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Coal Production Analysis using Machine Learning

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Abstract: ***Coal will keep on giving a significant segment of energy prerequisites in the US for at any rate the following quite a few years. It is basic that exact data portraying the sum, area, and nature of the coal assets and stores be accessible to satisfy energy needs. It is likewise significant that the US separate its coal assets productively, securely, and in a naturally mindful way. A restored center around government support for coal-related examination, facilitated across offices and with the dynamic cooperation of the states and modern area, is a basic component for every one of these necessities. In this project we attempt to predict the coal production using various features given the data set. We attempt to implement regression algorithms and find the best algorithm along with fine tuning the parameters of the algorithm. The existing system uses the linear regression model one of the main issues with this basic linear regression is that it does not have a regularization parameter and hence overfits the data. The system also does not provide enough pre-processing and visualization or Exploratory Data Analysis (EDA). We aim to build advanced regression models like ridge and lasso regression and also fine tune the parameters of the model. These models would be trained on a data set which will be engineered carefully after performing the feature engineering.***

Keywords: Linear regressions, Ridge, lasso, pre-processing and visualization.

I. INTRODUCTION

The venture "Coal production estimation using machine learning" contains the highlights which will give wellbeing to individuals working around there. In the event of calamity, it is extremely hard for the mine administration to distinguish the real individual caught, their number and precise area. A few excavators are coming out from underground mine before finishing of the booked shift time.

A. Existing System

The existing system uses the linear regression model one of the main issues with this basic linear regression is that it does not have a regularization parameter and hence overfits the data. The system also does not provide enough pre-processing and visualization or Exploratory Data Analysis (EDA).

B. Disadvantages of Existing System

1) The limitations of available systems are not sufficient to deal with the complex data. In this section, we present some of the limitations that are present in the existing system.
2) The model suffers from overfitting due to no generalization of data.
3) The error on test data is high due to overfitting.
4) The system also requires data extensive data preprocessing and Exploratory Data Analysis (EDA) inorder to perform feature engineering.

a) *Proposed System:* We aim to build advanced regression models like ridge and lasso regression and also fine tune the parameters of the model. These models would be trained on a data set which will be engineered carefully after performing the feature engineering

II. LITERATURE REVIEW

In 2017 this paper was published Coal is one of the pivotal normal fuel sources, which is successfully utilized in energy creation. iron or steel age. furthermore, family use. Enterprises use portrayal to comprehend coal quality for its functional utilization. They for the most part embrace the substance. minute. also, machine-subordinate interaction as the best quality level techniques for characterization. The proposed technique might be utilized in businesses just as aiding the development of a PC based coal test orders. Alpana ,Satish Chand[15] and [1].

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In 2007 this paper was published Li Meng; Wang Cong; Bai Xinli It is important to ensure that convenient determination of fanatics of coal issue is for mine security creation in ventures. To set up fanatics of coal deficiency conclusion master framework is a sort of compelling path for improving fans shortcoming finding. The harshness set is applied to fans flaw master framework for information; this way can improve the objectivity of mining information, which to build up successfully fans shortcoming determination rules. The thinking machine embraces the blended thinking instrument which is based standards and models, thus accomplished the capacity of master framework to self-learning and personal development. After aficionados of coal deficiency determination master framework is placed in to utilize, the activity and upkeep of fans is essentially improved [21].

In 2020 this paper was paper distributed Alpana Alpana; Satish Chand, Vivek Mishra Coal is the fundamental wellspring of fuel for making electrical energy through the consuming of pulverized coal. Unusual blends are conveyed during this cooperation, achieving the creation of varieties of sear segments. The morphology of sear parts can be requested into get-togethers, which reflects the particular level of coal affectability, that can be utilized to overview the effects of coal on burner undertakings. As of now, organizations follow the manual and semi-robotized minute procedures to see the reactivity of sear. These systems are drawn-out, conceptual and restricted to little model measures figuratively speaking. The objective of this assessment is to outfit insightful consume course of action techniques with benefits similar to speed, consistency, and exactness. This paper attempts to propose a robotized structure for cook reactivity course of action using RES-NET significant learning method. The result shows an exactness of 93.89% in less computational time. Therefore, the proposed system may be prescribed to ventures for burn.[3], [1] and [19]

III. PROPOSED METHOD

Utilizing Boa constrictor: Present Python and Jupyter using the Boa constrictor Appropriation, which joins Python, the Jupyter Scratch pad, and other conventionally used packs for sensible preparing and data science. To present Boa constrictor, go through How to present Boa constrictor on windows? additionally, stick to the rules gave.

