## CREDIT CARD FRAUD DETECTION USING MACHINE LEARNING

Project report submitted in partial fulfilment of the requirement for the degree of Bachelor of Technology

## Computer Science and Engineering/Information Technology

by
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To


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## Candidate's Declaration

I hereby declare that the work presented in this report entitled "Credit card fraud using Machine Learning" in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering/Information Technology submitted in the department of Computer Science \& Engineering and Information Technology, Jaypee University of Information Technology Waknaghat is an authentic record of my own work carried out over a period from Jan 2021 to May 2020 under the supervision of Dr. Monika Bharti, Computer Science \& Engineering and Information Technology).
The matter embodied in the report has not been submitted for the award of any other degree or diploma


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This is to certify that the above statement made by the candidate is true to the best of my knowledge.

Monica Burt
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## abstract

It is lively that most of the credit- card company are likely to spot fraudulent credit - card transaction so that clienteles are n't accused for objects which they are not buying. These kind of difficulties can be undertaken with the use of Data Science and its importance, along with Machine Learning, cannot be exaggerated. This task means to embody the demonstrating of an informational index utilizing AI with Credit Card Fraud Detection. The Credit Card Fraud Detection Problem includes demonstrating past Mastercard exchanges with the information of the singles that ended up being trick. This model is then used to recognize if another exchange is phony. Our goal here is to distinguish $100 \%$ of the phony exchanges while diminishing the ill-advised extortion arrangements. Visa Fraud Detection is a trademark test of characterization. In this interaction, we have retained on examining and pre-preparing informational collections just as the position of various anomaly discovering calculations, for example, Local Outlier Factor and Isolation Forest calculation on the PCA adjusted Credit Card Transaction information.

## Chapter 1: INTRODUCTION

## 1.1 introduction

Credit card fraud fraud and unauthorized use of the account by someone other than the holder of account. Essential preventive events container stay occupied to prevent misuse \& behaviour these fake does be deliberate reduce \& defend from like incidents in future. In extra disputes, credit card fraud can be denote as an offense where person usages another person's credit card aimed at private details while cardholder \& issue powers that be do not know that card is being used. Scam detection includes nursing the events of workers to measure, detect \& evade undesirable behavior, which contains intrusion, scam \& error. This an important issue that needs attention of groups such as data science \& machine learning where solution to this problematic can be automatic. This problematic is mainly thought-provoking after viewpoint of learning, as it is marked different factors, for example, class disparity. The quantity of substantial exchanges far exceed fake ones. Likewise, exchange plans frequently variety their arithmetical belongings finished course of time. These aren't just difficulties in the execution of a genuine trick identification framework, yet. In real world models, the colossal stream of installment demands is quickly checked via programmed apparatuses that means which exchanges to approve.

This problem poses a serious challenge to the learning perspective, as it is reflected in numerous issues such as class inequality. The value of a legal transaction goes distant beyond scam. Also, transaction designs frequently change their mathematical properties done time. These aren't the one challenges to the application of the scam detection system in the actual world, though. In actual world examples, significant supply of payment needs is fast perused by automated tools that fix which transactions will be authorized.

AI calculations are utilized to dissect every authority exchange and dubious reports. These reports are inspected by specialists who contact cardholders to confirm that the exchange was straightforward or counterfeit. Specialists give a reaction to a programmed framework used to prepare and refine the calculation to eventually recuperate the exhibition of trick recognition done time.

This deception is confidential as:

1. Online \& Offline Credit Card Fraud
2.Theft Credit Card
2. Account Development
3. Login Device
4. Request Fraud Application
5. Fake Card
7.Communication Fraud

### 1.2 Problem Statement

The Credit Card Determination Issue includes demonstrating past Mastercard exchanges with data that has ended up being phony. This model is utilized to decide if another exchange is phony or not. Our objective here is to land $100 \%$ phony positions while reducing the botch of phony trick.


## 1.3 purpose

The purpose of credit card fraud is to reduce losses due to payment fraud by both merchants \& to withdraw banks \& increase the chances of getting money from merchants.

### 1.4 Method of operation

The method suggested by the paper, uses newest machine learning algorithms sense unpopular tasks, called outliers.
Rudimentary diagram of the shocking construction can be represented by the following figure:


Our dataset is from Kaggle.
Confidential this dataset, there are 31 segments out of which 28 are named as v1-v28 to keep unobtrusive information. Different segments address Time, Amount and Class.

Time shows the delay $b / w$ the underlying exchange and the following one. Sum is the measure of executed. Class 0 addresses a legitimate exchange and 1 addresses a phony one. We intrigue dissimilar to diagrams to check for errors in the dataset and to outwardly acknowledge it:

Count of Fraudulent vs. Non-Fraudulent Transactions


This chart shows that the quantity of fake businesses is ample lesser than real singles.


This diagram shows the occasions on which arrangements were done inside 2 days. It tends to be seen that the most modest number of exchanges were made during evening time and greatest during the days.

### 1.5 Implementation

Impression is hard applying in actual life as it needs support as of banks, who are unwilling share data because of their competition in the market \& the protection of their user's information \& also for legal reasons.

So, we have observed at other reference papers that follow like methods \& collect results. As mentioned in one of these reference works
"This method was used for the capturing of complete application data provided by the German bank in 2006. For bankruptcy reasons, only the results obtained are summarized below. After using this method, the Level 1 list covers a few cases but has a high probability of being a fraud.

All the people mentioned on this list have their cards locked to avoid any risk due to their high-profile profile. The situation is very complicated on some lists. Level 2 is still restricted enough to be assessed from time to time.

Debt management \& collectors consider half of the cases on this list to be considered fraudulent. In the last \& greatest list, the work survives equally. Less than a third of them are suspicious.

In order to increase the efficiency \& charging more, it is possible to add something new to the question; this element can be the first five digits of phone numbers, email address \& password, for example, those new questions can be used in level $2 \&$ level 3."

