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Waste Segregation System using Image Classification and Deep Learning for Smart Cities - SmartWasteNet

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Abstract: Nowadays, automated waste segregation systems are crucial for sustainability and urban hygiene, effective waste management has become a major concern for smart cities in the modern era. In recent years, deep learning-based methods and image classification have demonstrated potential for waste identification automation. However, traditional approaches, like the base method described in Knowledge Based Systems, have drawbacks such as flat classification pipelines, low robustness to obscured or cluttered waste images, and only Convolution Neural Network (CNN) for feature extraction. Moreover, SmartWasteNet where a hybrid deep learning framework that combines Transformer-based global context modelling along with Deep Pyramid Convolutional Neural Network (DP-CNN) for multi-scale local feature extraction and confidence-guided hierarchical classification strategy for adaptive decision-making, to address these issues. Firstly, TACO (Trash Annotation in Context) and TrashNet dataset which contain different waste images conducts conceptual preprocessing using hierarchical labelling into coarse (organic vs. non-organic) and fine (plastic, metal, glass, paper, hazardous, residual) categories. Furthermore, Discriminative representations are created by fusing global and local features, and they are initially categorized at the coarse level. Moreover, identification of waste types and low-confidence predictions are adaptively routed to a fine-grained classifier. Furthermore, the Scalability and practical application are guaranteed by software design. Additionally, the efficacy of SmartWasteNet for intelligent urban waste segregation is demonstrated by experimental results that show a significant improvement in accuracy, precision, recall, F1-score, robustness to occlusion, and adaptivity when compared to the base method. Finally, adaptive hierarchical decision making is made by this novel model. The primary drawback is the increased conceptual complexity brought due to hierarchical architecture.
Keywords: SmartWasteNet, DP-CNN, Transformer, Confidence-guided hierarchical, fine-grained, coars

I. INTRODUCTION

In recent times, Rapid urbanization and population growth have significantly Boosted the volume of municipal solid waste, creating Harsh environmental, economic, and public health challenges for smart cities. Moreover, Efficient waste management is a key component of sustainable urban development, as improper disposal will impact to Soil pollution, greenhouse gas emissions, and resource depletion. Waste segregation at the source plays a vital role in improving recycling efficiency and reducing Excess landfill waste. However, manual segregation requires intensive labor, more time consuming, and leads to human error, especially in large-scale urban environments [1]. Moreover, Recent development in artificial intelligence, particularly image classification and deep learning, has improvised to enable automated waste segregation systems capable of identifying, and classifying waste into categories like organic, recyclable, and hazardous. Moreover, Deep learning models which are Convolutional Neural Networks (CNNs) that automatically extract appropriate visual features from waste images and obtain high classification accuracy. Furthermore, integrating such intelligent waste segregation systems into smart city infrastructure enhance operational efficiency led to reduce costs, and support environmentally sustainable practices. However, the progress in automated waste segregation systems face multiple challenges in Visual Blockages, variations lighting conditions, background clutter, different waste shapes and textures often lead to degrade classification performance. Moreover, a lot of deep learning models require large, well labeled datasets for training which are costly and complex to obtain in real-world waste management scenarios. [2] Additionally, high computational complexity and memory requirements of deep neural networks restrict deployment on low power embedded systems which are commonly used in smart bins.

Moreover, the lack of generalization across regions as waste composition and packaging methods or style may significantly vary among countries. In Additional to the work there arises the immediate need to develop a scalable, accurate, and efficient waste segregation system suitable for smart city applications. Furthermore, automating waste classification uses image-based deep learning techniques to improve recycling rates and reduce human actions. Moreover, optimizing models balance accuracy and computational efficiency to enable real-time deployment in smart bins and IoT-enabled waste collection systems [3]. In addition to existing challenges where systems play an important role in cleaner cities where there is reduced environmental impact and more sustainable urban living. Further, the State-of-the-Art methods followed by a basic Convolution Neural Network (CNN) model are mostly used for waste image classification due to its ability to automatically learn structural features from images without manual feature extraction. Moreover, CNNs have strong performance in visual recognition tasks and their relatively simple architecture compared to deeper models. However, CNNs often suffer from limited accuracy when dealing with complex waste images and may overfit when trained on small datasets [4]. Subsequently, ResNet is employed in waste classification tasks to overcome the vanishing gradient problem by using residual connections which enable very deep network architectures. Moreover, improved classification accuracy and better feature representation for complex and various stages of waste categories. However, ResNet has high computational cost and memory usage, which limits its suitability for real time and edge device deployment [5].

