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Structural Health Monitoring Using Drone Technology

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Abstract: This project introduces a wall crack detection system that uses computer vision and image processing techniques to identify and classify cracks. The system accepts an image or video input and analyzes it to detect crack types such as shrinkage, minor, major, and structural cracks. It calculates the length and area of each crack and creates a detailed health report of the wall. The system is designed to help civil engineers determine structural safety by automatically detecting faults. The final report includes visual findings, crack measurements, and a general evaluation of wall condition.
Keywords: Crack detection, computer vision, structural health, image processing, wall fault analysis, Gradio, contour detection, Canny edge, morphological operations.

I. INTRODUCTION

Wall surface cracks are among the most apparent symptoms of possible structural issues in buildings and civil engineering infrastructure. The cracks may result from several causes including thermal expansion and contraction, structural tension, moisture penetration, inadequate construction techniques, or degradation with time. Depending on their severity and type, cracks may vary from insignificant cosmetic imperfections to catastrophic structural hazards undermining the safety and longevity of a building.

Conventionally, the examination and grading of such cracks are manually done by civil engineers or skilled personnel. The manual method, though effective to a certain extent, is time-consuming, labor-intensive, and sometimes subjective in nature, resulting in inconsistent results. In mega-structures like bridges, tunnels, and skyscrapers, frequent and precise evaluation becomes a major challenge. For improving these drawbacks, this project has come up with an image-processing-based automatic crack detection and identification system in the walls. In this system, either a mobile device or camera is used for capturing images or video shots of walls. These visual inputs are then analyzed to detect cracks, classify them based on predefined criteria (such as minor, major, shrinkage, or structural), and measure each crack's length and area. This data is compiled into a detailed analytical report that provides both visual and quantitative assessments of the wall's condition.

The key objective of this work is to provide a low-cost, accessible solution for early fault detection, helping civil engineers make timely decisions about maintenance and repair. The solution does not require deep learning models at the initial stage, making it suitable for real-time applications without high computational requirements. Furthermore, a user-friendly graphical interface is developed using Gradio, allowing users to upload an image or stream live footage, process it, and instantly receive a report with labeled crack types, measurements, and a summary of the structural health of the surface.

The system is modular and scalable. Although it already employs edge detection and contour-based measurement, the future can hold machine learning for even more accurate classification and damage prediction. The general aim is to have a smart, efficient, and automated structural health monitoring in residential and industrial applications.

II. LITERATURE REVIEW

Recent developments in drone technology have radically changed the Structural Health Monitoring (SHM) practice. Drones with onboard sensors and imaging technologies provide a non-contact way to test and evaluate structure integrity, particularly in inaccessible or risky locations. Combination of drones with AI and ML algorithms improved accuracy and speed in defect identification and classification. In a detailed scientometric review by Fayyad et al. (2024), the development of SHM using drones is presented with focus on the integration of AI, deep learning, and digital twin technologies. The research involves the identification of four prominent clusters: UAV-based vision-based monitoring, combination of drones with high-tech sensor systems and AI, drone-based SHM using modal analysis and energy harvesting, and robotics and automation in drone-based SHM. In vision-based damage detection, Ataei et al. (2025) investigated the use of deep learning models like YOLOv7 and Faster R-CNN for identifying surface damages on wind turbine structures. The paper indicated that YOLOv7 had an mAP value of 82.4% at 50% IoU, showing it to be viable for real-time inspection.

Agyemanga et al. (2025) proposed DetectorX, a sturdy framework for structural damage detection through the use of micro drones. The framework has a stem block and spiral pooling method for optimizing feature representation with high precision and recall rates in structural damage detection. CorrDetector, proposed by Forkan et al. (2021), is an ensemble deep learning solution for structural corrosion detection from drone imagery. The system showed enhanced performance compared to other conventional approaches, and it revealed the promise of AI-based image analysis in corrosion monitoring. In India, scientists at IIT Indore created an AI-based drone system that can detect structural flaws within a mere 25 milliseconds with a success rate of 98.7%. This development highlights the potential in integrating UAVs with AI and ML to transform structural inspections. Non-destructive testing (NDT) techniques have also witnessed tremendous growth. Methods like terahertz imaging, digital radiography, and guided wave testing provide high-resolution information about structural integrity without damaging the structure. Combining drones with these NDT techniques increases the extent and effectiveness of infrastructure inspection.