Utilizing PIP: Present Jupyter using the PIP group boss used to present and manage programming packs/libraries written in Python. To present pip, go through How to present PIP on Windows? additionally, hold fast to the rules given. Introducing Jupyter Note pad:

Anaconda is an open-source programming that contains Jupyter, spider, and so forth that are utilized for enormous information preparing, information investigation, substantial logical figuringAnaconda works for R and python programming language. Spyder (sub-usage of Anaconda) is used for python. OpenCV for python will work in arachnid. Package forms are overseen by the bundle the board framework called cond.

Python was proposed for clarity, and has a couple of similarities to the English language with sway from science. Python uses new lines to complete a request, rather than other programming lingos which often use semicolons or sections. Python relies upon space, using whitespace, to portray scope; like the degree of circles, limits and classes. Other programming tongues routinely use wavy areas consequently. The Four models we have utilized

A. Random Forest

Random Forest is a stowing technique and not a boosting strategy. The trees in Random Forest are run in equivalent. There is n association between these trees while building the trees. It works by building a colossal number of decision trees at planning time and yielding the class that is the technique for the classes (request) or mean gauge (backslide) of the individual trees. A self-assertive forest area is a meta-assessor (for example it consolidates the aftereffect of different forecasts) which totals numerous choice trees, for certain accommodating alterations

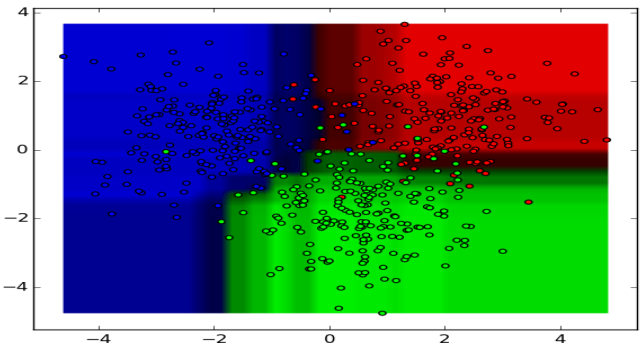

Figure 3.8 shows Output of Nine Tree.

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B. Ridge Regressor

For a relapse AI models, the standard relapse condition shapes the base which is composed as:

$$Y = XB + e$$

Where Y is the reliant variable, X addresses the free factors, B is the relapse coefficients to be assessed, and e addresses the blunders are residuals. When we add the lambda capacity to this condition, the difference that isn't assessed by the overall model is thought of. After the information is prepared and recognized to be essential for L2 regularization, there are steps that one can attempt.

C. LASSO

The lasso stands for least absolute shrinkage selection operator.

It is utilized over relapse techniques for a more precise forecast. IN lasso model we use shrinkage. Shrinkage is where data regards are contracted towards a primary issue as the mean. The tie system upholds essential, insufficient models. This particular kind of backslide is fitting for models showing obvious levels of multicollinearity or when you need to automate certain bits of model decision, like variable decision/limit end. Lasso Relapse utilizes L1 regularization method (will be talked about later in this article). It is utilized when we have a greater number of highlights since it naturally performs include choice.

$$\sum_{i=1}^{n}(y_i - \sum_{j} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Where,

λ it is amount of shrinkage.

$\lambda = 0$ implies all attributes are mentioned and it is equalt to the linear regression.

$\lambda = \infty$ implies no attribute is mentioned

The differnces are increased along with increase in λ.

variance are increased along with decrease in λ.

D. Decision Tree

One part of the choice tree I should specify is the way it really figures out. As a directed AI models, a choice tree figures out how to plan information to yields in the thing is known as the preparation period of model structure. During preparing, the model is fitted with any chronicled information that is pertinent to the difficult area and the genuine worth we need the model to figure out how to anticipate. The model learns any connections between the information and the objective variable.

Decision trees are prescient models that utilization a bunch of paired principles to ascertain an objective worth.

Every individual tree is a genuinely basic model that has branches, hubs and leaves.