II. LITERATURE

Megha Chhabra *et.al [6]* established an intelligence waste classification approach based on multi-layer using convolution neural network. Initially, data was collected from Kaggle, which contained food and waste images. Subsequently, these images were preprocessed by using normalization and data augmentation to reduce noise and ensure computational complexity. Additionally, these images were fed into feature extraction using a convolution layer which automatically extracts hierarchical spatial patterns between organic and recyclable waste. Moreover, the automated CNN easily observes complex visual patterns without manual features and leads to higher classification. However, CNN faced challenges in computational cost due to scalability and real-world deployment.

Faizul Rakib Sayem *et al. [7]* introduced the DenseNet-201 framework for classifying and detecting waste. Initially, the Waste Recycling Plant (WaRP) dataset consisted of 10,406 waste images. Subsequently, these images were preprocessed by using normalization, data augmentation, and image resizing to improve model robustness. Additionally, these preprocessed images were fed into dual-stream architecture combined with DenseNet-201, enabling both local and global feature learning. Moreover, the DenseNet-201 method has high classification accuracy and strong generalization in real recycling. However, the DenseNet-201 method failed in high computational complexity and increased training time.

Ahmet Alkilinc *et al. [8]* introduced the deep ensemble learning framework combination of multiple pre-trained CNN models for effective waste classification. Initially , the TrashNet, TrashBox, Waste Pictures and Garbage Classification datasets is consisting of labeled waste image data were used for training and evaluation. Then, these images were preprocessed using image resizing, normalization, and data augmentation to improve the model generalization. Subsequently, feature extraction was performed using pre-trained CNN models such as DenseNet, ResNet, EfficientNet, and ConvNeXt where followed by averaging and weighted ensemble strategies. Moreover, the pre-trained CNN models achieved the high classification accuracy and also the strong robustness across multiple datasets. However, the pre-trained CNN models suffer from high computational cost and increased inference complexity.

Moshrof Hossian Dipo *et al. [9]* demonstrated a deep learning–based waste classification system utilizing transfer learning for automatic waste recognition. Initially, a public waste image dataset containing multiple waste categories, composed of RGB image data, was employed. Subsequently, all these images were preprocessed using the image resizing, normalization, and augmentation techniques to decrease overfitting. Furthermore, feature extraction was has been carried out using pre-trained convolutional neural networks, enabling effective learning of discriminative visual patterns. Moreover, the proposed approach Yolo explained improved classification accuracy with reduced training effort. However, the YolO model showed limited performance in complex backgrounds and class-imbalanced scenarios.

Md. Nahiduzzaman *et al. [10]* established a three-stage automated waste classification system using a parallel lightweight depth-wise separable Convolution Neural Network combined with an ensemble Extreme Learning Machine (DP-CNN–En-ELM). Initially, the Tri Cascade WasteImage dataset, consisting of 35,264 waste images, was constructed for multi-stage classification. Then, these images were preprocessed by image resizing, pixel normalization and scaling to optimize computational efficiency. Additionally, feature extraction has performed by a custom lightweight DP-CNN architecture also followed by classification using the En-ELM classifier. Moreover, the DP-CNN–En-ELM has gained high accuracy with low computational overhead and real-time capability.

However, the DP-CNN–En-ELM multi-stage framework has introduced increased system complexity and implementation difficultly.