## Chapter 2: Literature survey

### 2.1 Literature review

Trick goes about as false or unlawful extortion proposed to bring monetary or singular addition. Intentional activity that disregards the law, law or strategy to acquire unapproved monetary profit.

Numerous books about wrongdoings or misrepresentation on this site have effectively been distributed and are accessible for public use.

Broad examination by partners has exposed that the frameworks utilized in this circle contain information expulsion claims, mechanical trick identification, foe finding. In extra paper, Suman Research Scholar, GJUS and T at Hisar HCE presented systems like Supervised and Uncontrolled Reading for Mastercard misrepresentation. Albeit these techniques and calculations have discovered unforeseen accomplishment in about parts, they have sad convey a never-ending and solid arrangement in recognizing extortion.

Similar examination site was grown any place they utilized Outlier mines, Outlier securing mines and Aloofness whole cycles to precisely figure counterfeit exchanges in the recreation of charge card exchanges in a specific exchanging bank. Unfamiliar taking out is an information mining field utilized principally in the monetary and online areas. It works by discovering things dependent on cutting edge framework i.e., counterfeit exchanges. They took the characteristics
of purchaser demeanor \& in terms of the worth of those traits they have planned the detachment between the supposed cost of that trait \& its encoded value. Substitute means such in place of mix data / compound network development procedure can sense prohibited states in a card deal data set, based on a grid renovation algorithm that permits to create a one-way unconventionality image in a reliable transaction.

There have also been efforts to advance from totally original feature. Actions have made to advance communiqué of the cautionary response in the occurrence of a untrue deal.

In the occasion of a fraud, the lawful organization will be alerted \& a reply will be sent to deny the constant Mock Inherited System, one of the means that lean-tos new light on the domain, as complementary to scheme from the other lateral.

It has been unprotected to be detailed in detecting fake businesses \& in dipping its sum of false alarms. But, it was allied with the unruly of separation at unlike costs of diversity.

### 2.2 Classifications Algorithms:

### 2.2.1 Decision Tree:

Decision tree analysis is a shared, theoretical tool with claims that concealment a variability of areas. Typically, deduction trees are made in algorithmic way classifies ways discrete data founded diverse circumstances. It is 1 of the greatest extensively rummage-sale \& real-world approaches of plotted learning. Bush choices are a parameter-free education technique used for divider \& deduction actions. The box is to generate a classical that envisages the amount of target disparities by interpretation humble result rules from data features. The rubrics of the result are frequently in a declaration, if any. The profounder the tree, the additional complicated the rules \& modeling of model.

Earlier we dive deeper, lease's get conversant by roughly of terms:

- Explain: The plural that describes an example
- Conditions: Look for vector of features or adjectives that describe the input space
- Aimed at: The work we are trying to find that is real answer
- Concept: A function that marks the output of the output
- Hypothesis Class: Set all possible activities
- Sample: Input set mutual with the label, which is the apt result
- Vote Idea: A concept that we reason is a target concept
- Test Set: Alike to a training set \& used for yeast testing


## Expressiveness of decision trees

Decision trees can show any Boolean capacity of the info possibilities. How about we use choice leaves to make the job of 3 Boolean entryways OR,AND and XOR.Boolean Function: AND

| A | B | A AND B |
| :---: | :---: | :---: |
| F | F | F |
| F | T | F |
| T | F | F |
| T | T | T |


F
OR


Decision tree of AND operation.
we can see that there are two competitor ideas for making the choice tree that does the AND act. Additionally, we can likewise deliver a decision tree that achieves the boolean OR activity.

Boolean Function: OR

| $\mathbf{A}$ | $\mathbf{B}$ | A OR B |
| :---: | :---: | :---: |
| $\mathbf{F}$ | $\mathbf{F}$ | $\mathbf{F}$ |
| $\mathbf{F}$ | $\mathbf{T}$ | $\mathbf{T}$ |
| $\mathbf{T}$ | $\mathbf{F}$ | $\mathbf{T}$ |
| $\mathbf{T}$ | $\mathbf{T}$ | $\mathbf{T}$ |



Decision tree of OR operation

Boolean Function: XOR

| A | B | A XOR B |
| :---: | :---: | :---: |
| F | F | F |
| F | T | T |
| $T$ | $F$ | $T$ |
| $T$ | $T$ | $F$ |



Decision tree of XOR operation.

How about we crop a choice tree performing XOR usefulness utilizing 3 credits:


In the decision tree, shown overhead with three codes there are 7 lumps in the tree, i.e., at $\mathrm{n}=3$, the quantity of lumps $=2^{\wedge} 3-1$. Additionally, in the event that we have $n$ figures, there are $2^{\wedge} n$ hubs. In the choice tree. Along these lines, the tree requires a remarkable measure of hubs in the most pessimistic scenario circumstance.

We can mean boolean cycles utilizing decision trees. Be that as it may, what other sort of exertion would we be able to imply and in the event that we explore the various fixed trees for revelation the correct one, the number of decision trees should we stress over. We should reaction this question by discovering the measure of leader trees that we can give divergent N characteristics (we think the properties are boolean). Since the genuine seat can be restored into a decision tree, we will make a genuine N table for N figures as info.

| $\mathbf{X 1}$ | $\mathbf{X 2}$ | $\mathbf{X 3}$ | $\ldots$. | $\mathbf{X N}$ | OUTPUT |
| :---: | :---: | :---: | :---: | :---: | :---: |
| T | T | T | $\ldots$ | T |  |
| T | T | T | $\ldots$ | F |  |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |  |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |  |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |  |
| $\ldots$ | F | F | $\ldots$ | F |  |
| $\ldots$ |  |  |  |  |  |

True seat upstairs has $2^{\wedge} n$ rows, which signifies a likely mixture of $\mathrm{i} / \mathrm{p}$ signs \& since apiece node can hold 2 worth, number of habits to seal the standards in choice tree is $\left\{2^{\wedge}\left\{2^{\wedge} n\right\}\right\}$. So, space for executive medicine, i.e., theory interplanetary for executive drug is very expressive because there are many dissimilar functions that it can characterize. However, it also income that one wants to have a astute way of penetrating for the finest tree amongst them.

