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The Box Effect: Forensic Analysis of Signature Variation Under Spatial Constraint

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Abstract: ***The present study examines the "box effect" in forensic document examination by evaluating the influence of spatial constraints on English script signatures. A total of 1000 participants (500 males and 500 females), aged 15–75 years, provided paired signature specimens. Each participant produced signatures under two conditions: within a predefined box and on an unconstrained blank space. All specimens were created using the same writing instrument and paper quality (75 GSM). Handwriting characteristics were analysed at both macro and micro levels, including signature dimensions, spacing, slant, alignment, and initial and terminal strokes. Since the dataset comprised paired observations, statistical analysis was performed using McNemar's test. In addition, a Random Forest model was applied to classify signatures based on writing conditions and to identify the most discriminative handwriting features affected by spatial constraints. The findings indicate systematic variation in signature characteristics under constrained conditions, particularly in terms of dimensional reduction and alterations in slant and stroke execution. The study highlights the forensic significance of understanding natural variation in signatures executed under imposed spatial limitations, contributing to the evaluation of questioned documents where signatures are produced within fixed boundaries.***

Keywords: Questioned document examination, Signature analysis, Box effect, Statistical analysis, Machine learning.

I. INTRODUCTION

Handwritten signatures have long been regarded as one of the most widely accepted means of personal authentication in forensic document examination. Despite rapid advancements in digital identification technologies, signatures continue to hold legal and administrative importance in banking, government documentation, and contractual agreements. In forensic science, signatures are considered behavioural biometric traits that reflect a combination of individual consistency and natural variability, making them valuable for personal identification and questioned document examination (Srihari et al., 2008). However, signature examination presents inherent challenges due to intra-writer variability, which refers to natural differences observed when the same individual produces multiple signatures under varying conditions. These variations may be influenced by factors such as writing speed, emotional state, fatigue, writing surface, and writing instrument. Plamondon and Srihari (2000) emphasized that handwriting and signatures are dynamic motor activities governed by neuromuscular control, which contributes to variability even within the same writer. Such variability complicates forensic analysis, particularly in distinguishing genuine variations from forged signatures.

Traditional forensic approaches rely on expert visual examination of signature characteristics, including slant, spacing, proportions, and stroke quality. With the emergence of computational techniques, machine learning and deep learning methods have increasingly been adopted to automate and enhance signature verification systems. Bensefia et al. (2005) demonstrated that handwriting features can be effectively used for writer identification, while Fierrez et al. (2007) introduced machine learning-based models that capture sequential patterns in handwriting data for verification purposes. These studies laid the foundation for modern automated signature analysis systems. In recent years, deep learning approaches have significantly improved the performance of offline signature verification systems. Hafemann et al. (2017) showed that convolutional neural networks (CNNs) can automatically learn discriminative feature representations from signature images, outperforming traditional handcrafted feature methods. Similarly, Dey et al. (2019) highlighted the effectiveness of feature fusion and hybrid machine learning techniques in improving classification accuracy. Sigari et al. (2020) further reviewed deep learning-based signature verification systems and emphasized their robustness in handling complex signature variations.

More recent studies have focused on enhancing interpretability and forensic applicability. Diaz et al. (2024) proposed an explainable offline automatic signature verification system designed to assist forensic handwriting examiners by providing interpretable model outputs. This aligns with the growing need for transparency in AI-based forensic tools, where decisions must be justifiable in legal contexts. Guo et al. (2023) highlighted ongoing challenges in offline signature verification, including limited datasets and variability