Gaffari Celik *et al. [11]* introduced multi-layer feature fusion for solid waste classification and detection of waste segregation. Initially, the Household-Garbage and TrashNet dataset were considered waste images. Then, these images were pre-processed by using image resizing, normalization, and data augmentation to enhance the model performance. Subsequently, these pre-processed images were fed into EfficientNetB0, InceptionV3 and HypeColumn for enabling the extraction of both general and detailed features. Moreover, the XGBClassifier was performed in the classification and detection by optimizing performance. However, this XGBClassifier suffered from high computational cost and increased inference complexity.

Sehrish Munawar Cheema *et al. [12]* presented a deep learning–based waste classification framework by utilizing the Convolutional Neural Network (CNN) to enhance solid waste management system. Initially, a large-scale labeled Waste Image dataset considering multiple waste categories.

Subsequently, the images were preprocessed by using image resizing, normalization, and data augmentation techniques to enrich the model significantly and reduce overfitting. These preprocessed images were then fed into CNN-based architecture, which effectively extracts texture-based and spatial features. Moreover, Smart Waste Management and Classification Mechanism using a Cutting-edge Approach (SWMACM-CA) illustrated high classification accuracy and generalized performance under real-time situations. However, the model exhibited increased training complexity and high computational cost.

Zhaoqi Wang *et al. [13]* implemented Deep learning–based waste classification framework using a convolutional neural network (CNN) improve automated solid waste sorting. Initially, A large scale waste image dataset is collected and differentiate into multiple recyclable and non-recyclable classes. Subsequently, the images were pre-processed using normalization, data augmentation, and resizing techniques to improve feature representation and reduce overfitting. The pre-processed images are trained using a CNN architecture with transfer learning to extract discriminative visual features. Moreover, the CNN enhanced high classification accuracy and improved robustness under different lighting and background conditions. However, the model suffered from increased computational cost and required high memory resources limiting its deployment on low-power embedded systems.

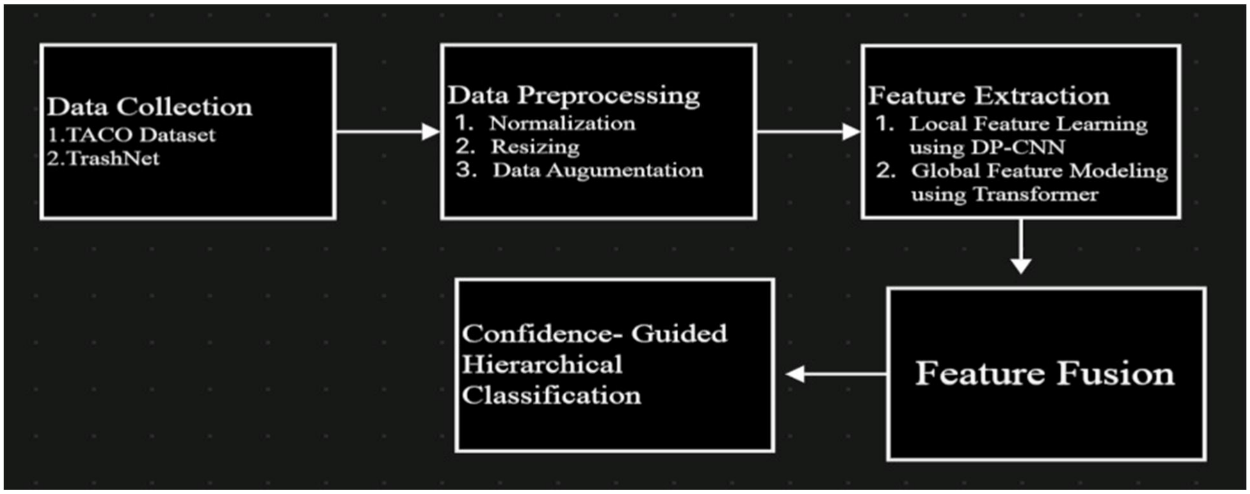
Nonso Nnamoko *et al. [14]* illustrated an Intelligent Waste Segregation System using Deep Learning techniques for smart infrastructure applications.

