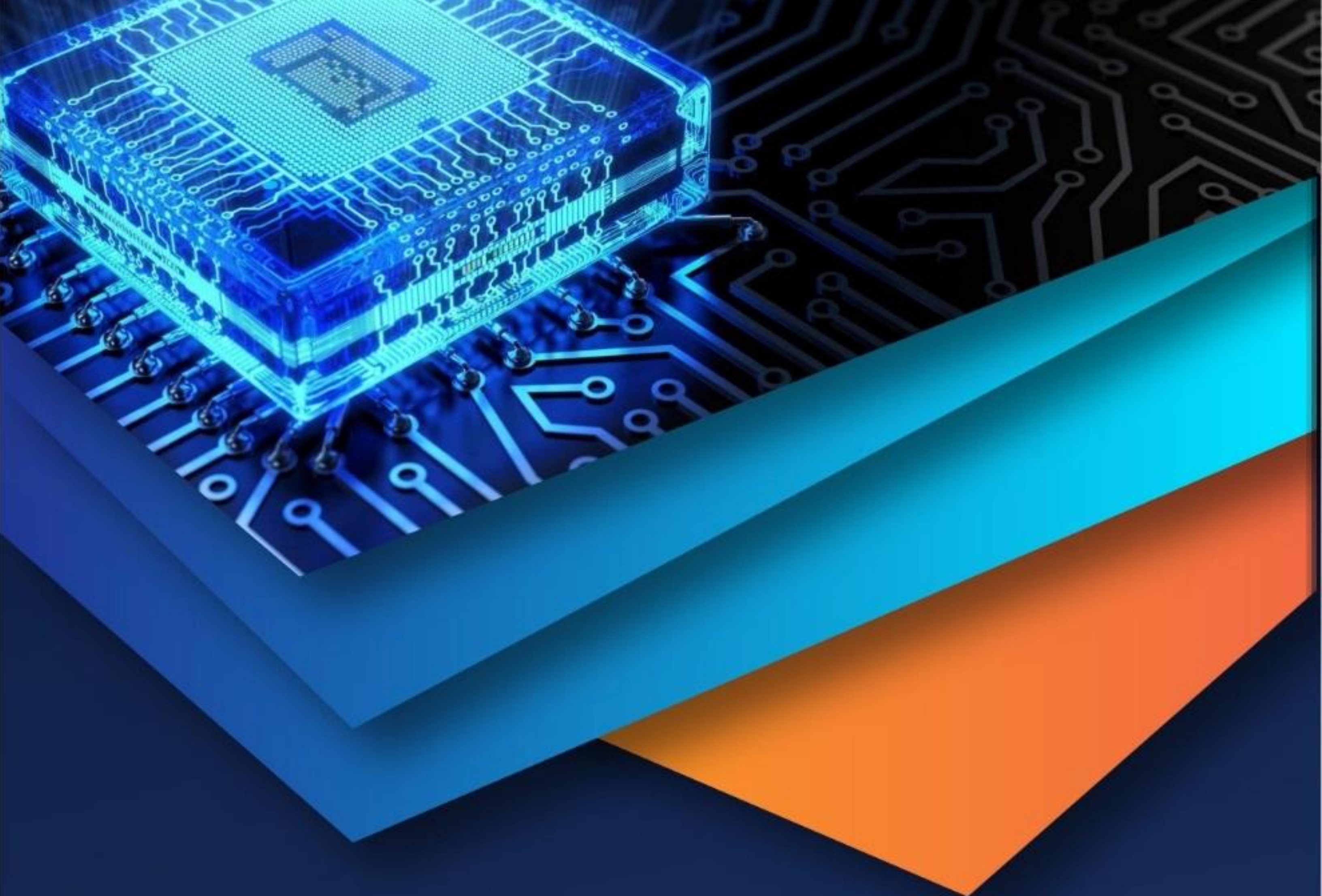

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