In addition, the integration of Internet of Things (IoT) technologies allows for real-time monitoring, which enables engineers to quickly evaluate structural performance and detect potential problems. This integration enables proactive maintenance approaches, guaranteeing the longevity and safety of infrastructure.

Together, these research works highlight the revolutionary effect of combining drones with AI, ML, and sophisticated NDT techniques in SHM. The coming together of all these technologies holds the potential for improved precision, effectiveness, and safety in structural inspections, leading to intelligent and more durable infrastructure management.

III. RESEARCH METHODOLOGY

The main issue tackled in this work is the absence of effective, automated systems for early crack detection and analysis of wall cracks. The manual inspection process is usually slow, subjective, and not practical for large or inaccessible structures. This work focuses on developing an automated tool that identifies cracks, determines their severity, and provides a report stating the structural condition of the wall based on simple image processing techniques.

To solve the problem, the project uses a rule-based computer vision pipeline built using Python. The system is designed to analyze images or video streams, identify cracks in wall surfaces, and generate a detailed report. Gradio, a user interface tool, is used to make the system easy for non-technical users to operate. Instead of using complex deep learning models initially, we use proven image processing techniques like grayscale conversion, Gaussian blur, Canny edge detection, and contour analysis to extract crack features such as length and area. This approach was selected because it requires fewer computational resources. It works well for clearly visible cracks. It allows for real-time or near-real-time processing.

A. Image Processing

Image processing is the foundation of the crack detection system. It transforms raw input images or video frames into analyzable data by highlighting crack features, removing noise, and simplifying complex patterns. The major image processing steps and filters used are described below:

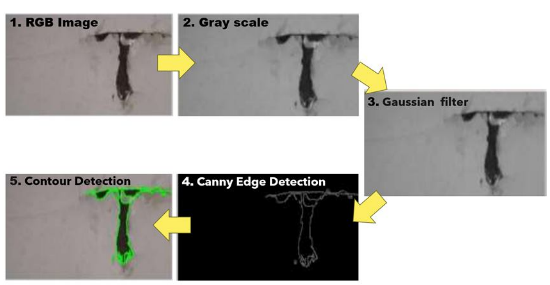

Figure 1. Steps for Image Processing & Filtration.

It may be possible to classify cracked and uncracked images directly from the original images by using Artificial Neural Network (ANN). However, the method using only ANN without image processing will require more computation time, since the training images have so much information. Thus, it is required to include the image processing before applying ANN steps in order to develop an effective process. Image processing step for concrete crack detection consists of the following procedures. These 4 procedures are shown in Image processing step including parameter optimization architecture

1) Grayscale Conversion

The first step is converting a color image (RGB) into grayscale. This simplifies the image from three channels (Red, Green, Blue) to one channel of intensity values, which reduces computational complexity and removes irrelevant color information.

Formula:

$$I(x,y) = 0.299 \cdot R(x,y) + 0.587 \cdot G(x,y) + 0.114 \cdot B(x,y)$$

This weighted average is based on human visual sensitivity. Green is perceived more strongly than red or blue as shown in Fig 2.

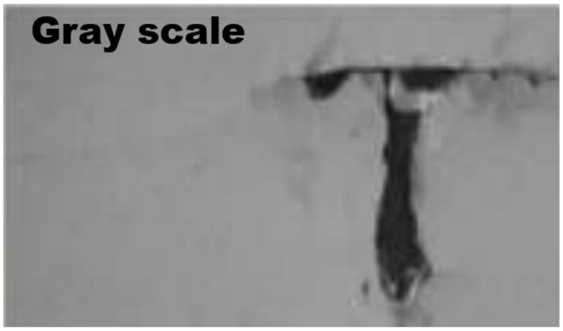

Figure 2. Gray Scaled Image.

2) Gaussian Low-pass Filter

Gaussian blur is applied to smooth the image and reduce noise or minor texture that could be misidentified as cracks. It's a convolution filter that gives higher weight to the center pixel and lower weights to surrounding ones.

Kernel Example (3x3 Gaussian):

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

General 2D Gaussian function:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where:

- σ controls the spread (standard deviation).
- Larger σ = more blurring.