IV. SIMULATION RESULTS

In this Chapter we will implement linear Regression models by comparing with few other models like Random Forest, Lasso, Ridge Regression and decision tree regression to find the errors and analyze it. In this project we will see the of MSE, RMSE, R^2 and accuracy.

Steps we used for solving problem.

Read the Input dataset.

Perform all necessary Data Normalization, Standardization processing to prepare the transformed format of given input dataset.

Perform Exploratory Data Analysis/Visualization and bring insights of the predictor variables.

Apply Various Regression algorithms by splitting the data into train and test.

Measure and compare the performance of the models using MSE, R2and Adjusted R2

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A. Training Dataset and Pre-Processing

The test dataset is a dataset used to give an unprejudiced assessment of a last model fit on the preparation dataset. The dataset is also used to provide the information in form of excel sheet which is uploaded and opened with CSV file.

MSHA ID	Year	Production (short tons)	Average Employees	Labor Hours	Mine Name	Mine State	Mine County	Mine Status	Mine Type	Company Type	Operation Type	Operating Company	Operating Company Address	Union Code	Coal Supply Region
103381	2015.0	62598.0	6.0	13713.0	441.0	0.0	10.0	0.0	1.0	1.0	1.0	307.0	88.0	5.0	2.0
103246	2015.0	25481.0	9.0	17641.0	71.0	0.0	43.0	3.0	1.0	1.0	1.0	67.0	382.0	5.0	2.0
103451	2015.0	121474.0	21.0	51729.0	483.0	0.0	43.0	3.0	1.0	1.0	1.0	67.0	547.0	5.0	2.0
102933	2015.0	3939.0	5.0	5287.0	598.0	0.0	59.0	3.0	1.0	1.0	1.0	9.0	321.0	5.0	2.0
100329	2015.0	0.0	52.0	119679.0	212.0	0.0	60.0	0.0	2.0	2.0	2.0	432.0	373.0	3.0	2.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1103247	2015.0	70701.0	7.0	3097.0	263.0	21.0	121.0	0.0	0.0	1.0	1.0	324.0	60.0	5.0	3.0
4407325	2015.0	123573.0	10.0	10676.0	368.0	21.0	120.0	2.0	0.0	1.0	1.0	407.0	626.0	5.0	0.0
4407329	2015.0	261788.0	11.0	15233.0	426.0	21.0	120.0	1.0	0.0	1.0	1.0	407.0	625.0	5.0	0.0
4407354	2015.0	20977.0	11.0	1104.0	367.0	21.0	120.0	0.0	0.0	1.0	1.0	407.0	626.0	5.0	0.0
1518524	2015.0	6388.0	2.0	621.0	973.0	21.0	111.0	2.0	0.0	1.0	1.0	57.0	153.0	5.0	0.0

1171 rows × 15 columns

Figure 4.1 Shows the 16 features present in the Dataset.

The figure 4.1 shows all the features in dataset are Year - Data in Datapoint belong to which year, MSHA ID -unique identification number of a mine site, Mine Name - Name of Mine Site, Mine State - State in which the Mine Site is located, Mine County - To which County this Mine Site belong to, Mine Status - Mining status of Mine Site, Mine Type - Type of Mine Site (Underground, Surface, Refuse), Operation Type - Operation type of company (Mine only, preparation plant,, mine and preparation plant).

The data normalization will be working on the dataset. Database normalization data set pattern plan strategy, by which an existing schema is altered to limit repetition and reliance of information. Standardization split a huge table into small tables and characterize connections between them to expands the clearness in getting organizing data. We will be doing two normalization data description and data objects, Operating Company - Name of Operating Company, Operating Company Address - Address of Operating Address, Union Code - union code of the mine site, Coal Supply Region - To which region produced coal delivered, Production (short tons) - How many tons of coal is produced, Average Employees - How many Employees Worked, Labor Hours - Total hours the average no of employees worked.

```
data.describe()
```

	Year	Production (short tons)	Average Employees	Labor Hours
count	1171.0	1.171000e+03	1171.000000	1.171000e+03
mean	2015.0	7.659612e+05	56.337319	1.219438e+05
std	0.0	4.792195e+06	121.721462	2.691105e+05
min	2015.0	0.000000e+00	0.000000	6.000000e+01
25%	2015.0	0.000000e+00	6.000000	8.568500e+03
50%	2015.0	3.347200e+04	16.000000	3.064900e+04
75%	2015.0	2.284815e+05	43.000000	9.972500e+04
max	2015.0	1.093439e+08	1628.000000	3.349283e+06

