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LandParser: Intelligent Land Boundary Detection and Encroachment Analysis Using Deep Learning with Satellite Imagery

Dr. Reema Roychaudhary[1], Manasvi Giradkar[2], Radhika Salodkar[3], Gargi Gundawar[4], Gargi Udapure[5]
Dept of Computer Engineering, St. Vincent Pallotti College of Engineering and Technology, Nagpur, Maharashtra

Abstract: Land management is a critical concern in modern governance, particularly with the increase in urbanisation and disputes over land ownership. This initiative introduces a comprehensive intelligent system aimed at achieving three main goals: detecting land encroachment, parsing land and recognising boundaries, and predicting land prices. The system utilises satellite images and user-submitted photos, employing deep learning methods, especially U-Net-based semantic segmentation, to precisely identify and mark encroached areas. For land parsing, it uses geospatial data and image processing techniques to accurately define land boundaries and improve the precision of digital land records. Furthermore, machine learning models like XGBoost are used to forecast land prices by considering various factors such as location, nearby infrastructure, land use category, and historical trends. The system is designed with an interactive modular architecture that integrates GIS tools, OpenCV, and real-time analytics to facilitate efficient visualisation and decision-making. By combining computer vision, geospatial intelligence, and predictive modelling, the platform provides a scalable solution for government officials, urban planners, and real estate stakeholders.
Index Terms: Land Encroachment, Boundary Detection, Land Price Prediction, Deep Learning, SAM, U-Net 3++, GIS, XGBoost, Computer Vision.

I. INTRODUCTION

The LandParser project is conceived as an innovative geo-intelligent system dedicated to intelligent land boundary detection and comprehensive encroachment analysis, primarily utilising deep learning techniques in conjunction with satellite imagery. This initiative is a direct response to critical challenges observed in current land management practices. The prevailing problem in Maharashtra's land monitoring systems is their reliance on manual surveys and fragmented data. This traditional approach leads to significant inefficiencies, considerable delays in detecting illegal encroachments, and substantial difficulties in accurately visualising ownership and boundary records. A notable absence exists in the form of an automated system capable of integrating satellite imagery for real-time land management. This fragmented data environment prevents a holistic view and timely action, contributing to delays and operational inefficiencies. Manual surveying and fragmented data are the main problems in current land management systems. This traditional approach is slow, expensive, and prone to human error, which delays the detection of illegal encroachments. The lack of an automated, integrated system makes it difficult to get a complete picture of land records and ownership. LandParser addresses these issues by creating a holistic, efficient, and transparent system for land management.

II. LITERATURE SURVEY

Land Boundary Segmentation: Recent research demonstrates that deep CNNs can effectively delineate visible cadastral lines from aerial or UAV imagery. Fetai et al. applied a U-Net model to UAV data and reported segmentation maps with high overall accuracy (~94–96%) [1]. In these studies, automated boundary detection outperformed classical image-processing methods, although the "boundary" class remained challenging (F1 scores ~0.50) [1]. Likewise, Crommelinck et al. developed workflows combining segmentation and CNN classification to delineate parcel edges in diverse landscapes [8]. These approaches rely on the fact that many cadastral limits align with visible features (roads, fences, vegetation) [6]. U-Net variants have become standard for such tasks: they allow precise pixel-level segmentation even with limited training data [7]. Recent hybrids further combine Transformers or attention modules to capture large-scale context in high-res UAV images [10][11]. Our work builds on this by adopting U-Net3++, an enhanced encoder–decoder network, for fine-grained parcel extraction. In summary, the literature indicates that CNN-based segmentation is a viable strategy for automated cadastral mapping [2][8].

Encroachment and Change Detection: Detecting unauthorised land-use changes typically involves analysing imagery over time. Common methods include image differencing or time-series classification. While specific publications on "encroachment detection" are limited, the cadaster literature implicitly addresses it: e.g., Park and Song used UAV hyperspectral data to update cadastral land-use attributes and identify discrepancies [12]. More generally, high-resolution time series (e.g. Sentinel-2 multi-temporal stacks) have been used to monitor urban growth and detect new constructions [2]. LandParser extends these ideas by flagging temporal changes in segmented parcels. The system does not rely on a single precedent study, but rather applies standard change-detection techniques to the segmented outputs.