Figure 3. Gaussian Filtered Image.

This step removes high-frequency noise and helps prevent false edges in later stages as shown in the Fig 3. The process is executed using a Gaussian type of linear spatial filtering, categorized within the broader context of spatial filtering techniques. The purpose of this application is to smoothen the image by reducing noise and connecting discontinuities within crack lines, employing a specific type of linear spatial filter known as the Gaussian filter. This operation is designed to enhance the crack line's visual coherence by processing the image through the defined Gaussian filter.

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3) Creation of binary image by Canny Edge Detection Algorithm

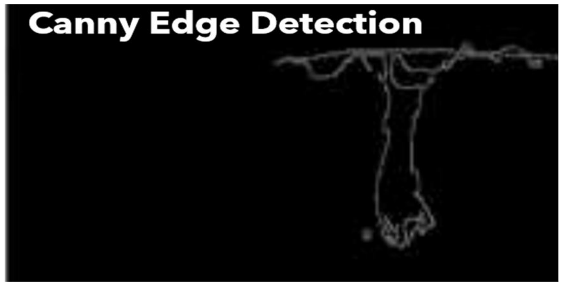

Figure 4. Canny Edge Detecting Filtering.

It first finds gradients in the image, where the pixel intensity changes sharply. Then it applies two thresholds (50 and 150 in this case). Pixels with gradients above the high threshold are marked as edges, and those below the low threshold are discarded. Pixels with gradients between the thresholds are classified as edges only if they are connected to other strong edge pixels. The Canny edge detector is a multi-stage algorithm used to detect meaningful edges (like cracks). It consists of:

Gradient Calculation: Sobel operators are applied to find intensity change in x and y direction:

$$G_x = \frac{\partial I}{\partial x}, \qquad G_y = \frac{\partial I}{\partial y}$$

$$G = \sqrt{G_x^2 + G_y^2}, \qquad \theta = \tan^{-1}\left(\frac{G_x}{G_y}\right)$$

Non-Maximum Suppression: Keeps only the sharpest edge points along the direction of gradient.

Double Thresholding: Two thresholds (e.g., 50 and 150) are used:

- Strong edges (above high threshold) are retained.
- Weak edges (between thresholds) are kept only if connected to strong edges.

Edge Tracking by Hysteresis: Ensures continuous edges are preserved and isolated noise is removed.

4) Morphological Operations

Morphological transformations like *closing* are used to connect broken parts of edges and remove small holes or gaps in detected contours.

Dilation: Expands the edges outward.

Erosion: Shrinks the edges inward.

Closing = Dilation followed by Erosion

Mathematical Morphology:

$$A \cdot B = (A \oplus B) \ominus B$$

where:

- A = input binary image (edge map)
- B = structuring element (e.g. 5x5 square)

This helps to join fragmented cracks and improve contour detection.

5) Contour Detection

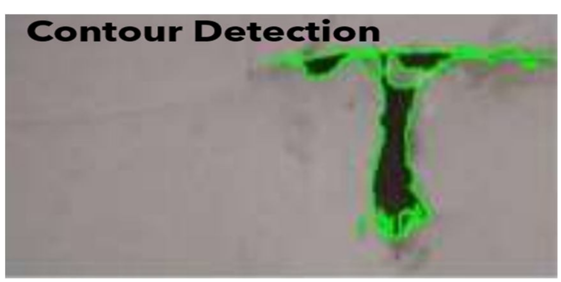

Figure 5. Contouring of the Edges.

It identifies continuous curves or boundaries around objects in a binary image (edges identified by Canny). Here, the edges refer to crack profiles or other important boundary features on the surface of the concrete.
The contours are identified by using the cv2.findContours() method from the OpenCV library. The function returns the contours as a list of points that outline the shape or boundary of an object in the image. The contours are specified by a set of x, y coordinates outlining the edge of the identified crack.