Initially, a labeled waste image dataset was collected from real-world conditions. Subsequently, these images are preprocessed by using image scaling, noise removal and normalization techniques to improve data quality. Additionally, the processed images were input into a Deep Convolutional Neural Network (DCNN), which permits the model to observe reliable features for waste classification. Furthermore, the DCNN method established high robustness and reliable concert in waste segregation tasks. However, the system demonstrated challenges in scalability, and this is essential for significant computational resources for training and deployment of waste segregation.

Mansura Naznine *et al. [15]* introduced the lightweight deep learning framework for real-time waste classification which aims at the smart city applications. Initially, waste images were collected from publicly available datasets and resized to standard dimensions. Then, applied into pre-process using Data augmentation and normalization techniques which has applied to improve robustness against environmental variations. Additionally, the processed images were then trained using a compact CNN architecture optimized for efficiency. Moreover, the Parallel Depth-wise Separable Convolutional Neural Network (PLDs-CNN) model has achieved acceptable accuracy with faster inference speed making it suitable for real-world deployment. However, the lightweight design were resulted in reduced performance when classifying complex or overlapping waste objects.

III. METHODOLOGY

This research proposed a hybrid deep learning-based waste segregation method called SmartWasteNet for smart city applications. Firstly, data is collected which contains waste images from datasets like TACO and TrashNet. Moreover, due to differences in lighting, scale, and background, data is preprocessed by resizing, normalizing, and using data augmentation techniques. Further, they used a DP-CNN method to extract multi-scale local features while a Transformer-based method captured global contextual information. Finally, they applied a confidence-guided hierarchical classification method to differentiate the waste into organic and non-organic classes. Furthermore, refining the samples into more specific categories. The overall methodology flow is shown in Figure 1.



A. *Data Collection*

The first step in developing SmartWasteNet contains collecting a comprehensive and diverse set of waste images. Moreover, the primary dataset TACO (Trash Annotations in Context) contains real-world waste images with complex backgrounds representing multiple different categories of waste like residual, organic, recyclable, and hazardous. Additionally, to enhance generalization and validate model performance where the dataset may be supplemented with TrashNet, that provides labeled, clean images of common waste items. Furthermore, this ensures that the models handle both real-world and controlled urban scenarios which cover variability in scale differences, object appearance, and background clutter.

B. *Data Preprocessing*

Furthermore, Preprocessing is executed to ensure that the networks learn meaningful patterns in case of environmental variability. Moreover, Images are normalized, resized, and further data augmentation is applied by brightness adjustment, rotating, and flipping to simulate multiple different real-world conditions. In addition, the waste categories are organized into a hierarchical structure, with coarse-level categories such as (Organic vs Non-Organic) and fine-level categories such as (Residual, Plastic, Metal, Glass, Paper, Hazardous). Further, this hierarchical labeling sets the foundation for the confidence-guided classification framework.

1) Normalization: Normalization is applied to standardize the pixel intensity distribution over all input images, decreasing variations which are caused by various lighting conditions and camera sensors. Further, scaling the pixel values to a consistent range where normalization makes numerical stability while learning and prevents certain features from dominating the training process. Moreover, this step facilitates faster convergence and enables the model to focus on learning discriminative visual patterns rather than being influenced by illumination inconsistencies.
2) Resizing: All input images are resized to a uniform equal spatial resolution to maintain consistency along the dataset and to make compatibility with deep learning architecture. Moreover, Resizing allows efficient batch processing, and both local and global features are extracted at a compatible scale. Further, this step is particularly important for allowing the model to generalize across images containing waste items of varying dimensions and capturing size-invariant characteristics of waste objects.
3) Data augmentation: Data augmentation is trained to improve the diversity of the training data and improve the model's robustness to real-world variability. moreover, Augmentation techniques like horizontal flipping, brightness adjustment, and rotation are used to simulate different environmental conditions, object orientations, and camera viewpoints. Furthermore, this process reduces overfitting and allows the model to learn invariant features, by improving its ability to handle viewpoint changes, occlusion, and background clutter commonly encountered in smart city waste management scenarios.