(a)

```
data.dtypes
```

```
Year                        int64
Mine Name                  object
Mine State                 object
Mine County                object
Mine Status                object
Mine Type                  object
Company Type               object
Operation Type             object
Operating Company          object
Operating Company Address  object
Union Code                 object
Coal Supply Region         object
Production (short tons)     int64
Average Employees           int64
Labor Hours                 int64
dtype: object
```

(b)

Figure4.2 (a) shows the normalized data.describe (b) shows the normalized data.type

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B. Visualization with Matplotlib

Matplotlib is a 2-Dimensional plotting library that helps in visualizing pictures. The figure contains the general window where plotting occurs, contained inside the figure are the place where actual charts are plotted.

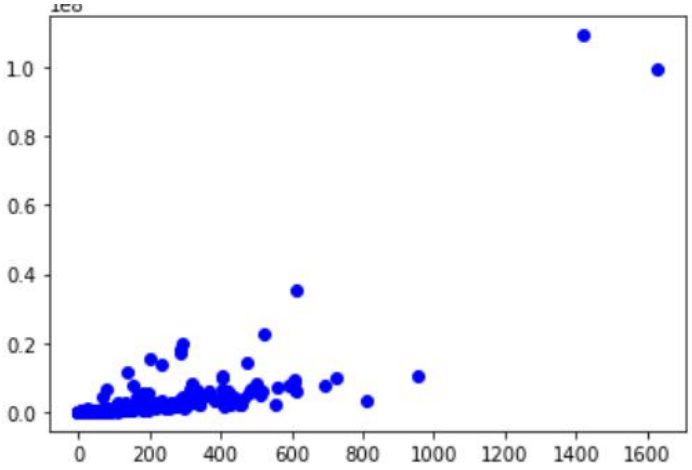

Figure 4.3 Shows pyplot between the average employees and production short ton.

In figure 4.3 The Matplotlib library function is used to plot the data in graph between the average employees (x-axis) and production short ton (y-axis).

C. Split training with Histogram

The histogram is implemented in the data describe dataset which is 2nd normalized dataset.

The main purpose we used histogram for bar graph-like representation of data that buckets a range of outcomes into columns along the x-axis. The y-axis represents the number count or percentage of occurrences in the data for each column and can be used to visualize data distributions. The data is trained separately with 14 features available in dataset called data. describe. The data describe has 14 features they are mine types, mine country, operation type, supply region, avg employees, production, mine states, mine status, company type.

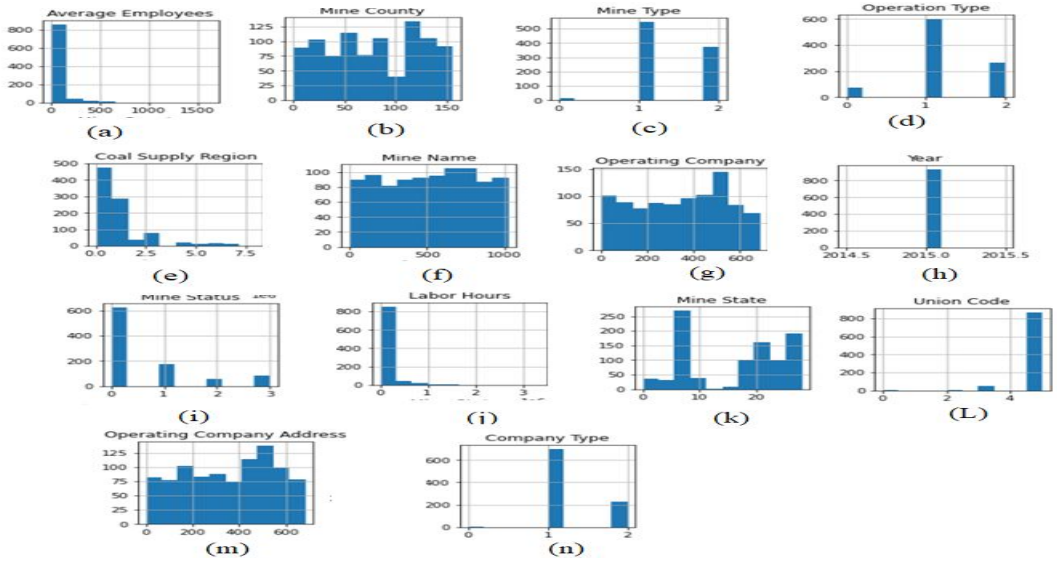

Figure 4.4 Shows Data.describe represented in histogram.