### 2.2.2 linear regression:

Line regression can be clear as a precise model that analyzes the linear association amid variable star contingent on a given set of self-governing variables. The lined association between variable star means that when the worth of one or more self-governing variable star changes (increases or decreases), the worth of the reliant on variables will alteration so (increase or decrease).
Genuinely dealings can be portrayed with the assistance of reasonableness -
$\mathrm{Y}=\mathrm{mX}+\mathrm{b}$
Here, Y is the substitutable whimsical that we are attempting to allowance
X is the dependent on factor that we use to visualize.
$m$ is the splatter of the spine line in lieu of the impact $X$ has on $Y$
b is enduring, known as the Y -catch. In the event that $\mathrm{X}=0, \mathrm{Y}$ will be indistinguishable from b .9

## Positive Linear Relationship

Equal relationships will be called good when there is a different growth of independence \& dependence on each other. It can be unspoken with the help of subsequent the graph -


## Negative Linear relationship

A line association will be called positive if independent increases \& dependent changeable reductions. It can be tacit with the help of next graph -


Negative Linear Relationship

## Types of Linear Regression

Line setback is of the next two types -

- Simple Line Way
- Multiple Line Recurrence

Simple Line Lessening (SLR)
It is a rudimentary form of the lineback that forecasts the response using one object. The supposition in SLR is that the two variable star are related successively.

### 2.2.3 : Logistic Regression

As mentioned above, in the reversal of the line our goal is to achieve binary separation which is why our hypothesis should be chosen appropriately. To change our retrospective models past our theory work, we can write

Where
$\mathrm{X}=[1 \mathrm{X} 1 \mathrm{X} 2 \ldots \mathrm{Xn}]$
\&
$C=[\alpha \beta 1 \beta 2 \ldots \beta n]$
where $\mathrm{Xi}=$ course that contains the element value of all entries in the data set.

The sigmoidal function is used in adding to the well-known theory function to place it in the choice of $(0,1)$. This will developed clearer when we discuss the boundaries. The work of Sigmoidal is as follows, so our new function of theory develops
$\operatorname{sg}(y)=\operatorname{sg}(C T x)=11+e-C T x$
Boundary limitations

The new theory function stretches a value among $0 \& 1 \&$ therefore can be taken as the chance that the value will be 1 for that exact x . This report can be properly defer to to the subsequent form:
$\operatorname{sg}(y)=P(y=1 \mid x ; C)$
\& subsequently you can only take $0 \& 1$, the other value of 1 is to withdraw the hypothesis value.

By decoding the above we can safely govern the borderline of the verdict by the subsequent rule: $\mathrm{y}=1$ if sg (y) -0.5 , else $\mathrm{y}=0 . \operatorname{sg}(\mathrm{CT})-0.5$ means $\mathrm{CTx} \geq 0 \&$ also under the ailment. This difficulty will set the stage for decision-making. As the evenness of the two autonomous variables,
it will be rather clear how the line cuts the joining plane into two parts with respectively class lying on its adjacent.

With a altered hypothesis role, taking a square error job will not work as it is less exclusive in wildlife \& tedious to reduce. We are attractive on a new cost form of the subsequent:
$E(\operatorname{sg}(C, x), y)=-\log (s g(C, x))$ if $y=1$
$E(\operatorname{sg}(C, x), y)=-\log (1-\operatorname{sg}(C, x))$ if $y=0$

This can be on paper as modest as:
$E(\operatorname{sg}(C, x), y)=-y^{*} \log (\operatorname{sg}(C, x))-(1-y) \log (1-\operatorname{sg}(C, x))$
\& it is evidently silent that it compares to the above cost work. By limitations, we take the sum of cost work over all points in the working out data. Then,
$\mathrm{H}(\mathrm{C})=1 \mathrm{~m} \sum \mathrm{i}=1 \mathrm{mE}(\mathrm{sg}(\mathrm{C}, \mathrm{xi}), \mathrm{yi})$

For the limit dimension, we use a iterative aspect technique named the incline ancestry that recovers the strictures over each step \& decreases the cost purpose H(C) to the most likely value. Incline interruption necessitates curved cost work so that the discount step is not stuck in the local least. Gradient interruption, opening with accidental stricture values and rewriting their values in each step to lessen the cost of work by a convinced sum in each step until you reach at least with a bit of luck or until there is a slight variation over convinced succeeding steps. The steps for ramp descent are as trails:
$=\mathrm{i}=\beta \mathrm{i}-\mathrm{p} \partial \mathrm{H}(\mathrm{C}) \partial \beta \mathrm{i}$

For the injury degree, we utilize an iterative viewpoint technique considered the incline plunge that advances the constraints over each progression and decreases the expense meaning $H(C)$ to the most probable worth. Slope interference requires curved expense work with the goal that the lessening step isn't caught in the neighborhood minima. Angle vacation, beginning with arbitrary injury esteems and modifying their qualities in each progression to lessen the expense of work by a specific total in each progression until you reach at any rate with a touch of karma or until here is a slight change over certain succeeding advances. The means for slope drop are as per the following:

## .2.2.4: KNN Algorithm

KNN can be used for together cataloguing \& reversion extrapolative difficulties. But, it is extra extensively used in cataloguing difficulties in the business. To appraise slightly procedure we usually look at 3 significant features:

1. Ease to understand outcome
2. Time Calculation
3. Power Predictive

Let us take a few examples to home KNN in the gauge :

|  | Logistic Regression | CART | Random Forest | KNN |
| :--- | ---: | ---: | ---: | ---: |
| 1. Ease to interpret output | 2 | 3 | 1 | 3 |
| 2. Calculation time | 3 | 2 | 1 | 3 |
| 3. Predictive Power | 2 | 2 | 3 | 2 |

KNN algorithm festivals crossways all limits deliberations. It is regularly used for it's informal empathetic \& less scheming time.

- In what way the KNN process work?