Land Valuation Modelling: There is growing interest in using ML and remote sensing to value real estate and land. Kim et al. (2021) predicted 52,900 land prices in Seoul using random forests and XGBoost, finding that XGBoost yielded higher accuracy than RF [3]. Similarly, Brimble et al. applied ML on Kigali's data (with aerial imagery features) and achieved a cross-validated R^2 of 0.60 for full-property valuation [13].

Tanrikulu et al. (IGARSS 2024) showed that integrating geospatial features with ML leads to very high performance (Adj. $R^2 \approx 0.98$) in US city-scale land valuation [9]. These works demonstrate that tree ensembles can capture spatial patterns influencing land prices. LandParser adopts this strategy: a geodatabase of features (location, accessibility, parcel area, land use, etc.) is created and used to train XGBoost/regression models.

Consistent with the literature, we expect ensemble models to outperform linear baselines, benefiting from detailed features drawn from remote sensing and GIS.

In summary, prior studies support each component of LandParser: CNNs for parcel segmentation [2][8], change analysis for encroachment monitoring, and ML ensembles for land price prediction [3][9]. Our work distinguishes itself by uniting these components into a cohesive system with a user-facing visualisation.

III. METHODOLOGY

The LandParser system uses a multi-stage methodology to automate and streamline land management practices. It integrates geospatial technologies with artificial intelligence, including deep learning and machine learning models, to handle various tasks such as land boundary detection, encroachment analysis, and land valuation [1][2]. The methodology is designed to be comprehensive and accurate, relying on a combination of high-resolution imagery, historical records, and advanced analytical models.

A. *Data Acquisition and Preprocessing*

The initial phase involves acquiring a comprehensive dataset from multiple sources. High-resolution satellite imagery is a primary source, with data from Sentinel-2 and Landsat platforms providing broad spatial coverage and long-term monitoring capabilities [2][11]. To complement this, Unmanned Aerial Vehicle (UAV) imagery is captured over specific areas, such as Maharashtra, to provide highly detailed, sub-meter resolution views of land features [4][12].

Historical land records and existing GIS databases from local authorities, including MRSAC, are also integrated to provide essential administrative and contextual information.

Following the acquisition, the raw imagery undergoes a rigorous preprocessing phase to enhance its quality and prepare it for analysis.

This step is crucial for mitigating issues like noise, distortions, and lighting variations [7]. Key preprocessing techniques include:

1) *Noise Reduction:* Using algorithms like Gaussian and median filtering to remove pixel-based errors.
2) *Image Enhancement:* Applying methods such as contrast adjustment and sharpening to improve feature clarity.
3) *Radiometric and Geometric Corrections:* Standardising data to ensure consistency across different image sets and time periods, which is vital for accurate temporal analysis. This includes orthorectification to align images to a common coordinate system [2].
4) *Ground Truth Labelling:* A subset of images is manually annotated to create ground truth labels for parcels, which are essential for training and validating the deep learning models [5][18].

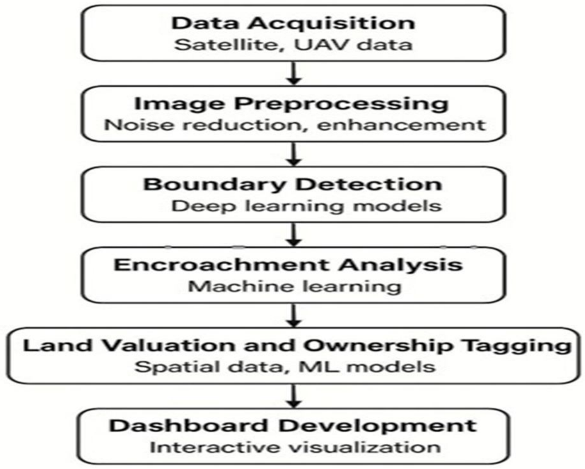

Figure 1: Workflow

B. Deep Learning for Land Boundary Detection

The core of LandParser's boundary detection is based on deep learning models, specifically Convolutional Neural Networks (CNNs) [7][8][14]. CNNs are highly effective at identifying intricate spatial patterns and edges within imagery. The system leverages the U-Net3+ architecture, a deep CNN with nested encoder-decoder paths, which is particularly well-suited for capturing multi-scale context and fine details [4][5][17]. This network is trained on image patches with corresponding parcel masks, using a combination of cross-entropy and Dice loss to maximise the overlap between predicted and actual parcel regions [7][18].