In figure 4.4 the bar graphs are displayed of (a) Avg employee in Histogram, (b) Mine Country in Histogram, (c) Mine type in Histogram, (d) Operation type in Histogram, (e) Coal Supply Region in Histogram, (f)Mine name in Histogram, (g) Operation Company in Histogram, (h) Year in Histogram, (i) Mine status in Histogram, (j) Labor hours in Histogram, (k)Mine state in Histogram, (l) Union Code in Histogram, (m) Operation company address in Histogram, (n) Company type in Histogram. These are 14 Bar chart data is represented from that dataset, which make data been and observed the changes.

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D. Standardization and Outputs

We are using linear regression models Random Forest model, Ridge, Lasso, Decision tree regressor: These four models would be trained on a dataset which will be engineered carefully after performing the feature engineering. The requirement is to come up with novel features based on the functional understanding of the dataset. It is important to keep in mind to avoid correlated features during this process. Each feature should only improve the information contained in the dataset. Visualize the dataset without cleaning the data and understanding the distribution of the dataset. The standard error of the regression is also known as the standard error of the estimate, represents the average distance that the observed values fall from the regression line. The linear regression model one of the main issues with this basic linear regression is that it does not have a regularization parameter and hence overfits the data. The system also does not provide enough preprocessing and visualization, it tells you how wrong the regression model is on average using the units of the response variable. Smaller values are better because it indicates that the observations are closer to the fitted line. From the standardization we are training the data set with the transformed dataset of production short ton by taking the test size = 0.2 and random state = 0. The random state = 0 is taken this parameter used for initializing the internal random number generator, which will decide the splitting of data into train and test indices in our case. This standardization is implemented with all the Data comparing with Production short ton. We are train the data with linear regression to obtain the test score of trained data, RMSE and R^2 (Root square). By training the data we have obtained Test Score (MSE), RMSE and R^2, respectively.

Test Score: 0.6014284
RMSE: 4643081.4395
R^2: 0.601428

The same process should be implemented in other model of linear regressor to analyze future production rate how it can be improved. By considering the MSE, RMSE and R^2 we will analyze the prediction of coal production by obtaining data of Avg employees and production short ton followed by:

1) MSE (Mean Square Error)
2) RMSE (Root Mean Square Error)
3) R^2 (Root Square)

E. MSE (Mean Square Error)

When analyzing various data it's always useful to create across plot of all the available data points in addition to look it Looking for a normal as values that should be questioned accuracy the overall trend The data can also be observed from the scatter of the individual that a point a simple linear regression can be calculated and plotted to help highlight the overall data trend in creating this type of trend analysis it's fair to ask how accurately the regression line represents the actual data points we can make use of various statistical calculations better understand this best fit model.

$$mse = \frac{1}{n}\sum_{i=0}^{n} \quad (y_i - \hat{y}_i)^2$$

If a vector of {\displaystyle n} predictions is generated from a sample of n data points on all variables, and {\displaystyle Y} is the vector of observed values of the variable being predicted, with {\displaystyle {\hat {Y}}}being the predicted values.

The values of MSE of Different model:

Ridge Regressor MSE: 215582052.914
Lasso Regressor MSE: 227552624.02
Decision Tree Regressor MSE: 7732169.868
Random Forest Regressor MSE: 5390172.0949

We Observe by the results Decision tree regressor value is less that other model. This value rate can be calculated or predicted we need to further more cross down the values. The Root M-eam Square Error helps us in more Precising the values.

