iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: III Month of publication: March 2023

DOI: https://doi.org/10.22214/ijraset.2023.49542

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 11 Issue III Mar 2023- Available at www.ijraset.com*

# Predicting Stability of Slope by Amplitude and Coherence Using a Naïve Bayes Classifier

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***Abstract: Slope instability is a challenge in both mining and civil engineering industries. Current ap-proaches to slope stability analysis are mostly based on slope deformation data provided by mon-itoring equipment. This study proposes a new method to estimate slope stability using amplitude and coherence obtained from slope stability radar data. More than 160,000 data points from 10 slope failures were collected with GroundProbe's slope stability radar systems. They were used as input dataset in a Naive Bayes model for classification into two groups of stable and unstable slopes. The classifications were conducted based on different range limit values for amplitude and coherence. The findings were validated against slope deformation behavior in each case. The results show that 91 percent of the data that are classified as unstable slope by the Naive Bayes Gaussian method belong to slope failure events and are categorized correctly. The coherence and amplitude range values proposed in this research can be utilized by mining operations to determine the stability of slopes in conjunction with slope deformation and inverse velocity data.***

## I. INTRODUCTION

Slope failures can damage equipment and structures and even lead to loss of life. Monitoring equipment plays a significant role in slope failure predictions and could prevent damage and fatalities caused by slope failures. Depending on the type of monitoring equipment, different information such as slope deformation, velocity, coherence, amplitude, etc. are collected and used by geotechnical engineers to evaluate slope instabilities. Among the most effective slope monitoring equipment is the Slope Stability Radar (SSR) which can detect slope deformations with sub-millimeter precision. This technique eliminates the need for reflectors or equipment mounted on the wall. Radar waves can penetrate effectively through rain, dust, and smoke, 24 hours a day (Harries et al. 2006). Although the SSR operation is based on the concept of differential interferometry developed for synthetic aperture radar that detects minor land movements from satellites, it uses a real aperture on a stationary platform at a distance of 50 to 400 meters from the slope toe. SSR detects slope changes by comparing the phase measurements in each slope scan footprint (Reeves et al. 2001). Slope deformation information provided by monitoring equipment such as SSR is crucial to slope failure prediction. In theory, slope displacement occurs when resistance forces such as friction are less than the driving forces such as weight. Determining slope velocity and the ratio of slope displacement from SSR data opened a new chapter in predicting the TSF. Initial studies using SSR data provided successful results showing that slope failure time can be predicted by using an extrapolated trend line towards an inverse velocity of zero in an inverse velocity-time plot (Saito 1969; FUKUZONO 1985; Cruden and Masoumzadeh 1987; Crosta and Agliardi 2003; Carlà et al.2017). Slope deformation sometimes occurs over a long period of time. According to Soldati et al. (Soldati et al. 2006), Deep-seated Gravitational Slope Deformations (DGSDs) are not considered hazardous due to their slowness, but they may cause damage in underground as well as open pit surfaces. In addition to slope deformation and inverse velocity, most slope monitoring radar equipment can provide other parameters to characterize slope behavior such as amplitude and coherence. Amplitude is the strength of the reflected signal and demonstrates the amount of energy that is scattered back from the wall to the radar.

A stronger signal or higher energy signal provides a higher amplitude due to significant radar echoes from a rougher surface. Coherence represents the consistency of the signal that returns from a given scatterer. Geotechnically speaking, it represents the consistency of the surface that the radar is scanning and carries information about changes in the pit wall. Any minor surface alteration can affect the coherence value. The type of slope changes such as rockfalls can be attributed to a specific coherence value. According to Arciniegas et al. (Arciniegas et al. 2007), coherence decreases as damage levels increase. Although coherence and amplitude information is already used by engineers as subsidiary factors for stability evaluations, the lack of a specific threshold on coherence and amplitude in relation to slope failure gives rise to the question of whether they can be sufficient parameters to evaluate the stability of slopes independently of deformation and velocity information.

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The purpose of this study is to propose a particular range of values related to the slope failure period helping engineers to be more confident in the assessment of slope stability. To achieve this goal, 166277 data points from 10 slope failures have been used and classified into two categories of stable and insatiable data based on different range values for both amplitude and coherence, using the Naïve Bayes Gaussian model. The below section explain about Gaussian Naive Bayes classifier.