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in acquisition conditions. Advanced architectures such as spatial transformer networks have been explored to address geometric variations in signature images. Xiao and Wu (2025) demonstrated that spatial transformer-based models improve feature learning by accounting for transformations such as scaling, rotation, and translation. Similarly, Alsuhimat et al. (2025) proposed a multi-classifier framework using deep feature extraction, showing that ensemble approaches enhance classification performance. Collectively, these studies indicate a shift toward more robust and adaptable machine learning frameworks capable of handling real-world variability. Despite these advancements, most existing research assumes that signatures are produced under unconstrained conditions. However, in practical scenarios, signatures are often executed within predefined spatial boundaries such as boxes in application forms, bank documents, and identification records. These spatial constraints may influence signature formation, potentially altering dimensions, stroke dynamics, slant, and overall structure. The effect of such constraints has not been extensively investigated in forensic literature. Recent work by Priya et al. (2026) examined intra-writer variation in offline handwritten signatures, emphasizing natural variability in forensic analysis; however, it does not explicitly address the influence of spatial constraints. Similarly, multiscript and multisystem approaches (Singh et al., 2024) demonstrate the applicability of machine learning in signature verification across different scripts but do not focus on constrained writing conditions. In practical forensic and administrative contexts, signatures are frequently written within confined spaces, which may force individuals to adapt their natural writing style. This phenomenon, referred to in this study as the “box effect,” may lead to dimensional compression, simplification of strokes, changes in slant, and variation in pen movement. Understanding whether these changes are systematic and predictable is critical for forensic evaluation of questioned documents containing boxed signatures. Therefore, the present study aims to systematically investigate the influence of spatial constraints on signature characteristics by comparing signatures written within a defined box and those produced in an unconstrained environment. A controlled dataset of 1000 participants were utilized, ensuring balanced representation across gender and age groups. Signature features were analysed at both macro and micro levels, including dimensions, slant, spacing, alignment, and initial and terminal strokes. Statistical methods and machine learning techniques, including Random Forest classification, were employed to evaluate the discriminative power of features affected by spatial constraints.

II. MATERIALS AND METHODS

Signature samples were collected from 1000 volunteers (500 males and 500 females) from the Punjab region of India. Each volunteer provided signature samples in three trials, and the average of the three trials was used for analysis. Written informed consent was obtained from all participants. Volunteers were selected using convenience sampling, and the basic inclusion criterion was completion of secondary education. Each participant was instructed to produce signatures under two conditions: within a predefined box and on an unconstrained blank space. Standard A4-size white sheets (75 GSM) and a blue ballpoint pen were provided for all samples. Volunteers were seated comfortably and asked to sign in their usual manner to ensure that the samples reflected natural handwriting without external pressure. The collected signatures were examined under normal lighting conditions. A magnifying glass, ruler, and protractor were used for detailed examination of handwriting characteristics.

III. FEATURE EXTRACTION

In the present study, signature features were categorized into macro-level and micro-level characteristics as shown in Table 1 (Srihari et al., 2015). The qualitative signature samples were converted into a structured dataset suitable for statistical and computational analysis.

Table no 1. Handwriting Characteristics and their coding

Feature Level	Handwriting Characteristics	Sub-Characteristics with code	Definition
Macro-level	Slant	Forward (1) Backward (2) Straight (3)	Angle of letters relative to a vertical line (Found & Rogers, 1998).
Macro-level	Dimension	Small (1) Medium (2) Large (3)	Overall size of individual letters (Srihari et al., 2002).
Macro-level	Spacing	Small (1) Medium (2) Large (3)	Horizontal distance between words (Ellen, 2006).

Macro-level	Alignment	Ascending (1) Descending (2) Straight (3)	Position of word baselines relative to a straight line (Harrison,1958).
Micro-level	Initial stroke	Spur (1) Sharp (2) Blunt (3)	Shape of the first stroke of a letter; indicates starting formation habits (Srihari et al., 2002).
Micro-level	Terminal stroke	Spur (1) Sharp (2) Blunt (3)	Shape of the ending stroke of a letter; indicates finishing formation habits (Found & Rogers, 1998).
Micro-level	Connecting strokes	Absent (0) Present (1)	Connecting strokes are the pen movements that join letters (Osborn, 1929).
Micro-level	Embellishment	Absent (0) Present (1)	Embellishment refers to decorative additions such as loops, flourishes (Hilton, 1982).
Micro-level	Line quality	Good (0) Bad (1)	Smoothness and consistency of writing lines (Found and Rogers, 1998).
Macro-level	Angularity	Angular (0) Round (1)	Degree of sharpness in letter strokes (Ellen, 2006).

A. Statistical Analysis

Statistical analysis was performed using McNemar's test, and chi-square values were calculated using Microsoft Excel 2016. Since the dataset consisted of paired observations, a non-parametric approach was adopted. For comparison of signature feature frequencies between boxed and blank conditions, McNemar's test was applied. This test is based on discordant pairs, i.e., cases where a feature is present in one condition but absent in the other. Observations were organized in a 2 × 2 contingency table (McNemar, 1947).