F. RMSE

The regression is somewhat muddled article. We have a lot of focuses; we have a regression line. It's good on the off chance that we can sum up things in a easy way. Furthermore, with regards to a straight relapse, there are two extremely, regularly utilized single number of a regression.

$$R^{MSE} = \sqrt{\sum_{i=0}^{n} \quad \frac{(y^{\wedge}-y)}{n}}$$

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The whole root of the Mean square error which is more simplified values which tends between the range of value -1 to 1.
Root Mean Squared Error is often given the acronym RMSE. It ends up being easy to be the square of the relationship amongst Y and X, yet it has a more pleasant translation, simply a straight forward connection. It is deciphered as the extent of fluctuation and Y clarified by X. Thus, any remaining things been equal to 1.
The value of the Root mean square of different models are:
Ridge Regressor RMSE: 46401.495
Lasso Regressor RMSE: 47707.629
Decision Tree Regressor RMSE: 8797.547
Random Forest Regressor RMSE: 73417.940

G. R^2 or R Squared

R Square is in pressure of how close each state of point fits to the regression line The a square tells us how well the regression line predicts the actual values We can make a regression man now any point that falls on the regression line corresponds to a predictive value soon general in the R Square there one it actually tells the predicted value and actual value are close to real one That the regression line doesn't fit the data that well and we can clearly see a large amount of predictive values and four square is exactly equal to 1 which means that we can predict the value of Y for any given value of X squared also tells is the percentage of variation in why there is accounted for by its regression on X. we can also typically prefers a higher R squared over a lower 1, because you're interpreting more variability. RMSE is a different one number summary from a regression. Now R squared is the number that measures the proportion of variability in Y explained by the regression mode

$$R^2 = 1 \quad \frac{SS_{RES}}{SS_{ToT}} = \frac{\sum_i (y_i \quad \hat{y}_i)^2}{\sum_i (y_i - \bar{y} \quad)^2}$$

The Euclidean distance between the real information focuses on the y pivot and their comparing anticipated qualities along the relapse line is SS(RES) and the distance between the real information focuses on the y hub, and the mean of Y again figuring out the outcome. The qualities are kept up by the 0 to 1 to be represented the percentage ex: 0.953422345 = (95.3%).
The values of the Root Square of Different models are:
Ridge Regressor R^2: 0.6014249
Lasso Regressor R^2: -3.942063
Decision Tree Regressor R^2: 0.872650
Random Forest Regressor R^2: 0.829308

H. Accuracy

Accuracy is characterized as the level of right forecasts for the test information. It very well may be determined effectively by isolating the quantity of right forecasts by the quantity of complete predictions.
We will be calculating the accuracy for all models.

$$\text{acc} = \left(\frac{\textit{Number of correct prediction}}{\textit{total number of prediction}}\right) \times 100\%$$

Ridge Regressor Accuracy: 58.9
Lasso Regressor Accuracy: 66.54
Decision Tree Regressor Accuracy: 97.47
Random Forest Regressor Accuracy: 26.1

Comparation of different models

Models	MSE	RMSE	R^2	Accuracy in %
Ridge	215582052.914	46401.495	0.6014249	58.9
Lasso	227552624.02	47707.629	-3.942063	66.54
Decision tree	7732169.868	8797.547	0.872650	97.47
Random Forest	5390172.0949	73417.940	0.829308	26.1

We used two types of datasets to check the error and accuracies of the training that can be observed in above table. The training of different model decision tree has more accuracy 97.47 and the random forest got least accuracy 26.1. Therefore, we can conclude that Decision tress regressor have the best accuracy.

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V. CONCLUSION AND FUTURE WORK

The main thing while at the same time making a model is the component designing and determination measure. You ought to have the option to separate greatest data from the highlights to make your model stronger and more exact. Highlight choice and extraction accompanies regard to time and experience. There could be a few different ways to manage the data accessible in the dataset. There is part of various approaches to make your model learn. The learning calculation should give you the best outcomes. You can likely utilize diverse learning calculations and afterward group them to make your model more powerful. A/B testing should likewise be possible while underway with the goal that you would realize which model is performing much better. can be improved further and can recover privileged data with considerably more precision. Plainly the utilization of mechanical technology, man-made intelligence and AI can essentially help save costs, increment productivity, improve wellbeing, increment disclosure potential and numerous different advantages for mining organizations. What has kept them down was the information challenge, as having the option to concentrate and make noteworthy experiences from a lot of information has regularly been excessively troublesome. Notwithstanding, mining organizations are presently dealing with scaling the utilization of simulated intelligence in mining and we will begin to see more complex utilization of man-made intelligence in the mining business. Beside cost investment funds, man-made intelligence utilizes constant information and investigation to help mining organizations forestall mishaps and wounds at work. In the event that enough great information can be gathered, the applied innovation ought to have the option to anticipate disappointments changing safeguard upkeep into prescient support. Albeit the sheer measure of information to measure may seem like just another hindrance for inspectors to survive, with the correct devices, it gives the chance to make more exact reviews than recently expected