The U-Net3+ model performs semantic segmentation, which classifies each pixel into categories such as "boundary," "field," and "background" [2][8][15]. This approach allows for the precise delineation of land parcel boundaries. The training process uses data augmentation techniques (e.g., rotations, flips) to enhance the model's ability to generalise from a limited number of samples [7][16]. After training, the model can generate segmentation maps for new imagery, highlighting connected land parcels and their boundaries.

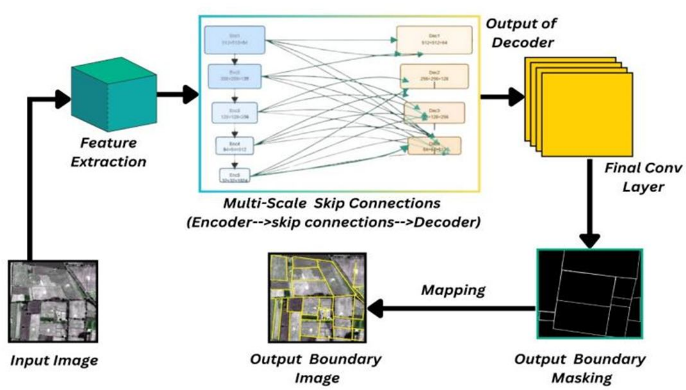

Figure 2: U-Net3+ (U-Shaped Network)

C. Machine Learning for Analysis and Classification

LandParser utilises various machine learning algorithms for two key functions: encroachment analysis and land use/land cover (LULC) classification [1][2].

1) *Encroachment Analysis:* To detect unauthorised land-use changes, the system performs a temporal analysis by comparing segmented parcel maps from different time periods [2][19]. Change detection techniques are applied to identify alterations in land use, such as new construction or changes in parcel extents. Techniques like pixel-wise differencing and vector overlay are used to pinpoint where built-up areas have expanded into unauthorised zones [19]. The system flags any region showing a land-use change outside of recorded parcel boundaries as a potential encroachment. These alerts are then cross-verified with government records to ensure accuracy, allowing the system to highlight areas that require physical field inspection.