B. Mathematical Expression

Following the identification of crack contours using image processing, the subsequent vital step is to mathematically examine these cracks to derive useful physical parameters like length, area, and severity classification. The following section details the important mathematical equations employed in the code and their applicability to actual crack analysis. First, the length of every identified crack is calculated based on contour perimeter. This is done in OpenCV with the cv2.arcLength() function, which computes the overall perimeter around the contour that has been detected. In mathematical terms, this is just the sum of the Euclidean distances between every pair of successive points along the contour:

$$L = \sum_{i=1}^{n} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}$$

where (x_i, y_i) are coordinates of the points on the contour. This gives the length in pixels. As well as length, the area of each crack is found with OpenCV's cv2.contourArea() function. It uses the Shoelace formula internally, which is a geometric method to determine the area covered by a closed polygon:

$$A = \frac{1}{2}\left|\sum_{i=1}^{n} (x_i . y_{i+1} - x_{i+1} . y_i)\right|$$

Once again, this is expressed in square pixels, which then need to be translated into the actual physical measurements in order to be useful to a civil engineer. To get around this divide between pixel dimensions and real measurements, a conversion from pixels to meters is utilized. If a constant scaling factor s (such as s = 0.000264 meters/pixel, given camera settings or DPI) can be assumed, then the length of the crack in meters can be calculated as:

$$L_{meters} = L_{pixels} \times s$$

In the same manner, the crack area is computed as:

$$A_{meters} = A_{pixels} \times s^2$$

These transformed values enable us to express crack dimensions in meters and square meters, which are data that structural engineers can use in assessing damage.
Next, every crack is categorized into types such as ‘shrinkage crack’, ‘minor crack’, ‘major crack’, or ‘structural crack’ depending on its calculated length. The category is rule-based, applying the following logical ranges:

- If $L < 0.03m$, it is labeled as a Shrinkage Crack
- If $0.03 \leq L < 0.1m$, it is a Minor Crack
- If $0.1 \leq L < 0.4m$, it is considered a Major Crack
- If $L \geq 0.4m$, it is marked as a Structural Crack

This categorization gives a clue to the extent of damage to the wall.
Also, extremely small contours (such as dust or noise) are removed by imposing a minimum area threshold prior to any calculation. This operation enhances detection accuracy and makes sure that only significant crack areas are processed further.
With this blend of image geometry, pixel-level computation, and physical scaling, the math layer converts raw visual information into actionable engineering knowledge.

IV. RESULT & DISCUSSION

The crack detection system designed in this project was programmed using Python and OpenCV and used a live video feed from an IP camera. The central part of the system included real-time image acquisition, pre-processing with filters, edge detection, contour analysis, and measurement of crack size. The image processing pipeline used a Gaussian Blur filter to dampen noise and soften the image, then Canny Edge Detection to accentuate possible cracks. Morphological operations such as dilation and closing were used next to make crack-like features more visible, particularly those discontinuous or weak. This improved dramatically the continuity and consistency of crack edges, which is vital for true detection.

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The system then used contour detection to identify cracks, and only contours within a specific area range (defined using a threshold) were considered as actual cracks to avoid false detections from noise or irrelevant background details. For each detected crack, the area, bounding box, and length (approximated using the arc length of the contour) were calculated. This information was stored and updated in real-time in an Excel sheet, providing an automatic report of the crack count and individual crack dimensions.

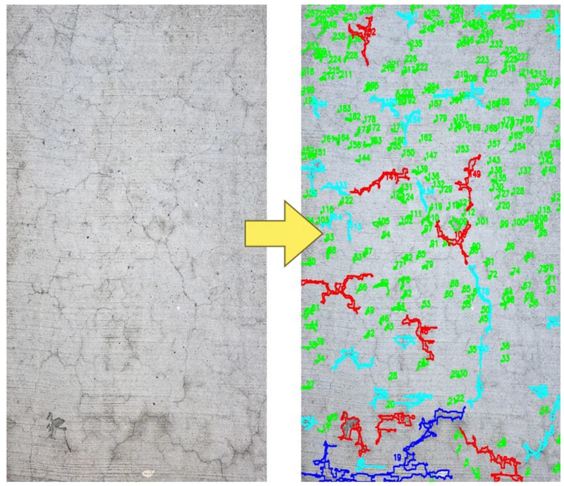

Figure 6. Result of Crack Detection & Classification

During testing, the system was able to accurately detect fine cracks, including shrinkage cracks, in well-lit conditions as show in Figure 6. The accuracy was high when the cracks were well-formed and distinguishable from the background. The use of thresholding and noise filtering techniques helped reduce false positives, especially in cases of texture or marks on the wall that were not actual cracks.