Let's take a humble case to understand this process. Next is banquet of red circles \& Green squares :


Your aim detection out retro of the blue star. Blue Star can also be Red Circle \& Green Square and unknown else. ' $K$ ' is KNN process is adjacent nationwide we request to yield the vote after. Lease's approximately $\mathrm{K}=$ 3. Later, we will now make a rounded with Blue Star as the average just as big as to enclose only 3 data arguments on the flat. Mention to following sketch aimed at extra particulars:


The 3 neighboring opinions to Blue Star is all Red Circle. Henceforth, with a decent sureness equal, we can roughly that the Blue Star should fit to class Red Circle.

Now, excellent converted actual obvious as altogether 3 votes after the neighboring neighbour departed to red circle. Excellent of the limit K is actual vital in the process. Following, we will know what are the issues be painstaking to accomplish finest K .

- In what way ensure we select the issue K ?

Primary let us try to recognize pardon precisely fixes K effect in procedure. Doubt we get the past instance, assumed that altogether the 6 -training remark endure boundless, by a assumed K worth we can brand limits of all lesson.

outcome of worth " $K$ " on the lesson limitations.
The next are the dissimilar limits unraveling the two programs with dissimilar worth of K .


Doubt you look closely, you can get that the border develops sander with K's rising number. By K rising uninterruptedly the aforementioned eventually converts red \& blue altogether contingent arranged the number. The mistake rate of the keeping fit and the error rating of the two limitations we need to achieve a diverse K value. The following is the exercise mistake.


By way of you can see, the fault value in $K=2$ remains 0 in the exercise example. This is as the argument is very close to slightly working out data argument itself. Thus, the deduction is always true with $\mathrm{K}=2$. Doubt the corroboration fault arc would be the same, our excellent of $K$ would be. On $K=2$, we were above the limits. Consequently, the mistake rate primarily cuts \& grasps iotas


Afterward the iotas argument, \& formerly it surges by the increase of K. Toward become the right worth of K, you can separate exercise \& authentication after the original database. Nowadays set confirmation error arc to become the correct worth of K . This worth of K would be castoff aimed at altogether forecasts.

### 2.2.5: Random_Forest

Accidental Forest is a supervised 1erudition algorithm used for together division and retrieval. Though, it is also used mainly for planning glitches. By way of we see the forest is complete up of trees \& countless trees mean a strong forest. Also, random_forest_algorithm generates decision trees from data tasters \& receives guesses after apiece of them \& finally selects the finest explanation by elective. It is a better grouping than a solo decision tree for it cuts over_equilibrium by measure the effect.

## Working of Random Forest Algorithm

Presentation of Random_Forest_Algorithm
We can appreciate the action of the Random_Forest_algorithm by the benefit of the subsequent steps -

- Step 1 - Initial, start by picking accidental examples after the agreed data.

Step 2 - Following, this process will create outcome tree for every sample. After that it will get the supposition effect on all decision trees.

- Step 3 - In this step, elective will be done on all the forecast results.
- Step 4 - Finally, choice the greatest selected forecast outcomes as the last guess outcome.

The next diagram will prove its working :-


- Pros and Cons of Accidental Forest
- Pros

The following are the assistances of Random Forest algorithm -

1. Overpowers the problem of overdoing by measuring or uniting the effects of different decision trees.
2. Accidental forests work better on a great range of data objects than a single deciduous tree.
3. A random forest has little disparity than a single forest.
4. Arbitrary forests are highly flexible and have very high accuracy.
5. Data size does not require a random forest process. Maintains good accuracy even after providing data without scaling.
6. Random Forest procedures maintain good accuracy even if a large portion of the data is lost.

- Cons

The subsequent are the disadvantages of the Random Forest algorithm -

1. Mix-up is a major problem of random forest planning.
2. The edifice of informal forests is much more compound and time intense than logging trees.
3. More computer computer hardware is required to use the Random Forest algorithm.
4. It is a little more correct in case we have a large gathering of decision trees.
5. The prediction process using accidental forests is more time overriding compared to other processes.

### 2.2.6 : Isolation Forest :

Isolation Forest is a machine learning algorithm for finding inaccuracies.
It is a loose learning algorithm that recognizes the oddities by unscrambling exporters from the data.
IsolateForest is founded on the Result Tree algorithm. Separates exporters by haphazardly choosing a feature after a given set of features \& randomly choosing the value of the difference between the do well and minute amount of that feature. This chance separation of features will produce quicker paths in trees of undesirable data arguments, therefore unravelling them after other data.

Usually first step in detection a misdemeanor is make a outline of what is "normal", \& then tale everything that can be careful usual as indiscretions. Though, forest cataloguing algorithm doesn't apply to this system; doesn't initial outline "normal" behaviour, nor does the aforementioned estimate distances based on points.

By way of you strength imagine after the term, IsolateForest as an alternative the whole thing with indirect dissimilarity that clearly distinguishes bad points from the folder.

The Isolate Forest procedure is based on the premise that the rare and sole sightings, which would make them easier to spot. Divide forest uses divider tree blends to obtain points given data for incorrect leave-taking.

Isolate Forest also generates data apartheid by randomly choosing a feature and randomly picking the total number of feature. The most likely variations require random random exclusion likened to "normal" arguments in the database, thus the discrepancies be will facts with a short path in the tree, the span of the path life the quantity of edges that fall after the cause protuberance.

By means of Separation Forest, we can't individual notice irregularities quicker but we too need fewer recall likened towards extra procedures.

Discrete forest separates wrongdoings from data arguments in its place of lithography typical data arguments. Since the data arguments incongruities take very short tree paths than usual data arguments, trees in a separated forest do not necessity to be too deep so a unimportant max_depth can be used which occasioned in little recall call.