The chi-square statistic was calculated using:

$$x^2 = \frac{(|b-c|-1)^2}{(b+c)} \quad (1)$$

Were:

- b = number of cases where the feature is present in boxed condition but absent in blank condition
- c = number of cases where the feature is absent in boxed condition but present in blank condition

This test evaluates whether the observed disagreements significantly differ from expected frequencies under the null hypothesis of no difference between conditions. It is widely used in paired categorical forensic data analysis (Agresti, 2018).

- H_0: There is no difference in signature characteristics between boxed and blank conditions.
- H_1: There is a significant difference in signature characteristics between boxed and blank conditions.

The level of significance was set at 0.05. A p-value > 0.05 indicates failure to reject the null hypothesis, whereas a p-value < 0.05 indicates a statistically significant difference.

B. Machine Learning Model

In the present study, a machine learning model was employed to examine whether boxed and blank writing conditions could be differentiated based on signature characteristics. Machine learning techniques are increasingly used in forensic handwriting analysis due to their ability to detect complex patterns and improve classification performance (Srihari et al., 2002; Impedovo & Pirlo, 2011). A Random Forest classifier, an ensemble learning method proposed by Breiman (2001), was used for predictive analysis. It combines multiple decision trees to improve classification accuracy and reduce overfitting.

$$\hat{f(x)} = \frac{1}{N}\sum_{i=1}^{N} fi(x) \quad (2)$$

The method is widely used in forensic document examination due to its robustness, ability to handle categorical variables, and effectiveness in multidimensional datasets (Kumar & Sharma, 2016). The dataset was transformed into a structured numerical format and implemented in Python using Jupyter Notebook (Anaconda environment). Independent variables included macro- and

micro-level features such as slant, dimension, spacing, alignment, initial stroke, terminal stroke, connecting strokes, embellishment, line quality, angularity, and gender. The dependent variable was the writing condition (boxed vs. blank).

The dataset was split into training and testing sets in a 70:30 ratio. The Random Forest model was trained using 300 decision trees, with a maximum depth of 10 and a minimum sample split of 5 to improve stability and reduce overfitting. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and AUC (Fawcett, 2006). Feature importance plots, ROC curves, confusion matrices, box plots, correlation heatmaps, and p-value comparison graphs were generated for interpretation.

IV. RESULTS

The collected signature samples under boxed and blank writing conditions were analysed using McNemar's test and a Random Forest machine learning classifier. The objective was to determine whether significant differences exist in selected handwriting characteristics across the two writing conditions.

A. Statistical Analysis

The present study examined whether signature characteristics remain consistent when the same writer produces signatures under two different conditions: boxed and blank. Since the dataset consisted of paired observations (each participant provided both samples), McNemar's test was applied to determine whether differences observed in specific features were statistically significant. The results are presented in Table 2.

Table 2. McNemar Test for Signature Characteristics under Boxed and Blank Writing Conditions

Sr. No.	Characteristic	Chi-Square Value	P-Value
1	Slant	1.484	0.4762
2	Height	0.533	0.7659
3	Width	3.183	0.2036
4	Spacing	3.436	0.1795
5	Alignment	1.996	0.3685
6	Initial Stroke	12.619	0.0018
7	Terminal Stroke	4.757	0.0927
8	Connecting Strokes	0.201	0.6537
9	Embellishment	0.032	0.8580
10	Line Quality	0.634	0.4261
11	Angularity	5.410	0.0200

The McNemar test results indicate that most handwriting characteristics did not exhibit statistically significant differences between boxed and blank writing conditions ($p > 0.05$). However, Initial Stroke ($\chi^2 = 12.619$, $p = 0.0018$) and Angularity ($\chi^2 = 5.410$, $p = 0.0200$) showed statistically significant variation. The remaining characteristics including slant, height, width, spacing, alignment, terminal stroke, connecting strokes, embellishment, and line quality showed non-significant differences, indicating relative stability across writing conditions.