Visually, the cracks were clearly outlined on the output frame, with each crack numbered and labeled with its size (area in pixels and length in pixels). This helped in visual confirmation and analysis. The system also responded well to changes in lighting and small camera movements, demonstrating its robustness in real-time conditions. Overall, the code achieved its purpose of real-time crack detection, classification (based on size), and reporting, and proved to be efficient for use in practical Structural Health Monitoring scenarios. It provides a good foundation for future integration with machine learning models for automatic classification of crack types (shrinkage, structural, etc.) and severity estimation.

V. FUTURE SCOPE

In the coming years, the use of drones and artificial intelligence (AI) for Structural Health Monitoring (SHM) is expected to grow even more. There are many exciting possibilities to improve and expand this technology. One of the largest future directions is applying 3D mapping. Drones can be paired with mapping methods such as SLAM (Simultaneous Localization and Mapping) to generate a 3D model of the building in real-time. This will assist in finding the precise location of cracks and damages more effectively, particularly in giant buildings, bridges, and towers. Another potential field is the creation of systems that not only identify cracks but also recommend what type of repair is required. By integrating drone photos with decision-making systems by experts, we can assist engineers in determining the most appropriate and economical repair methods based on the damage severity and type. This will reduce time and enhance the maintenance process. One of the large steps in the future is merging this system with Digital Twin technology. A digital twin is a dynamic 3D virtual model of an actual building that is updated as new information is received. If we have our system integrated with a digital twin, we can track the condition of a structure in real-time and even forecast when and where damage is likely to occur in the future. This will assist in transitioning from routine maintenance to intelligent, predictive maintenance. In the future, drones can be outfitted with thermal and multispectral cameras as well. Such cameras are able to identify hidden or internal damage that cannot be viewed using regular cameras, such as water leaks, cracks beneath the surface, and temperature variations that may indicate structural issues. They may also be enormously helpful following an earthquake, a flood, or a storm. Rather than bringing people into areas of risk, drones can scout out buildings or bridges rapidly to find damage while keeping inspectors human and safe while accelerating rescue efforts and repairs. There's similarly enormous potential here to deploy it on a macro scale, to survey all roads, buildings, and bridges of a city. City officials could use a network of drones to continuously monitor infrastructure health and send alerts in the case of a problem. This would improve public safety and help avoid major accidents.

Another long-term objective is to enhance the battery life and range of drones. With solar panels or improved power systems, drones would be able to fly longer and go to remote or hard-to-reach locations like hills, forests, or even underwater buildings. This would further increase the usefulness of the technology. Simplifying the system so that engineers and workers can use it more easily is also highly significant. In the future, mobile apps and web dashboards might display cracks that are detected, live video, and repair reports. The platforms can also utilize GPS to display the precise location of the damage, and possibly even utilize Augmented Reality (AR) so that workers are able to view the fault on their phone or tablet in real-time. As we gather more data, the AI models working within this system can be trained to identify more varieties of damage more accurately. They can also be optimized to be smaller and faster, so they can execute directly on the drone itself, rather than requiring a large computer on the ground.
Last but not least, as the technology continues to advance, it needs to be incorporated into official safety regulations and guidelines for buildings and infrastructure. Governments and engineering bodies can develop standard processes that incorporate drone inspections and AI analysis as routine maintenance. This will lead more individuals to believe in and utilize the technology in day-to-day work.

VI. CONCLUSION

We can conclude here that the integration of drone technology with Structural Health Monitoring (SHM) systems constitutes a revolutionizing step in the evaluation and maintenance of vital infrastructure. The merger of cutting-edge aerial technology with advanced analytical techniques represents a groundbreaking shift, as emphasized by various literature and on-going study. Unprecedented efficiency and remote access to spaces long difficult or considered risky are provided by drones. Their capacity to carry out detailed inspections without compromising human safety is a foundation for timely evaluation of infrastructure integrity. With the integration of high-resolution imaging sensors and the application of sophisticated image processing methods, drones facilitate the acquisition of detailed data, setting the stage for strong analysis. Automated defect detection and classification algorithms greatly assist in the detection of structural anomalies, offering a vehicle for proactive and precise assessment. In addition, the use of non-destructive techniques highlighted in a number of research works identifies the ability of drones to carry out remote, non-contact inspections. This feature is necessary for periodic, damage-free inspection of structures to enable maintenance without destruction. The automation of defect detection, classification, and thresholding processes is important in order to accelerate the detection of structural anomalies. These automated processes, combined with drone technology, simplify inspection and analysis, especially for mass infrastructure.