C. *Feature Extraction*

The preprocessed data is fed in feature extraction where a SmartWasteNet follows a hybrid feature extraction plan to efficiently capture both local characteristics and global contextual information from waste images. Moreover, this dual-representation design addresses the limitations of single-path feature extractors and allows for robust understanding of complex urban waste scenes.

1) Local Feature Learning using DP-CNN

The DP-CNN segment which is responsible for learning multi-scale local representations that including edge information, fine-grained textures, and structural patterns of waste objects. Further, by processing features at multiple receptive fields DP-CNN efficiently captures variations in object surface, size, and shape properties. Moreover, this capability overcomes the limitations of conventional CNN architectures which often struggle to recognize detailed patterns and scale variations commonly observed in heterogeneous and cluttered urban waste environments.

2) Global Feature Modeling using Transformer

Further, SmartWasteNet includes a Transformer-based model for global context modeling. Moreover, using self-attention mechanisms, the transformer captures spatial relationships and long-range dependencies among the entire images. Additionally, this allows the model to understand scene-level context and object interactions. Furthermore, these are critical for resolving ambiguities and distinguishing similar waste categories which are caused by partial occlusion or background clutter.

D. Feature Fusion

Furthermore, the local features extracted by DP-CNN and the global contextual representations extracted by the Transformer are conceptually fused together into a discriminative and unified feature vector. Moreover, these fusion balances both local information with comprehensive scene understanding resulting in a robust representation that enhances downstream classification. Additionally, by integrating completing feature perspectives SmartWasteNet gains improved reliability and generalization in real-world waste segregation scenarios.

E. Confidence-Guided Hierarchical Classification

The fused feature vector is first classified at a coarse level into Organic or Non-Organic categories. Moreover, a confidence score is computed for this prediction conceptually representing the model's certainty about its decision. Further, if the confidence exceeds a predefined threshold, then the coarse-level prediction gets finalized that reducing unnecessary computation. Furthermore, if confidence is below the threshold, then the sample is routed to a fine-grained classification stage where it is classified into detailed waste categories like Residual, Plastic, Metal, Glass, Paper, or Hazardous. Then, this adaptive and hierarchical mechanism conceptually prevents misclassification, minimizes error propagation in ambiguous cases, and optimizes processing efficiency by calculating the depth analysis to the difficulty of each sample.

F. Training and Conceptual Learning

The training and conceptual learning of the SmartWasteNet has been trained under a supervised learning framework conceptually guided by cross entropy loss to reduce the classification errors across both coarse and fine levels. However, Early stopping or other generalization strategies are considered to prevent overfitting. Conceptually the theory behind it is where the network learns to jointly leverage local patterns from DP-CNN (Deep Pyramid Convolutional Neural Network) and global context from the Transformer while using the confidence-guided hierarchy to make adaptive reliable decisions particularly in challenging urban waste environment.

IV. EXPERIMENTAL RESULTS

The proposed SmartWasteNet framework was implemented as a software-based deep learning model to evaluate its effectiveness for automated waste segregation in smart city environments. The system was configured with an NVIDIA GPU with CUDA support along with a multi-core CPU for data handling and preprocessing tasks. Moreover, Adequate system memory (RAM) was allocated to manage large-scale waste image datasets. The metrices which were used our proposed SmartWasteNet method were namely Accuracy, Precision, Recall, and F1-score are mentioned in below equation (1) - equation (4):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1-score = \frac{2\,x\,Precison\,x\,Recall}{Precision + Recall} \quad (4)$$

The above mentioned are the metrices where TP notes True Positive, TN denotes True Negative FP denotes False Positive, and FN denotes False Negative. These metrics estimate overall correctness, balanced performance, prediction of exactness, and classification of completeness.