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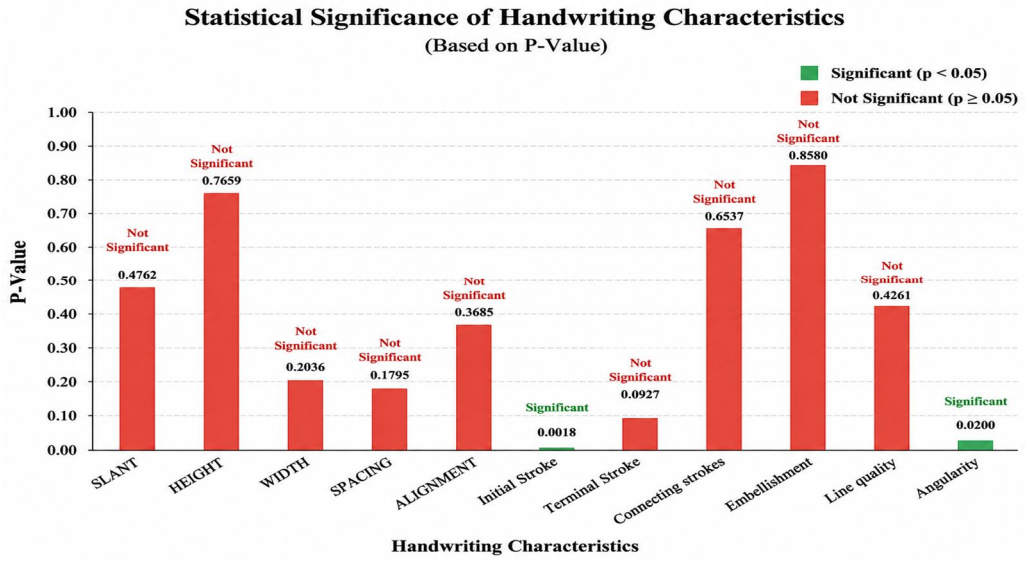


Figure 1. P-value graph

Figure 1 illustrates the p-value distribution of all examined characteristics, highlighting that only Initial Stroke and Angularity fall below the significance threshold ($p < 0.05$).

B. Machine Learning Analysis

A Random Forest classifier was employed to evaluate whether boxed and blank signatures could be distinguished based on selected handwriting characteristics. The model was trained and tested using a coded dataset containing both macro-level and micro-level features.

Table 3. Performance Metrics

Metric	Value
Accuracy	0.5283
Precision	0.5215
Recall	0.5338
F1-score	0.5275

The Random Forest classifier achieved an overall accuracy of 52.83%, as shown in table 3 indicating limited discriminative capability between boxed and blank writing conditions. Precision, recall, and F1-score values were relatively balanced, suggesting that the model performed similarly across both classes without strong bias.

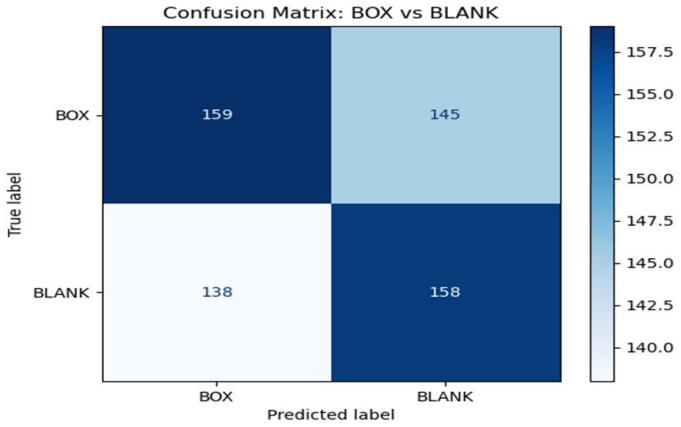


Figure 2. Confusion matrix

Figure 2 (Confusion Matrix) shows that the classifier correctly identified a portion of signatures from both conditions; however, noticeable overlap between classes was observed, indicating similarity in feature distributions.

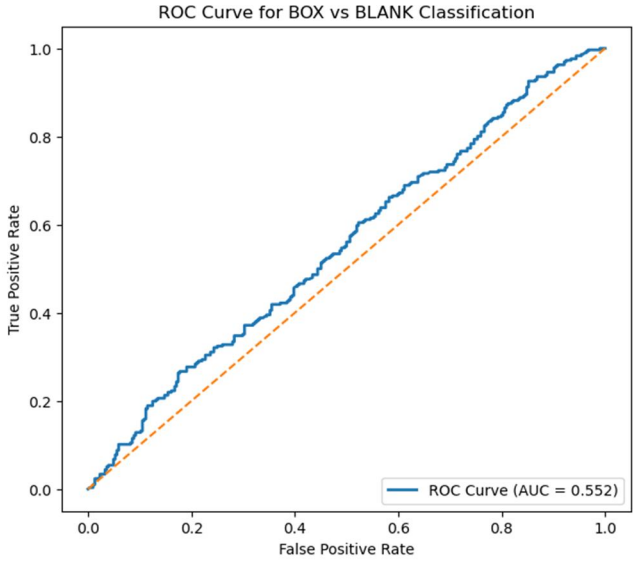


Figure 3. ROC curve

Figure 3 (ROC Curve) further demonstrates moderate classification performance, supporting the observation that signatures under both conditions are not strongly separable based on the selected features.