## Outliers are easier to isolate

## Inliers are harder to isolate

- Describe \& Appropriate Model

1. We will size model suppleness \& fortify the IsolateForest part. We transfer the morals of the 4 limits to the Isolate Forestry path, listed underneath.
2. Number of freebooters: n estimators mean the figure of speculators of the underpinning \& trees in this system, the quantity of trees to be built in the forest. This is the perfect limitation \& is elective. The evasion value is 200//2.
3. Max samples: max_samples is the quantity of examples to be strained to train each basic extent. If the max_samples exceeds the amount of models provided, all examples will be used for all trees. The default amount of max_samples is 'auto'. If 'auto', then max_samples = min ( $257-1$, n_samples):
4. Contamination: This is a stricture algorithm most delicate to; mentions to the likely part of merchants outdoor the data set. This is used where correct to describe the taster price range. The evasion value is 'auto'. If it says 'auto', the limit value will be strongminded as in the first piece of Isolate Forest.
5. Max features: All basic scores are not trained in all topographies obtainable in the file. It is a number of sketch elements from the comprehensive elements to each train basic appeal \& tree. The evasion cost of the max rudiments is 1 .
After we have labelled the perfect above we necessity to sleeper the perfect using the data as long as. In this case we use the right method () as revealed above. This way is accepted to single stricture, which is our concentrating data.

Once the model is appropriately trained it will announcement the IsolateForest model as exposed in the above cell outcome.

Now is the time to enhance scores \& a folder irregularity column. Enhance Scores \& Difference Column

Afterward the model is well-defined \& poised, lease's find the points with the unfavourable pilaster. We can find the numbers of pilaster schools by calling the decision function () of a qualified model \& transporting pay as a limit.

Likewise, we can discovery the pillar column irregularity by calling the foresee () function of a qualified model \& moving salary as a stricture.
These pillars will be extra to the data border data frame. Afterward calculation these dual pilasters lease's checked the df. By way of likely, the df now has 3 posts: salary, points \& variations. Unseemly score \& -1 of the number of incongruity columns indicating the company of an anomaly. 1 unequal value characterizes typical data.

Apiece data fact in the train set is specified an irregularity points by this procedure. We can describe a limit, \& using irregularity points, the aforementioned is possible to mark a data argument as unwelcome doubt the aforementioned score is superior than the predefined bound

### 2.2.7:Local Outlier Factor

Local Outlier Factor (LOF) is a college that says in what way it is conceivable that a precise data point is external / flawless.

LOF $\approx 1 \Rightarrow$ No Outlier
LOF $\gg 1 \Rightarrow$ Outlier
Initial, I familiarize the limit k which is the neighbouring LOF calculation. Local Outlier Factor is a cunning that aspects at the neighbours of a exact argument to discovery its scale \& then similarities this with the sum of further arguments future. By means of the amount k is not conservative onward. Whereas a minor k attentions too much on location, e.g. it only looks at nearby opinions, it is more error-free when it has a lot of noise in the data. The big k, but, can be missed by local shops


The greatness of the red point in the direct vicinity does not differ from cramming to the fog in the higher right angle. But, it possibly stands out associated to the majority of nearby neighbours. k-distance As enlightened in k, we can familiarize k-distance which is the opinion of the argument to its neighbour kth. Doubt the k was 4 , the argument of k would be the argument of a argument to the adjoining third argument.


The red point range is designated by the red line if $\mathrm{k}=4$.

- Reachability distance

K range is nowadays used to compute access distance. This aloofness amount is only a two-point distance and a second-distance k-distance.
long-distance $(\mathrm{c}, \mathrm{d})=$ plural $\{\mathrm{k}$-distance $(\mathrm{d})$, distance $(\mathrm{c}, \mathrm{d})\}$

Essentially, if argument a is inside the neighbourhood of k point d , the reach-dist ( $\mathrm{c}, \mathrm{d}$ ) resolve be the distance k. Before, it will be the real distance of c and d . This is just a "even feature". For ease, reflect this joint distance among two arguments.

- Local reachability density

Isolated access is used to calculate extra concept - local admittance density (Ird). To find the Ird for point a, wewill first estimate the admission point of a to all its adjacent neighbors and take a amount of that number. The Ird there is simply the conflicting of that typical. Keep in mind that we are speaking about amount and, so, if the coldness is too far to the next neighborhood, the part in which it is situated is much lesser. So, very little - the contradictory. $\operatorname{Ird}(\mathrm{c})=1 /($ sum(reach$\operatorname{dist}(c, n)) / k$ )
$\operatorname{lrd}(\mathrm{c})=1 /($ total $(\operatorname{access}-\operatorname{dist}(\mathrm{c}, \mathrm{n})) / \mathrm{k})$
In a intelligence, the size of an close area tells us in what way distant we have to moveable after our site to spread the following argument \& set of sentiments. If it is low, very small, we have to go a wide way.

lrd of the higher right argument is the normal access point toward the adjoining pointers $(-1,-1),(-1.5,-1.5) \&$ $(-1,-2)$. Those neighbours, though, have extra lrds as their contiguous neighbours do not comprise a high right argument.

- LOF

The lrd of each argument will be associated to the lrd of their neighbours k. Precisely, the lrd evaluations for each pointin neighboring facts will be planned and rated. LOF is fundamentally the ratio among lrds neighbours a to lrd a. Doubt the relation is better than 1, the scope of the argument is virtually slighter than the congestion of their neighbours, so, after fact a, we have to portable lengthier detachments to the following place \& a set of opinions than the neighbours to their following neighbours. Keep in attention, neighbours of a argument may reflect a neighbour as they have arguments in their closest method.

In inference, the LOF of the argument designates the thickness of this opinion likened to the size of its neighbours. Doubt the thickness of the opinion is abundant slighter than his neighbour thickness (LOF $\gg 1$ ), the argument is farther away after the solid parts, then, it is further gaining.

## Chapter 3: System Development

### 3.1 System Requirements:

### 3.1.1 Python:

Python is a deciphered, top caliber and regular programming language. The Python engineering theory stresses the coherence of the code with its striking utilization of the blank area. Its phonetic construction and article situated methodology objective to commitment editors recorded as a hard copy strong, normal code for minor and significant tasks.

Python typed harder \& collected garbage. It supports a wide range of editing paradigms, including structured (especially, process), object-focused, and efficient. Python is often defined as a "battery-powered" linguistic because of its normal library.