A. *Performance Analysis*

This section presents the evaluation of proposed SmartWasteNet model Waste to evaluate its effectiveness in both extraction of images and classification. For this, the SmartWasteNet model is evaluated against CNN-based waste classifier, Hybrid CNN (Convolutional Neural Network) which is shown in the below table 1:

Table 1: performance Analysis of proposed SmartWasteNet method

Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN-based waste Classifier model	89.6	88.9	88.2	88.5
Hybrid CNN model	92.1	91.3	90.9	91.1
Proposed Smart WasteNet model	96.1	95.3	95.0	95.1

Table 1 shows the performance analysis of the proposed method SmartWasteNet with various traditional methods which are CNN-based waste classifier, Hybrid CNN. The proposed SmartWasteNet method has achieved consistent outcomes in terms of Accuracy (96.1%), Precision (95.3%), Recall (95.0%), and F1-Score (95.1%) respectively.

B. *Comparative Analysis*

The comparative Analysis section compares the performance of the proposed SmartWasteNet method against existing model Knowledge-Based Systems of Multi-layer CNN model [11] using their respective evaluation metrices. The comparison is done to compare the improvement over the novel method which is shown in below table 2:

Table 2: Comparative Analysis of the Proposed method

Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1- Score (%)
Knowledge – Based System Using Multi Layer CNN model [11]	92.3	91.5	90.8	91.1
Proposed Smart Waste Net model	96.1	95.3	95.0	95.1

Table 2 shows the comparative analysis of the proposed method against the existing Knowledge Based Systems using a Multi-layer CNN model [11]. The exiting methods of metrics resulted in terms of Accuracy (92.3%), Precision (91.5%), Recall (90.8%), and F1-Score (91.1%). The proposed SmartWasteNet method achieved varying results in terms of Accuracy (96.1%), Precision (95.3%), Recall (95.0%), and F1-Score (95.1%) respectively.

V. DISCUSSION

The main goal of this research is to improve automated waste sorting in smart cities by addressing the problems of current image classification-based waste management systems. Previous methods, including traditional CNN-based approaches reported in Knowledge-Based Systems, relied on single-stream convolutional feature extraction and flat classification pipelines. Moreover, this reduced the ability to face real-world challenges like changes in size, visually similar materials, messy backgrounds, and hidden waste items. These methods also lacked the ability to make adaptive decisions and understand the global context. As a result, their classification performance was inconsistent and not very robust. To meet this goal, the proposed SmartWasteNet introduces a hybrid deep learning framework. Moreover, this framework combines Transformer-based global context modeling with a Deep Pyramid Convolutional Neural Network (DP-CNN) at multiple scale in extracting local features. Further, the Transformer component captures scene-level context and long-range dependencies that help in understanding complex waste categories.

Moreover, Smart WasteNet has been assimilated with confidence-guided hierarchical classification thyeory. Here, waste images are first sorted into broad categories, such as organic and non-organic. Furthermore, for low confidence outcomes, a classifier used for more detailed identification including materials like plastic, metal, glass, paper, and hazardous waste. This can be modified decision process improves robustness, increases reliability, and reduces misclassification. Finally, the experiments were performed on TACO and TrashNet datasets where SmartWasteNet significantly vary with respect to existing methods in terms of accuracy, precision, recall, F1-score, and resistance to occlusion while maintaining scalability for real-world application. Hence, the SmartWasteNet framework successfully achieves the objective by offering a context-aware, adaptive, and robust solution for intelligent waste segregation in smart city environments.

VI. CONCLUSION

This research presented SmartWasteNet which is an intelligent deep learning–based waste segregation framework fitted for smart city environments. Moreover, the proposed model integrates Deep Pyramid Convolutional Neural Networks that to capture multi-scale local visual features and Transformer-based global context modeling to learn long-range dependencies within complex waste scenarios. Further, a confidence-guided hierarchical classification strategy was performed to allow adaptive coarse-to-fine waste categorization, efficiently addressing the disadvantages of flat CNN-based pipelines, like reduced robustness under occlusion and visual ambiguity. Experimental evaluations on benchmark waste image datasets demonstrated that the proposed framework achieves consistent improvements in classification reliability and adaptability when compared with existing approaches. In fact, the hierarchical architecture introduces additional conceptual complexity; it allows decision scalability and reliability for real-world urban deployments. Moreover, future work will examine model efficiency and simplification optimization to support real-time operations and broader smart city integration.