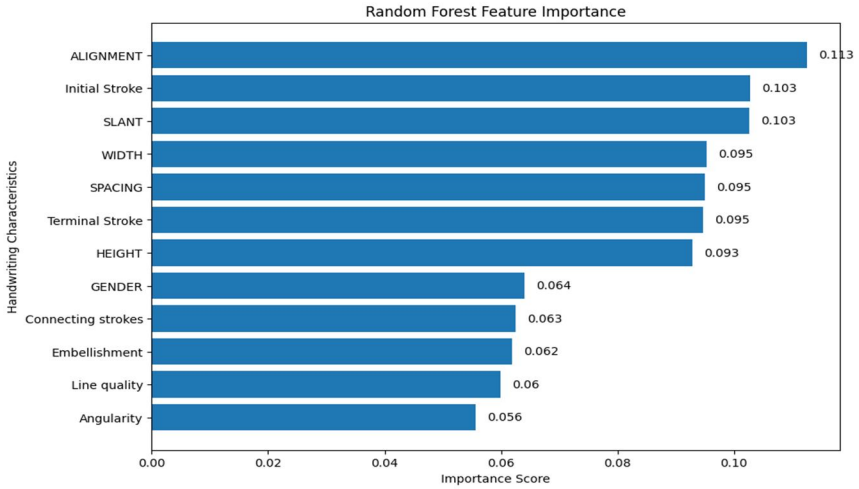


Figure 4. Feature importance

Figure 4 (Feature Importance Analysis) revealed that Alignment, Initial Stroke, Slant, Width, and Spacing were the most influential features in classification. Among these, Alignment contributed the highest importance, followed by Initial Stroke and Slant. Features such as Angularity, Line Quality, and Embellishment contributed comparatively less to the model. Overall, the machine learning results align with the statistical findings, indicating that only limited handwriting features are affected by spatial constraints. Despite minor variations, most signature characteristics remain stable across writing conditions.

V. DISCUSSION

The present study investigated whether signature characteristics vary under boxed and blank writing conditions using McNemar's test and a Random Forest classifier. The results indicate that most handwriting features remain stable across both conditions, with only Initial Stroke and Angularity showing statistically significant differences. The Random Forest model further demonstrated moderate performance (accuracy = 52.83%), suggesting limited separability between the two writing conditions.

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These findings are consistent with Srihari et al. (2002), who reported that handwriting individuality remains stable despite natural variations in writing conditions. Similarly, Found and Rogers (1998) emphasized that environmental factors generally affect only superficial handwriting features, while core structural characteristics remain largely unchanged. In the present study, features such as slant, height, width, spacing, and line quality also showed no significant variation.

The significant variation observed in Initial Stroke and Angularity aligns with Fazio (2015), who reported that spatial constraints can influence stroke initiation and directional movement. This suggests that adaptive features are more sensitive to environmental constraints compared to structural features. Recent studies further support these observations. Beniwal and Sharma (2025) reported minor but measurable variations in handwriting under different writing conditions, while Schomaker et al. (2021) found statistically significant differences that do not substantially affect forensic interpretation. The feature importance analysis indicated that Alignment, Initial Stroke, Slant, Width, and Spacing were the most influential variables, with Initial Stroke and Alignment showing the strongest contribution. Overall, both statistical and machine learning analyses suggest that boxed writing conditions have only a limited effect on signature characteristics. The majority of features remain stable, supporting the forensic reliability of signatures for identification purposes.

VI. CONCLUSION

The present study examined the effect of boxed and blank writing conditions on signature characteristics using McNemar's test and a Random Forest classification model. The findings demonstrate that most handwriting features remain stable across both conditions, with only Initial Stroke and Angularity showing statistically significant variation. This suggests that spatial constraints primarily influence adaptive aspects of handwriting, particularly stroke initiation and directional movement, while the overall structural integrity of signatures remains largely unaffected.