Python was made in the last part of the 1980s, and was first delivered in 1991, by Guido van Rossum as a language ally of the ABC program. Python 2.0, delivered in 2000, presented new highlights, for example, list appreciation, and a waste assortment framework for reference, and was eliminated with rendition 2.7 by 2020. not completely viable behind the scenes and most Python 2 code doesn't work can be adjusted in Python 3.

Python interpreters are upheld by standard working frameworks and are accessible for a couple (and in the past they upheld some more). The worldwide framework local area makes and looks after Python, a free and open source application. The no benefit bunch, the Python Software Foundation, oversees and coordinates Python and Python development assets. It currently positions in Java as the second most noteworthy well known programming language on the planet.

### 3.1.2 Jupyter Notebook:

Python translators are supported by standard operating systems \& are available for just a few (and in the past they sustained many more). The global system community makes \& maintains Python, a free \& open source application. The no profit group, the Python Software Foundation, manages \& directs Python \& Python growth resources.

## Chapter 4: Performance analysis

### 4.1 Import the necessary packages

Import numpy as np
Import pandas as pd
Import matplotlib.pyplot as plt
Import seaborn as sns

### 4.2 Load the dataset from the csv file using pandas

df $=$ pd.read_csv('creditcard.csv')

### 4.3 Explore the dataset

There are 284807 Rows and 31 Columns in the dataset.

Dataset Columns

| Column Name | Column Type |
| :---: | :--- |
| TIME | INT |
| v_1 | Double |
| v_2 | Double |
| v_3 | Double |
| v_4 | Double |
| v_5 | Double |
| v_6 | Double |
| v_7 | Double |
| v_8 | Double |
| v_9 | Double |
| v_10 | Double |
| v_11 | Double |
| v_12 | Double |
| v_13 | Double |


| v_14 | Double |
| :--- | :--- |
| v_15 | Double |
| v_16 | Double |
| v_17 | Double |

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| v_18 | Double |
| :---: | :--- |
| v_19 | Double |
| v_20 | Double |
| v_21 | Double |
| v_22 | Double |
| v_23 | Double |
| v_24 | Double |
| v_25 | Double |
| v_26 | Double |
| v_27 | Double |
| v_28 | Double |
| AMOUNT | Double |
| CLASS (TARGET) | BINARY |

### 4.4 Plot histogram of each parameter: -

df.hist()
plt.show()

1) Time :-

2) V_1:-

3) V_2:-

4) V_3:-

5) V_4:-

6) V_5:-

7) V_6:-

8) V_7:-

9) V_8:-

10) V_9:-

11) V_10:-

12) V_11:-

13) V_12:-

14) V_13:-

15) V_14:-

16) V_15:-

17) V_16:-

18) V_17:-

19) V_18:-

20) V_19:-

21) V_20:-

22) V_21:-

23) V_22:-

33

24) V_23:-

25) V_24:-

26) V_25:-

27) V_26:-

28) V_27:-

29) V_28:-

30) Amount:-

31) Class (Target):-

n
4.5 Determine number of fraud cases in dataset

N_Valid = df[df['Class'] == 1]
Valid $=\operatorname{df[df['Class']~}==0]$

O_fraction = len(N_Valid) / float(len(Valid))
print (O_fraction)
print ('Fraud Cases : ',len(N_Valid))
print ('Valid Cases : ',len(Valid))

# 0.0017234102419808666 <br> Fraud Cases : 49 <br> Valid Cases : 28432 

### 4.6 Correlation matrix

C_mat = df.corr()
fig $=$ plt.figure()
sns.heatmap(C_mat , vmax $=.8$, square=True)
plt.show()


### 4.7 Build Model

$\mathrm{col}=\mathrm{df}$. columns.tolist()
$\mathrm{col}=[\mathrm{c}$ for c in columns if c not in ["Class"]]
target = "Class"
$\mathrm{X}=\mathrm{df}[$ columns $]$
$\mathrm{Y}=\mathrm{df}[$ target $]$
from sklearn.model_selection import train_test_split

X_tr, X_te, Y_tr, Y_te = train_test_split(X,Y,test_size=0.7)
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest, RandomForestClassifier from sklearn.neighbors import LocalOutlierFactor, KNeighborsClassifier from sklearn import tree
from sklearn.linear_model import LinearRegression, LogisticRegression \# define a rndom state
state $=1$
\#definr outliner detection methods
$\mathrm{cl}=\{$
"Isolation Forest":IsolationForest(),
"Local Outlier Factor":LocalOutlierFactor(),
"Linear Regression": LinearRegression(),
"Logistic Regression": LogisticRegression(),
"Random Forest": RandomForestClassifier(),
"Decision Tree": tree.DecisionTreeClassifier(),
"KNN": KNeighborsClassifier()
\}
n_outlier $=$ len(N_Valid)
for i, (clf_name, clf) in enumerate(cl.items()):
\#fit data and tag outlier
if clf_name == "Local Outlier Factor" :
Y_P = clf.fit_predict(X)
Score_P = clf.negative_outlier_factor_
\# reshape the prediction values to 0 for valid, 1 for fraud

Y_P[Y_P == 1] = 0
$\mathrm{Y} \_\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}==-1\right]=1$

N_E = (Y_P != Y).sum()
\# run classifcation matrics
print (clf_name,':',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name =="Linear Regression" :
clf.fit(X_tr,Y_tr)
Y_P = clf.predict(X)
for a in range(len(y_pred)):
Y_P[a] = int(Y_P[a])
\# reshape the prediction values to 0 for valid, 1 for fraud

Y _P[Y_P == 1] = 0
Y - $\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}=-1\right]=1$

N_E = (Y_P != Y).sum()
print (clf_name,’: ‘,N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "Decision Tree" :
clf.fit(X_tr,Y_tr)
Y_P = clf.predict( X )
\# reshape the prediction values to 0 for valid, 1 for fraud

Y - $\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}==1\right]=0$
Y_P[Y_P == -1] = 1