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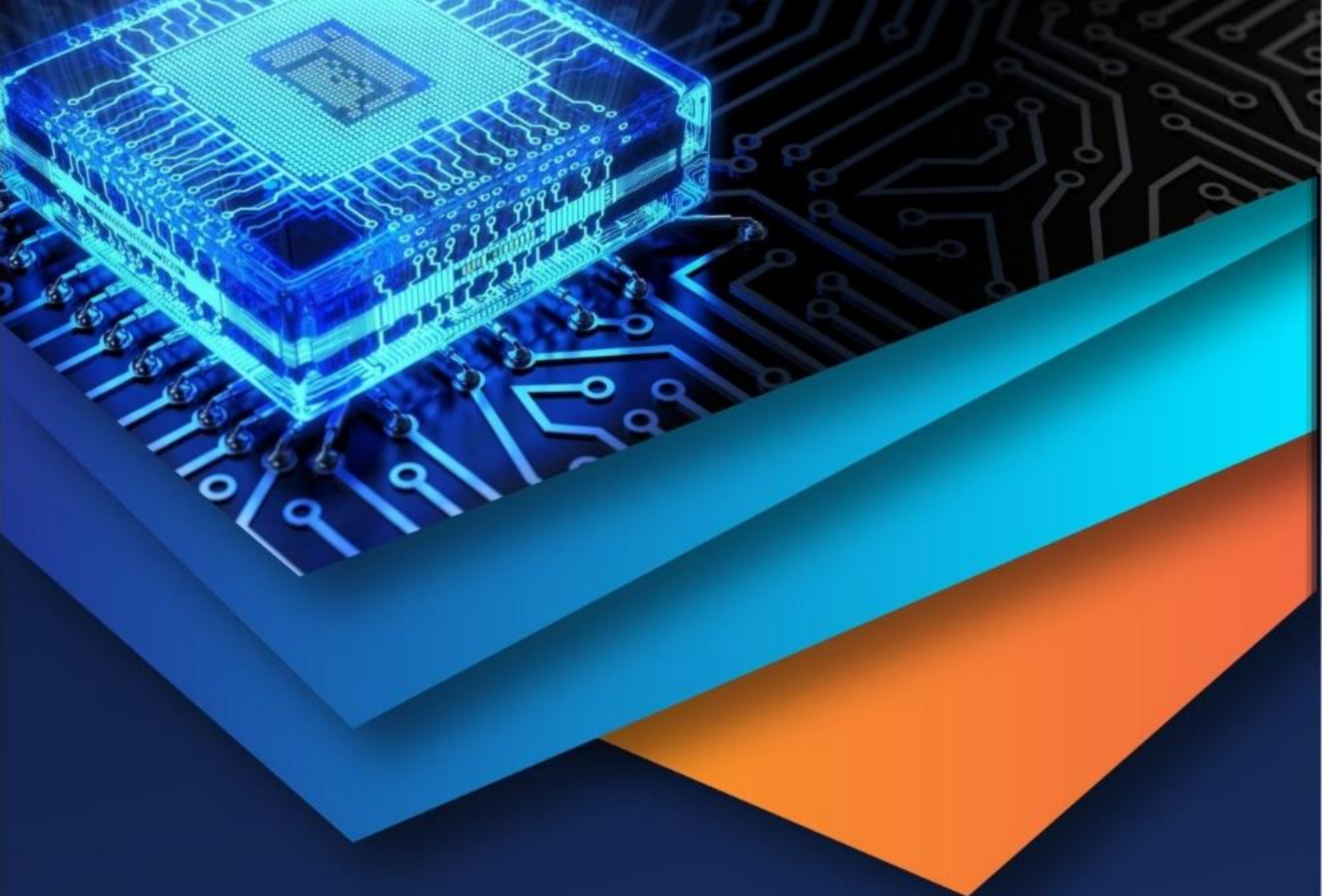

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