The Random Forest classifier achieved moderate performance (accuracy = 52.83%), indicating limited separability between boxed and blank signatures based on the selected features. Feature importance analysis further highlighted Alignment, Initial Stroke, Slant, Width, and Spacing as the most influential variables. Overall, the combined statistical and machine learning evidence suggests that although spatial constraints may induce minor variations in specific features, the core individuality of signatures remains preserved. This reinforces a key principle in forensic handwriting examination: signatures retain their evidential value even under varying spatial conditions. The study therefore supports the reliability of signature analysis in forensic practice and contributes to understanding handwriting variability under controlled constraints.

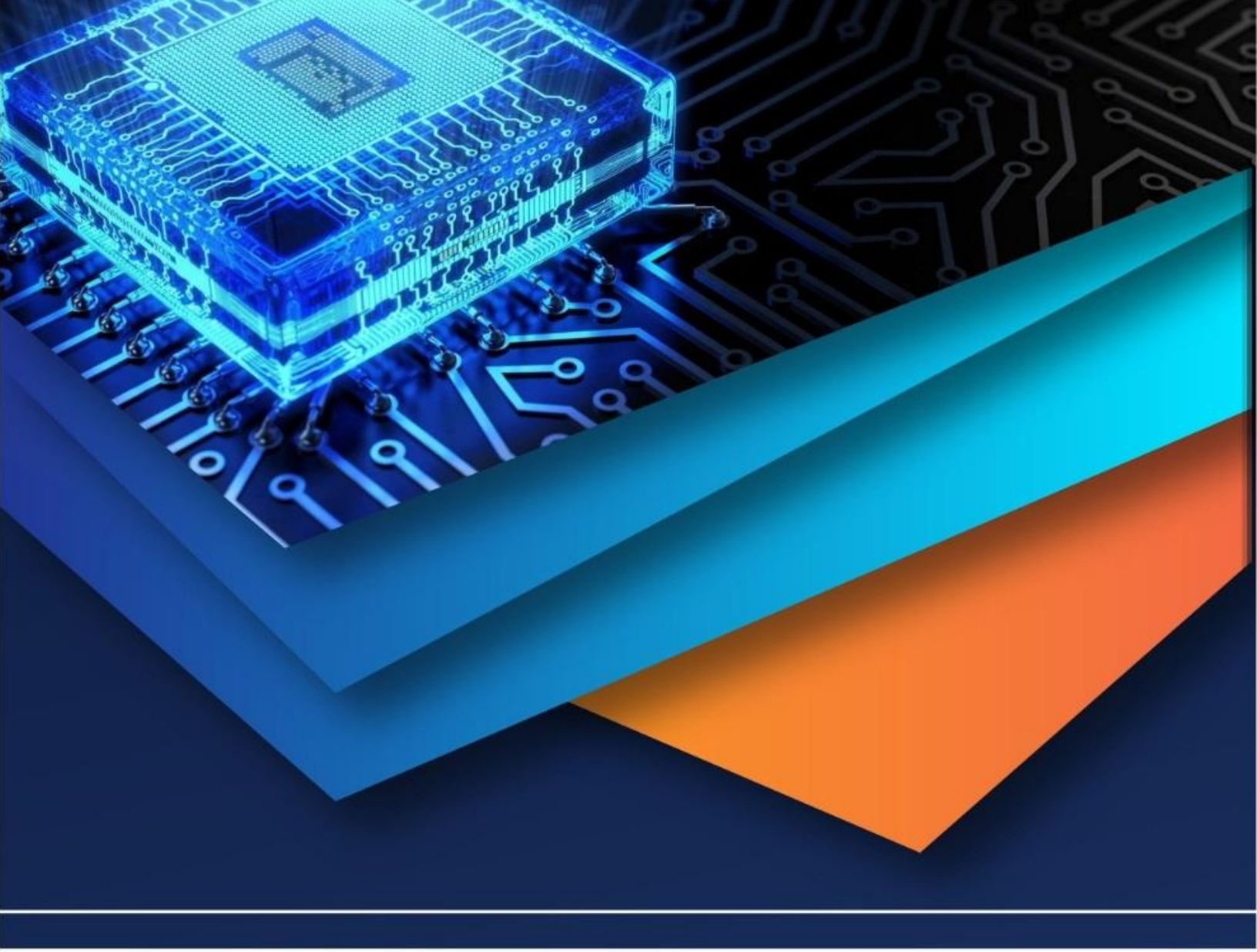
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