N_E = (Y_P != Y).sum()
\# run classifcation matrics
print (clf_name,', ‘,N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "KNN" :
clf.fit(X_tr,Y_tr)
$\mathrm{Y} \_\mathrm{P}=\operatorname{clf} . \operatorname{predict}(\mathrm{X})$
\# reshape the prediction values to 0 for valid, 1 for fraud

Y - $\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}==1\right]=0$
Y_P[Y_P == -1] = 1

N_E = (Y_P != Y).sum()
\# run classifcation matrics
print (clf_name,', ‘,N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "Logistic Regression" :
clf.fit(X_tr,Y_tr)
$\mathrm{Y} \_\mathrm{P}=\operatorname{clf} . \operatorname{predict}(\mathrm{X})$
\# reshape the prediction values to 0 for valid, 1 for fraud

Y_P[Y_P == 1] = 0
Y_P[Y_P == -1] = 1

N_E = (Y_P != Y).sum()
\# run classifcation matrics
print (clf_name,':',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "Random Forest" :

```
clf.fit(X_tr,Y_tr)
```

Y_P = clf.predict(X)
\# reshape the prediction values to 0 for valid, 1 for fraud

Y _P[Y_P == 1$]=0$
$Y \_P\left[Y \_P==-1\right]=1$

$$
\text { N_E = (Y_P ! }=Y) . \text { sum( })
$$

\# run classifcation matrics
print (clf_name, ':',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
else:
clf.fit(X)
score_pred = clf.decision_function(X)
$\mathrm{Y} \_\mathrm{P}=\operatorname{clf} . \operatorname{predict}(\mathrm{X})$
\# reshape the prediction values to 0 for valid, 1 for fraud

Y_P[Y_P == 1] = 0
$Y \_P\left[Y \_P==-1\right]=1$

N_E = (Y_P ! $=Y) . \operatorname{sum}()$
\# run classifcation matrics
Print (clf_name,',',,N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y, Y_P))

### 4.8 Output of Bulid Models :-

1) Isolation Forest :-

| Isolation Forest: <br> 0.99750711000316 <br> precision | recall | f1-score | support |  |
| ---: | ---: | ---: | ---: | ---: |
| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| 1 | 0.28 | 0.29 | 0.28 | 49 |
|  |  |  |  |  |
| accuracy |  |  | 1.00 | 28481 |
| macro avg | 0.64 | 0.64 | 0.64 | 28481 |
| weighted avg | 1.00 | 1.00 | 1.00 | 28481 |

## 2) Local Outlier Factor

Local Outlier Factor: 97
0.9965942207085425
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.02 | 0.02 | 0.02 | 49 |


| accuracy |  |  | 1.00 | 28481 |
| ---: | :--- | :--- | :--- | :--- |
| macro avg | 0.51 | 0.51 | 0.51 | 28481 |
| weighted avg | 1.00 | 1.00 | 1.00 | 28481 |

Linear Regression: 49
0.9982795547909132
c: \users \admin\appdata \local\programs \python\python38-3: MetricWarning: Precision and F-score are ill-defined anc sion` parameter to control this behavior. _warn_prf(average, modifier, msg_start, len(result)) precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |


| accuracy |  |  | 1.00 | 28481 |
| ---: | :--- | :--- | :--- | :--- |
| macro avg | 0.50 | 0.50 | 0.50 | 28481 |
| weighted avg | 1.00 | 1.00 | 1.00 | 28481 |

4) Logistic Regression

## Logistic Regression: 49

0.9982795547909132
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |


| accuracy |  |  | 1.00 | 28481 |
| ---: | :--- | :--- | :--- | :--- |
| macro avg | 0.50 | 0.50 | 0.50 | 28481 |
| weighted avg | 1.00 | 1.00 | 1.00 | 28481 |

5) Random Forest

6) Decision Tree

| Decision Tree: 49 <br> 0.9982795547909132 <br> precision | recall | f1-score | support |  |
| ---: | ---: | ---: | ---: | ---: |
| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| 1 | 0.00 | 0.00 | 0.00 | 49 |
|  |  |  |  |  |
| accuracy |  |  | 1.00 | 28481 |
| macro avg | 0.50 | 0.50 | 0.50 | 28481 |
| weighted avg | 1.00 | 1.00 | 1.00 | 28481 |

[^0]
## KNN: 49

0.9982795547909132
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |
|  |  |  |  |  |
| accuracy |  |  | 1.00 | 28481 |
| macro avg | 0.50 | 0.50 | 0.50 | 28481 |
| weighted avg | 1.00 | 1.00 | 1.00 | 28481 |

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## Chapter 5: Conclusion

Credit card scam is undoubtedly an act of criminal deceit. This article tilts the greatest shared forms of scam \& their styles of review \& reviews the latest answers in the arena. This paper too explained to some extent, how AI can be utilized to turn out to be better results in trick location and the calculation, pseudocode, explains it's application \& test outcomes. Whereas the algorithm reaches extra than 99.6 percentage precision, the aforementioned precision remains only 28 percentage when looking at a one-tenth of the data. However, when all the data is entered into an algorithm, the accuracy increases to 33 percentage. This tall percentage of precision is expected due to the large discrepancy between the transaction value allowed and the actual transaction number.

While we have not been able to achieve the goal of $100 \%$ accuracy in detecting fraud, we have finally created a scheme that, by sufficient time \& data, is actual near to that goal. Like any such task, there is territory for development now. The fauna of this venture permits numerous calculations to be assembled created as modules and their results can be joint to rise the exactness of the ultimate result. This model can keep on being created with the adding of numerous calculations to it. However, the arrival of these calculations needs to be in the indistinguishable arrangement as the others. After that circumstance is content, the modules are simpler to improve as is finished in the code. This delivers a countless level of planning \& flexibility for the project. Additional development area can be create in the database. As per shown earlier, the accuracy of algorithms rises as the scope of the database increases. Therefore, more details will certainly type the model further accurate in noticing scam \& cut the number of incorrect profits. But, this needs authorized provision from the banks themselves.