## II. NAÏVE BAYES AND GAUSSIAN NAÏVE BAYES (GNB) CLASSIFIER

The Naïve Bayes (NB) method, also known as Discrete or Multinomial NB, is a Bayesian Network Classifier, a form of Bayes' theorem, and is an accepted method for data classification. This method is based on independent attributes (classes) assumption:

$$P(Y|xi) = P(Y)P(xi|Y)/P(xi) . \qquad (1)$$

In the equation above, xi is the feature factor and Y is the class. In this study, the class is the stability of the slope, and the feature factors are coherence and amplitude. Despite the poor assumption of attribute independence, which does not always represent reality, the Naïve Bayes classifier is more reliable compared with more sophisticated models (Kononenko 1991; Rish et al. 2001; Friedman et al. 1997; Domingos and Pazzani 1997; Hilden 1984). This classifier does not need any specific structured learning (Langley et al. 1992). Also, the other advantage of NB is that it is an appropriate model for large amounts of independent input data while it can be trained with a small amount of data. The naive-Bayes method has been used in slope failure predictions and provided successful results (Bhargavi and Jyothi 2009; Lin et al. 2018). For example, the work by Feng et al. (Feng et al. 2018) used NB to predict slope stability based on six input parameters of slope height (H), slope angle (), cohesion (c), friction angle (), unit weight (), and pore pressure ratio (ru) and the results were more accurate and practical compared with the empirical method used therein. Ahmad et al.(Ahmad et al. 2022) also used the same input factors for predicting slope failure subjected to circular failures by using a new Tree Augmented Naive-Bayes (TAN) model and the results showed that the TAN model could predict better than empirical methods. As mentioned above, the NB method is suitable for discrete or multinomial variables. For continuous variables, however, a combination of Gaussian distribution and Naïve-Based method called Gaussian Naïve-Bayes method is used. In this investigation, the input data are coherence and amplitude which are continuous variables and GNB classifier was used on them. In the next section, we describe the data set and the GNB training method.

## III. DATA AND METHODS

### *A. Data Set*

10 slope failures containing a total number of 166,277 data points were exported from the indi- vidual pixels of GroundProbe slope stability radars, namely SSR-XT and SSR-FX. Although both radars monitor slope deformations, SSR-FX is a newer version and can provide rain accumulation data in addition to coherence and amplitude. The slope deformation values were also exported to determine the failure period. The data sets contain unstable and stable data. The unstable data includes coherence, amplitude, and rain accumulation values in the duration of slope failure which is denoted in To visualize the distribution of the data set, histogram graphs were constructed for coherence, amplitude, and rain accumulation data sets. Fig. 1 shows the coherence distribution plot. As can be seen, the highest frequency belongs to the coherence value of 1. It is because the number of stable data points is higher than unstable ones and the coherence value for stable data is usually 1. That is also the reason that the coherence distribution is skewed to the left. The orange line shows the cumulative distribution for the coherence. Fig. 2 is the histogram graph for the amplitude. Although it is skewed to the left, it has both a right and left tail. As can be seen from the graph, most of the amplitude values range between 48 and 56. Finally, Fig. 3 illustrates the multimodal distribution for rain accumulation in the dataset. Since the amount of precipitation in the majority of days was negligible or non-existence, the highest distribution belongs to no rain.