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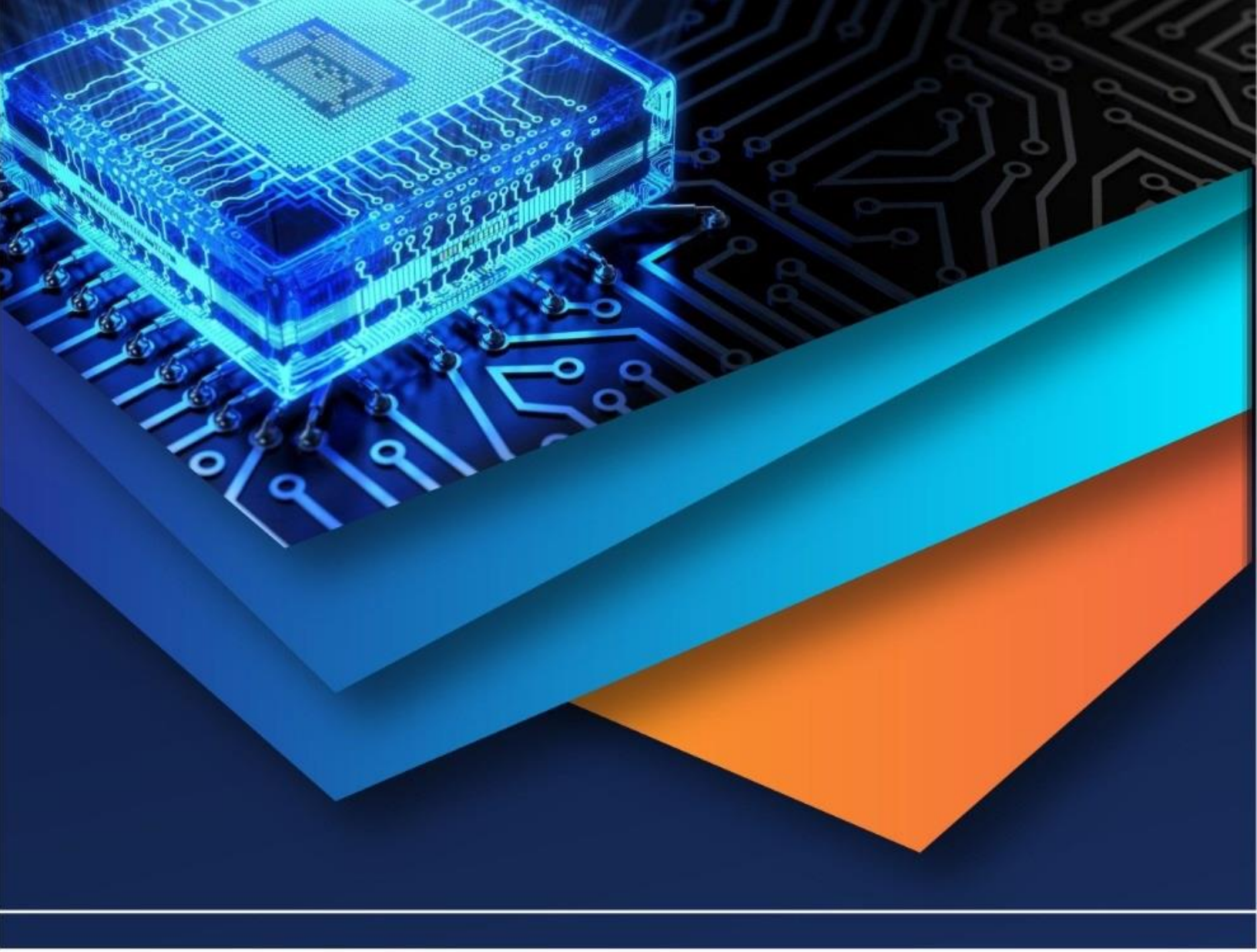

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