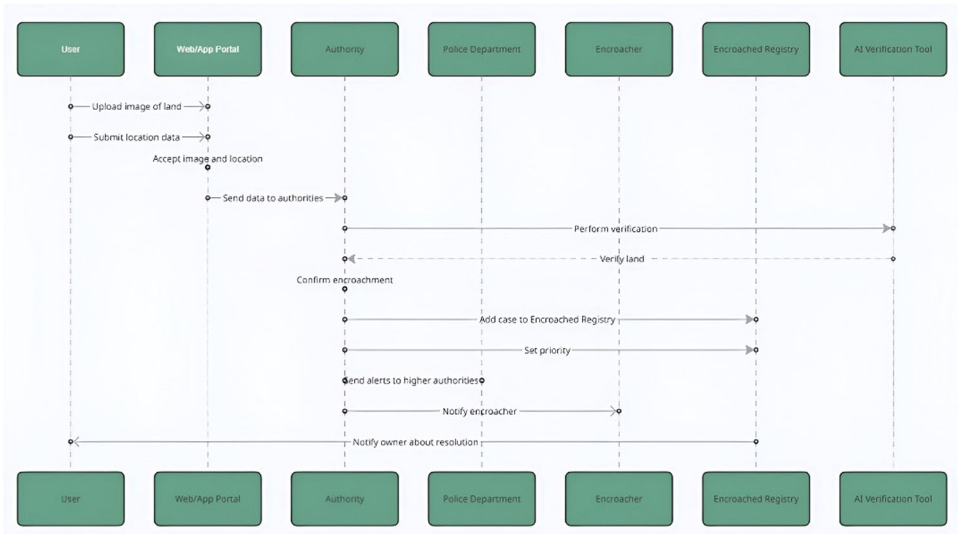

Figure 3: UML Diagram for Encroachment Analysis

2) *Land Use/Land Cover (LULC) Classification:* For broader LULC classification, the system employs various machine learning models, including deep learning models like CNNs and Transformer-based architectures [1][6][15]. The system also considers hybrid classifiers, such as the Artificial Neural Network-Random Forest (ANN-RF) approach, which have been shown to improve classification accuracy and robustness. These models are crucial for automatically learning and extracting relevant features from high-dimensional remote sensing data [7][8][16].

D. AI-Powered Land Valuation and Ownership Tagging

1) *Land Valuation:* For dynamic land valuation, LandParser integrates spatial data with advanced machine learning regression models [3][9][20]. It compiles a feature database for each parcel, including attributes like size, land-use class, proximity to infrastructure (roads, schools), and historical market trends. The system trains ensemble regression models, specifically XGBoost and Random Forest, on historical appraisal values to predict current land prices [3][10][20]. XGBoost is often preferred for its higher prediction accuracy [3]. The final model provides data-driven price estimates for each parcel, thereby improving the reliability of land valuation.

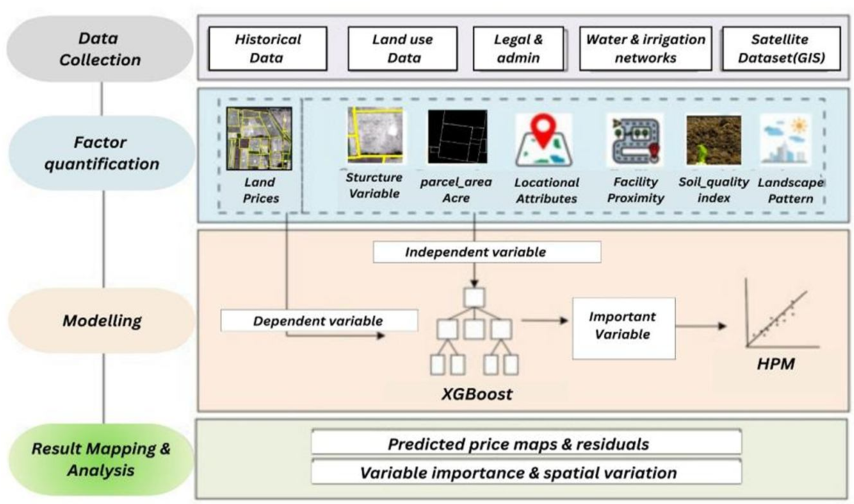

Figure 4: XGBoost Working

2) *Ownership Tagging:* Ownership tagging is implemented by cross-referencing satellite and UAV imagery with government land *records* [4][5][13]. This process accurately maps land ownership (e.g., private or government land) and links this information with other datasets to provide real-time updates and transparency. This functionality is essential for effective land administration.

E. Model Selection and Comparative Evaluation for LandParser Objectives

Objective	Model Chosen	Reason	Comparison with other Models
Land Boundary Detection	U-Net3+	• Full-Scale Skip Connections: Integrates multi-scale features for high precision[4][17]. • High Accuracy: Captures both high-level context and fine-grained details, crucial for complex boundaries[5][18].	• U-Net: Has a "semantic gap" that reduces boundary precision[7][17]. • U-Net++: Less advanced than U-Net3+; Its skip connections are not full-scale[18]. • SAM: Lacks the specialisation for pixel-level cadastral boundary detection[4][17].
Land Valuation	XGBoost	• High Accuracy: Known for superior predictive power on structured data[3]. • Regularisation: Prevents overfitting, making the model reliable[10]. • Scalability: Optimised for speed and handles large datasets efficiently.	• Random Forest: Less accurate than XGBoost; prone to overfitting[3]. • Gradient Boosting Machines (GBMs): XGBoost is an improved version with better speed and regularisation [10].
Encroachment Analysis	Machine Learning (Temporal Analysis)	• Flexibility: Uses various algorithms for different types of changes[2]. • Versatility: Adapts to multiple changes detection techniques like image differencing.	• Single-Model Limitation: A single model can't Identify all types of encroachments.