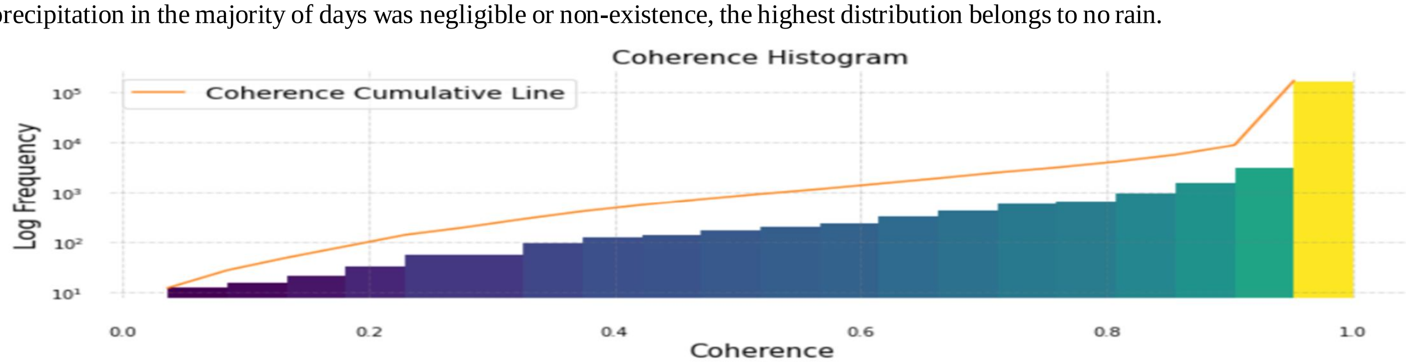



Fig. 1. Distribution of coherence in the data set

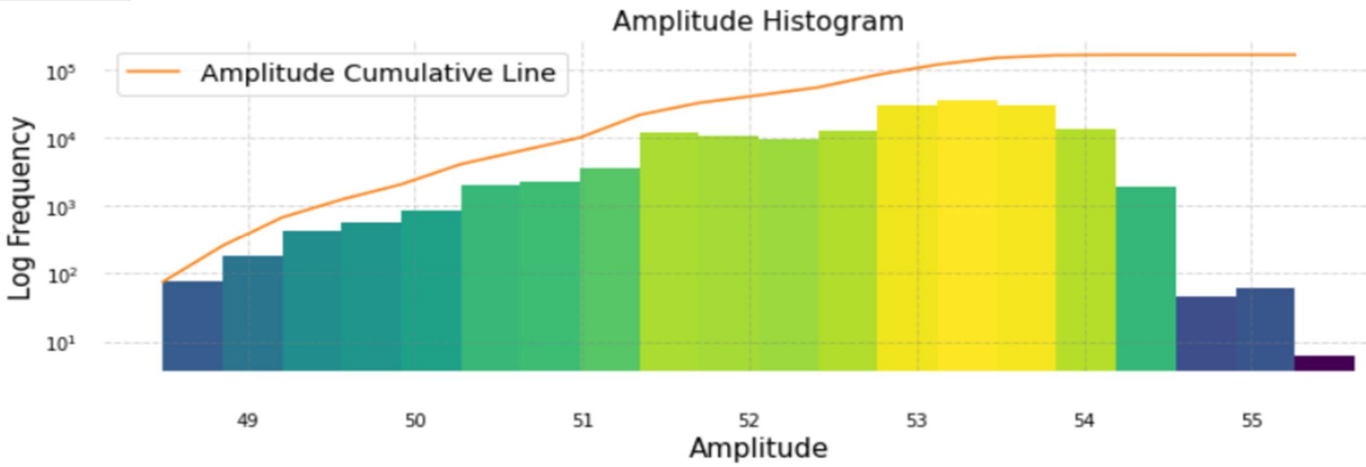



Fig. 2. Distribution of amplitude in the data set

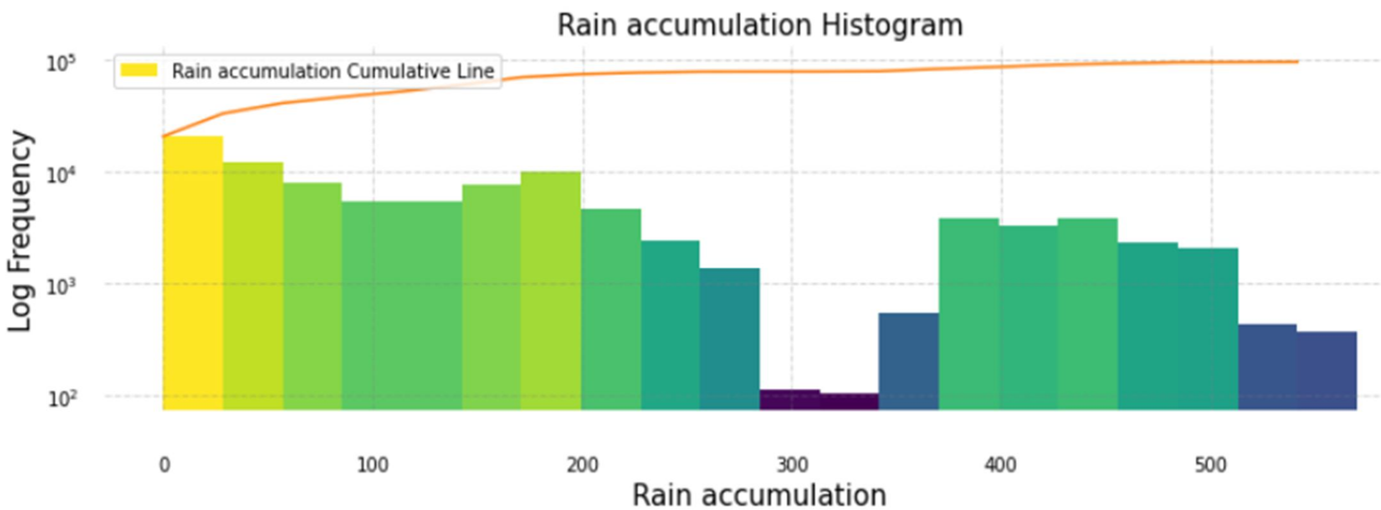



Fig. 3. Distribution of rain accumulation in the data set

The principal objective of this study is to provide the range for coherence and amplitude to help determine the stability of slopes with high confidence regardless of slope deformation and inverse velocity values. As mentioned earlier, the GNB assumes that the contributions are independent. To determine if coherence and amplitude are independent, a heat map, shown in Fig. 4, was constructed by using