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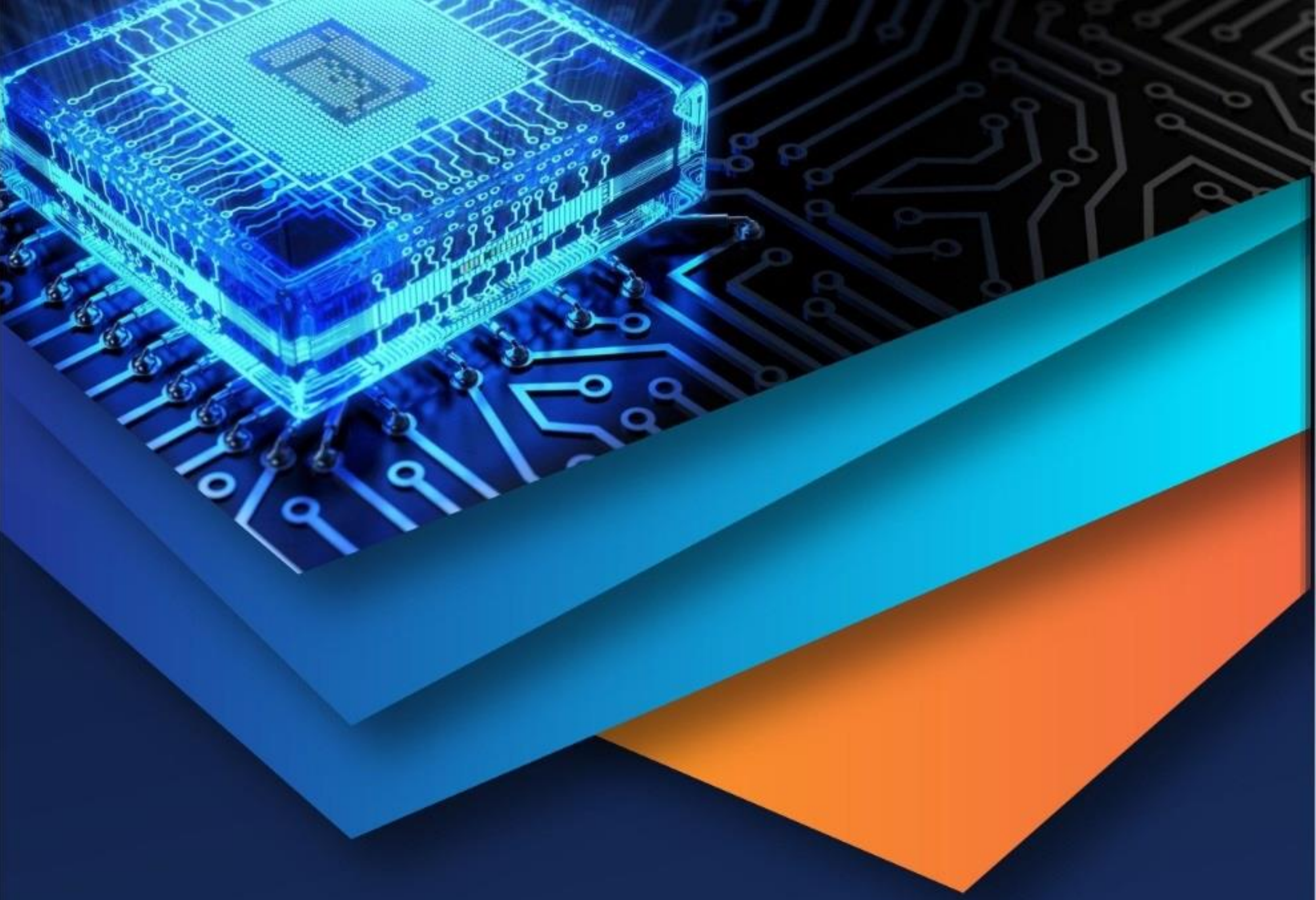

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