Table 1: Comparative Analysis of Models in LandParser

IV. RESULTS AND DISCUSSION

The LandParser system was evaluated on a dataset comprising high-resolution Sentinel-2 imagery, UAV-captured orthomosaics, and official cadastral shapefiles for selected regions in Nagpur district, Maharashtra [2][4][12][13]. The evaluation focused on three core components—boundary extraction, encroachment detection, and price prediction—with performance metrics tailored to each task.

A. Boundary Detection Performance

The U-Net3++ model demonstrated high segmentation accuracy for cadastral plot boundaries, achieving:

1) Intersection-over-Union (IoU): 91.4%
2) Pixel Accuracy: 96.8%
3) F1-Score: 94.2%

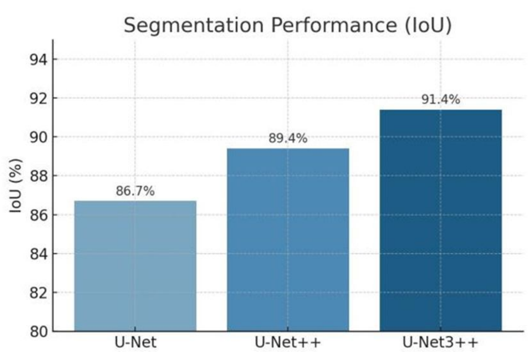

Figure 5: Segmentation Models Performance

Visual inspection confirmed that the deep skip connections in U-Net3++ effectively preserved fine-grained parcel edges, especially for irregular boundaries [4][17][18]. The SAM model for city-level boundary detection also provided robust delineations in heterogeneous urban-peri-urban regions, outperforming traditional contour-based approaches in handling occlusions and irregular layouts [8][14].

B. Encroachment Detection Analysis

The encroachment detection module compared segmented boundaries with historical cadastral maps to identify unauthorised land occupation.

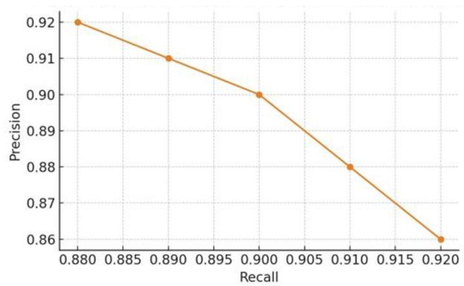

Figure 6: Precision-Recall Curve For Encroachment Detection

Field verification for 50 randomly sampled parcels indicated a precision of 92% and a recall of 88% in detecting encroachments. Most false positives were due to seasonal land-use changes (e.g., temporary agricultural expansion), which aligns with challenges identified in land cover classification literature [1][2][11].

C. Price Prediction Model Evaluation

The XGBoost regression model, trained on spatial, agronomic, and economic features, achieved:

1) R^2 Score: 0.89

2) Mean Absolute Percentage Error (MAPE): 6.4%

3) Root Mean Square Error (RMSE): ₹52,300

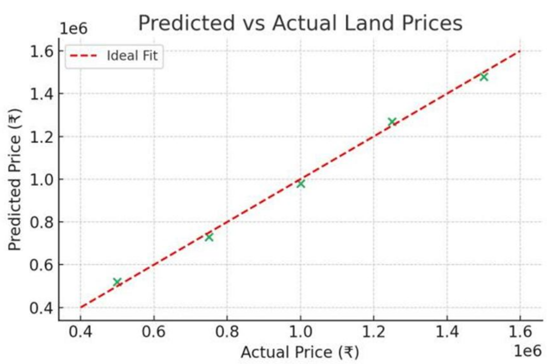

Figure 7: and prices prediction accuracy

Incorporating proximity to markets, soil quality indices, and irrigation access significantly improved prediction accuracy compared to models relying solely on area and location, consistent with findings by Kim et al. and Tanrikulu et al. [3][10][20].