the Pearson correlation coefficient score which measures the linear relationship strength between two variables. The heat map reveals that both coherence and amplitude have a correlation coefficient between 0 to -0.2, which means they are not completely independent of each other. Despite the moderate dependency of the two attributes, we relied on many studies such as Domingos et al. (Domingos and Pazzani 1997) which showed that a Bayesian classifier still can perform optimally even if the independence assumption for contributions is not fully established. Hence, we continued using the NBC for this study.

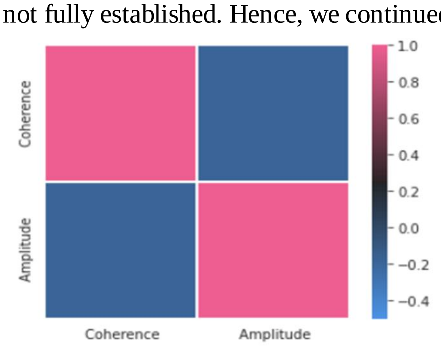
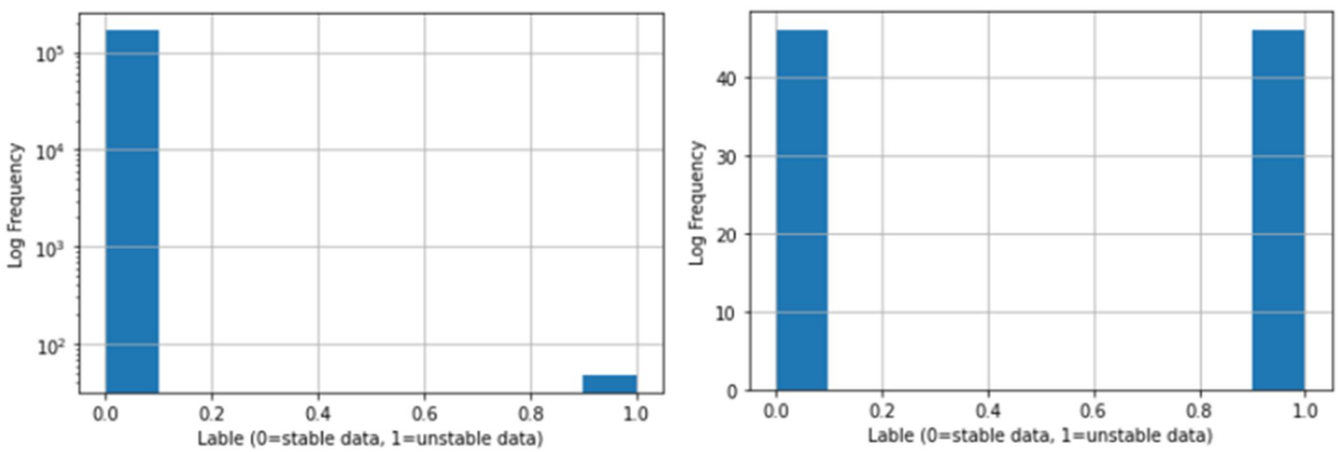



Fig. 4. Visualization of correlation score between coherence and amplitude

### *B. Training Gaussian Naïve Bayes Classifier*

80 percent of the data were used as a training set, and 20 percent for testing the model. The model was trained based on the value of coherence and amplitude. This research claims that if the coherence value is between 0.2 and 0.5, and the amplitude value is greater than 53, the slope is most likely in the failure zone and is not stable. Although they are many stable data with an amplitude of more than 53, or with a coherence between 0.2 and 0.5, when either the coherence or amplitude values satisfy the above conditions, they are classified in the unstable data category. For training the model, all coherence and amplitude values were concatenated, and the data were labeled based on their value. The data with coherence between 0.2 to 0.5 and amplitude of more than 53 were labeled 1 as unstable data and the rest of the data were labeled 0 as stable data. Fig. 5(A) shows the histogram of stable and unstable data after the labeling process. As can be seen, the results show that the size of the data are unequal and unbalanced. In other words, the stable dataset size is much larger than the unstable one. To balance the size between groups, we needed to decrease the size of stable data to the size of unstable data which is 48. Hence, a specific code in the Python environment was developed to randomly choose 48 data from a group of stable data and normalize the size of stable and unstable data, 96 in total (Fig 6.(B)).

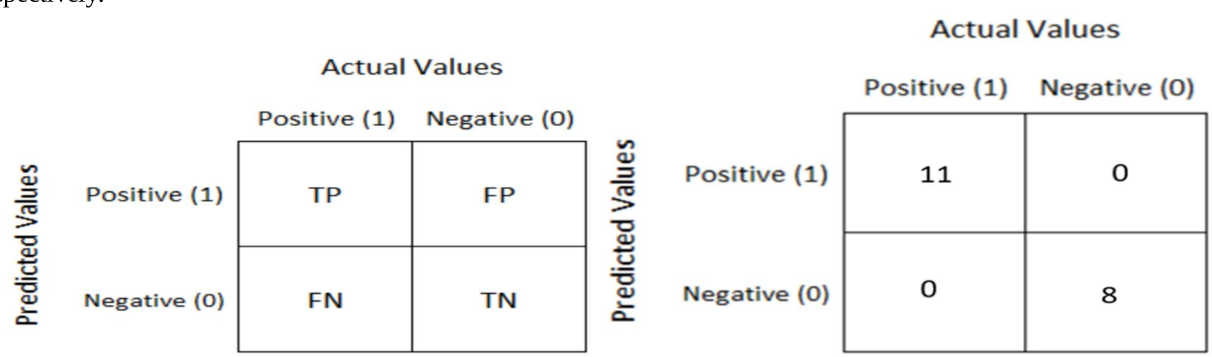



(A) (B)

Fig. 5. (A) histogram of stable and unstable data (B) the data set after normalizing the size

## IV. RESULTS AND DISCUSSION

The NBG classifier was tested on 20 percent of the datasets which were a combination of stable and unstable data. The results show that the developed model classifies the data efficiently. The confusion matrix in Fig. 6 suggests that 11 data points were unstable and GNB could identify them as unstable data. Also, 8 data points were stable, and the model detected them as stable data correctly. The 48 data points that were classified as unstable data were tested using deformation values to determine if they belong to slope failure periods. The analysis revealed that 91 percent of the data belong to the slope failure category. In other word, this indicated that 91 percent of the data had a coherence between 0.2 to 0.5 and an amplitude of greater than 53 belong to a failed slope. However, this does not mean that when the slope fails, the amplitude and coherence value should be necessarily more than 53 and between 0.2 to 0.5 respectively.




(A) (B)

Fig. 6. (A) the general feasibility matrix (B) shows the feasibility matrix for testing data

Rain can accelerate slope deformation and sometimes even causes slope failure and continuous rainfall can decrease the stability of the slope and increase the risk of failure. However, the exact amount of water that led to slope failure remains unknown and Slope failures occurred when a phreatic surface appeared on the slope face (Chen et al. 2009; Toll 2001). The results of this study show that continuous rain not only affects slope deformation but also it affects the coherence and amplitude directly. Although this study has not introduced a specific range for rain accumulation that guarantees slope failure, the data shows that continous precipitation over several days (usually more than 3 days) causes the slope to enter the progressive zone with high probability. Fig 7. Shows the primary stages of pre-failure evaluations where the tertiary stage is indicative of a rapid increase in the strain rate and leads to failure (Cho et al. 2021; Upasna and Moe 2018). The progressive zone is in the tertiary stage in this figure.