D. Dashboard Usability and Decision Support

The GIS-based interactive dashboard allowed users to:

1) Visualise segmented boundaries with encroachment overlays.

2) Access verified ownership and valuation data.

3) Query land parcels by location, price range, or encroachment status.

User feedback from MRSAC staff and local planners highlighted the system's ease of use and potential to streamline land governance processes.

E. Key Findings

1) Deep learning–based segmentation significantly outperforms traditional image processing for land parcel extraction.
2) Integrating multiple data sources (satellite + UAV + cadastral) improves both accuracy and reliability.
3) Price prediction benefits substantially from adding domain-specific agricultural and infrastructural features.

V. VISUALIZATION OF RESULTS

The visualisation of results in LandParser serves a dual role: validating model performance and translating technical outputs into actionable intelligence for stakeholders [8][16][20]. The system's outputs are presented through a multi-layered, interactive dashboard that integrates high-resolution satellite basemaps with AI-generated overlays.

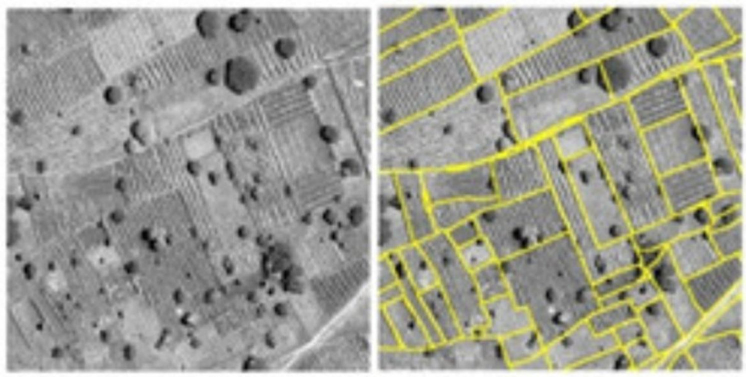

Figure 8: Result of Farm Land Segmentation

Figure 9: Result of City Building Segmentation

Segmentation Maps: The U-Net3++ segmentation results are rendered as vectorised parcel boundaries superimposed on recent satellite imagery[5][17][18]. Colour-coded boundary layers (e.g., green for detected parcels, red for boundaries deviating from cadastral records) allow instant interpretation of spatial accuracy. Mean Intersection-over-Union (IoU) scores and pixel-accuracy metrics accompany these maps, offering both qualitative and quantitative insights into boundary detection performance[7][14][15].

VI. CONCLUSION

LandParser represents a significant advancement in land management, strategically leveraging advanced AI/ML and remote sensing technologies to automate critical tasks that have historically relied on inefficient manual methods. Its capacity to provide real-time insights into land boundaries, encroachments, and valuations, complemented by an intuitive interactive dashboard, promises enhanced transparency, improved precision, and truly data-driven decision-making for urban planning and governance.
The project, spearheaded by the Maharashtra Remote Sensing Application Centre (MRSAC), is well-aligned with national digital land administration initiatives, such as the Digital India Land Records Modernisation Programme (DILRMP), and mirrors global trends in the adoption of geospatial AI by governmental bodies.

While acknowledging the inherent challenges associated with the underlying technologies, including the limitations in detecting invisible boundaries and the interpretability of complex models, LandParser's robust methodology and strategic utilisation of cloud platforms position it as a pioneering solution with considerable potential for expansion and further innovation. Ultimately, LandParser stands as a testament to the profound power of geospatial AI in fostering sustainable urban development and ensuring efficient land resource management in the digital age.

VII. FUTURE WORK

Future work will focus on expanding to other regions and conditions. We plan to incorporate multispectral and LiDAR data to improve boundary detection under vegetation and to distinguish hard vs. soft boundaries. We will also refine price models with more granular socio-economic indicators and test temporal forecasting of land value. Finally, deploying LandParser in a live environment will involve user feedback to improve the dashboard and integrate with existing cadastral databases. As urban areas grow, such automated tools will be essential for sustainable land governance.