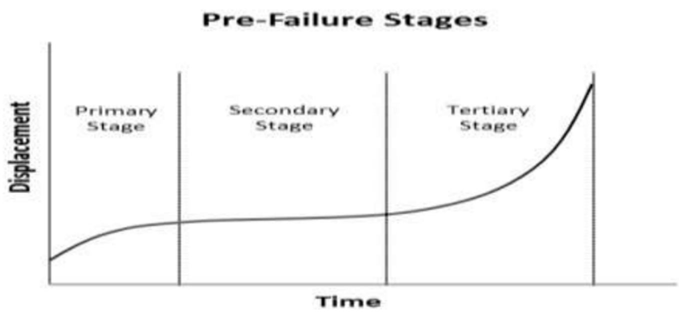



Fig. 7. Primary stages of pre-failure evolution (Upasna and Moe 2018)

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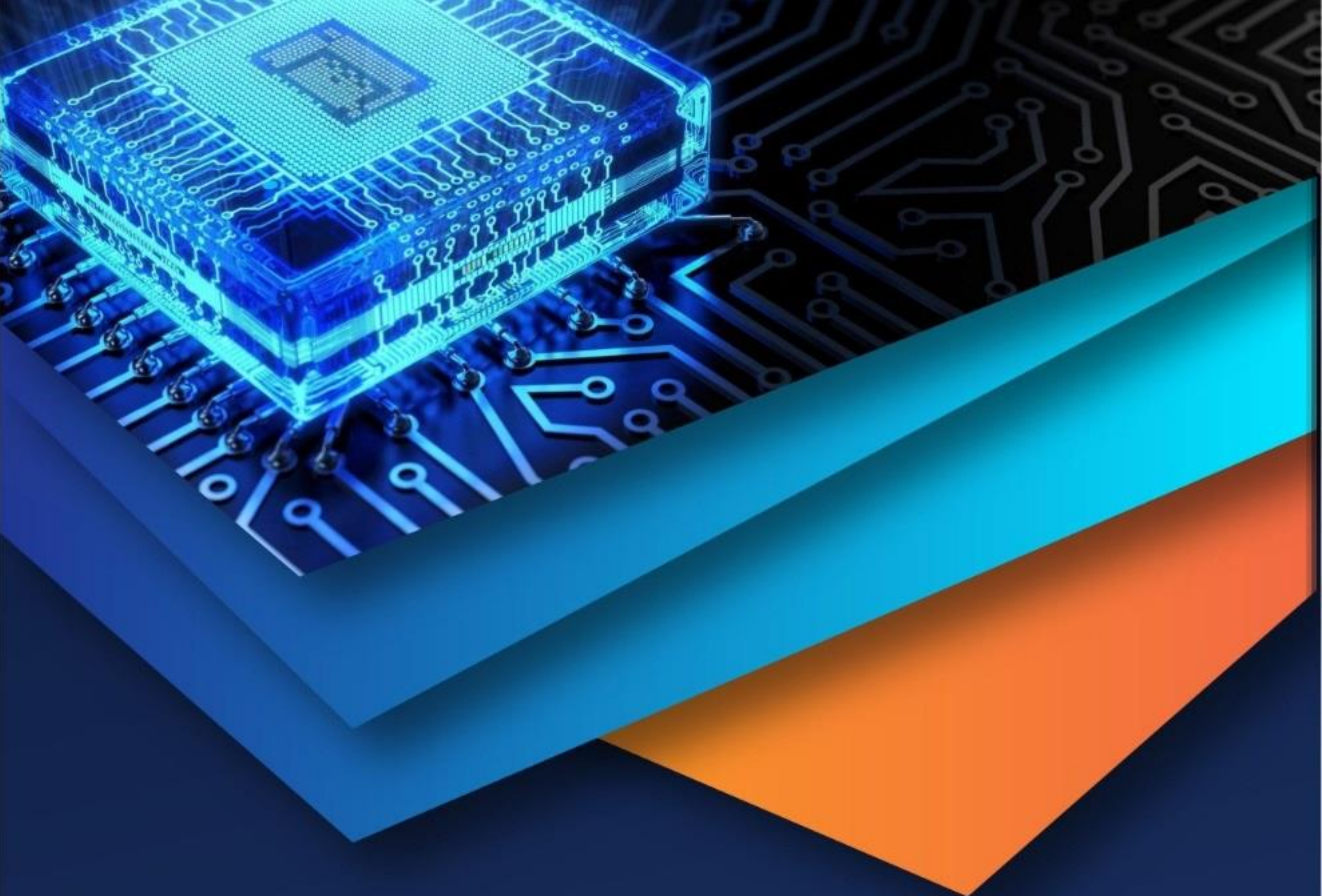


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