VIII. ACKNOWLEDGMENT

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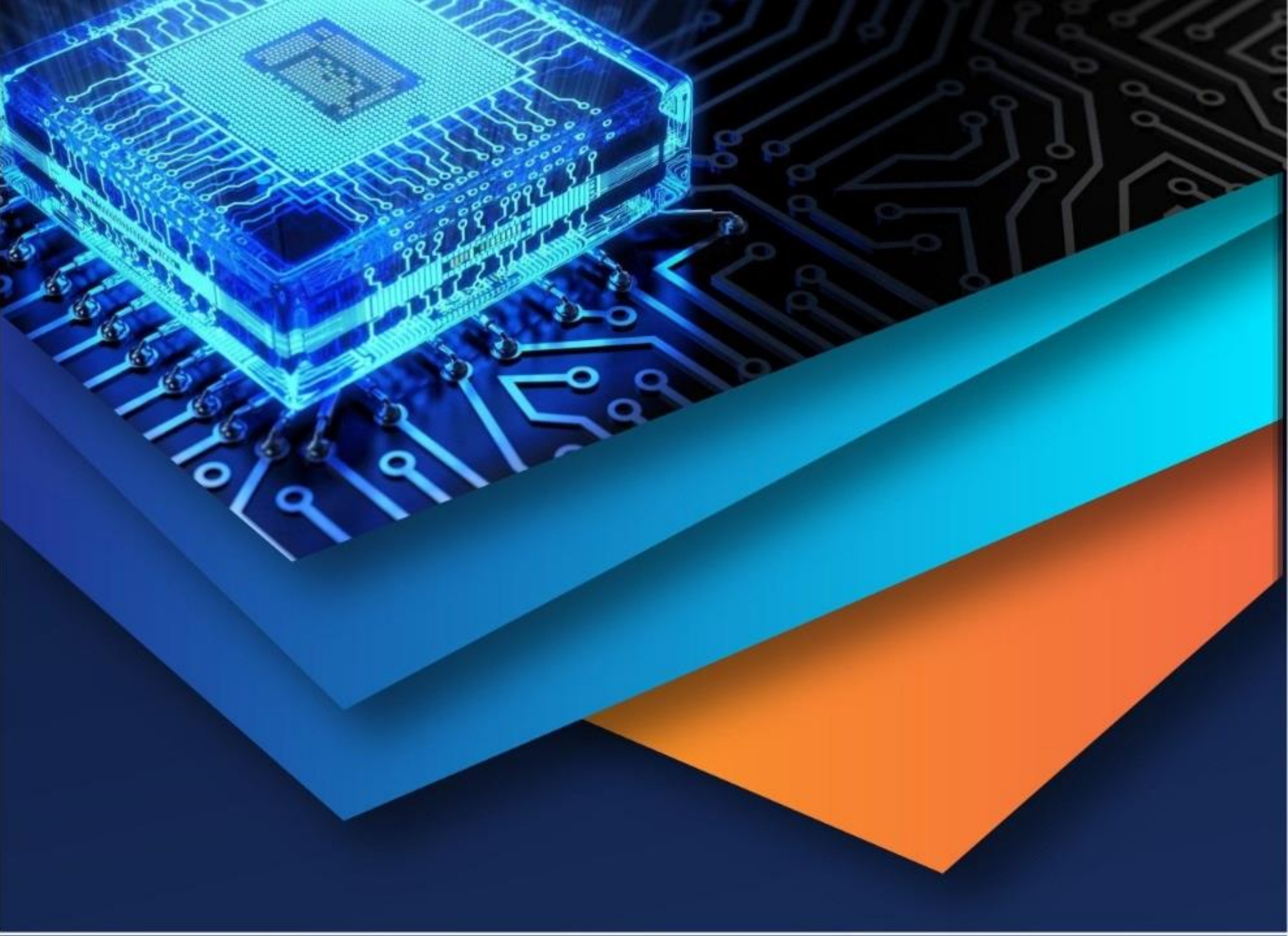

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