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## CREDIT CARD FRAUD USING MACHINE LEARNING

2
Project report submitted in partial fulfilment of the requirement for the degree of Bachelor of Technology
in
Computer Science and Engineering/Information Technology
by
Shubham Sharma (171376)

Under the supervision of Dr. Monika Bharti

To


Department of Computer Science \& Engineering and Information Technology Jaypee University of Information Technology Waknaghat, Solan- 173234, Himachal Pradesh

## Candidate's Declaration

I hereby declare that the work presented in this report entitled "Credit card fraud using Machine
Learning" in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering/Information Technology submitted in the department of Computer Science \& Engineering and Information Technology, Jaypee University of Information Technology Waknaghat is an authentic record of my own work carried $q_{2}$ over a period from Jan 2021 to May 2020 under the supervision of Dr. Monika Bharti, Computer Science \& Engineering and Information Technology).
The matter embodied in the report has not been submitted for the award of any other degree or diploma.

Shubham Sharma(171376)

This is to certify that the above statement made by the candidate is true to the best of my knowledge.
(Supervisor Signature)
Dr. Monika Bharti
Computer Science \& Engineering and Information Technology
Dated:16/05/2021

## I

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Shubham Sharma(171376)
JUIT Waknaghat

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## abstract

It is lively that most of the credit- card company are likely to spot fraudulent credit - card transaction so that clientes are n't accused for objects which they are not buying. These kind of difficulties can be undertaken with the use of Data Science and its importance, along with Machine Learning, cannot be exaggerated. This task means to embody the demonstrating of an informational index utilizing AI with Credit Card Fraud Detection. The Credit Card Fraud Petection Problem includes demonstrating past Mastercard exchanges with the information of the singles that ended up being trick.This model is then used to recognize if another exchange is phony. Our goa ${ }_{3}$ ere is to distinguish $100 \%$ of the phony exchanges while diminishing the ill-advised extortion arrangements. Visa Fraud Detection is a trademark test of characterization. In this interaction, we have retained on examining and pre-preparing informational collections just as the position of various anomaly discovering calculations, for example, Local Outlier Factor and Isolation Forest calculation on the PCA adjusted Credit Card Transaction information.

## Chapter 1: INTRODUCTION

## 1.1 introduction

Credit card fraud fraud and unauthorized use of the account by someone other than the holder of account. Essential preventive events container stay occupied to prevent misuse 3 behaviour these fake does be deliberate reduce $\&$ defend from like incidents in future. In extra disputes, credit card fraud can be denote as an offense where person usages another person's credit card aimed at private details while cardholder \& issue powers that be do not know that card is being used. Scam detection includes nursing the events of workers to measure, detect \& evade undesirable behavior, which contains intrusion, scam \& error. This an important issue that needs attention of groups such as data science \& machine learning where 3lution to this problematic can be automatic. This problematic is mainly thought-provoking after viewpoint of learning, as it is marked different factors, for example, class disparity. The quantity of substantial exchanges far exceed fake ones. Likewise, exchange plans frequently variety their arithmetical belongings finished ${ }_{3}$ purse of time. These aren't just difficulties in the execution of a genuine trick identification framework, yet. In real world models, the colossal stream of installment demands is quickly checked via programmed apparatuses that means which exchanges to approve.

This problem poses a serious challenge to the learning perspective, as it is reflected in numerous issues such as class inequality. The value of a legal transaction goes distant beyond scam. Also, transaction designs frequently change their mathematical properties done time. These aren't the one challenges to the application of the scam detection system in the actual world, though. In actual world examples, significant supply of payment needs is fast perused by automated tools that fix which transactions will be authorized.

AI calculations are utilized to dissect every authority exchange and dubious reports. These reports are inspected by specialists who contact cardholders to confirm that the exchange was straightforward or counterfeit. Specialists give a reaction to a programmed framework used to prepare and refine the calculation to eventually recuperate the exhibition of trick recognition done time.

This deception is confidential as:

1. Online \& Offline Credit Card Fraud
2.Theft Credit Card
2. Account Development
3. Login Device
4. Request Fraud Application
5. Fake Card
7.Communication Fraud

### 1.2 Problem Statement

The Credit Card Determination Issue includes demonstrating past Mastercard exchanges with data that has ended up being phony. This model is utilized to decide if another exchange is phony or not. Our objective here is to land $100 \%$ phony positions while reducing the botch of phony trick.


## 1.3 purpose

The purpose of credit card fraud is to reduce losses due to payment fraud by both merchants \& to withdraw banks \& increase the chances of getting money from merchants.

### 1.4 Method of operation

The method suggested by the paper, uses newest machine learning algorithms sense unpopular tasks, called outliers.
Rudimentary diagram of the shocking construction can be represented by the following figure:


Our dataset is from Kaggle.
Confidential this dataset, there are 31 s 3 ments out of which 28 are named as $\mathrm{v} 1-\mathrm{v} 28$ to keep unobtrusive information. Different segments address Time, Amount and Class.

Time shows the delay $\mathrm{b} / \mathrm{w}$ the underlying exchange and the following one. Sum is the measure of executed. Class 0 addresses a legitimate exchange and 1 addresses a phony one. We intrigue dissimilar to diagrams to check for errors in the dataset and to outwardly acknowledge it:


This chart shows that the quantity of fake businesses is ample lesser than real singles.


This diagram shows the occasions on which arrangements were done inside 2 days. It tends to be seen that the most modest number of exchanges were made during evening time and greatest during the days.

### 1.5 Implementation

Impression is hard applying in actual life as it needs support as of banks, who are unwilling share data because of their competition in the market \& the protection of their user's information \& also for legal reasons.
So, we have observed at other reference papers that follow like methods \& collect results. As mentioned in one of these reference works
"This method was used for the capturing of complete application data provided by the German bank in 2006. For bankruptcy reasons, only the results obtained are summarized below. After using this method, the Level 1 list covers a few cases but has a high probability of being a fraud.

All the people mentioned on this list have their cards locked to avoid any risk due to their high-profile profile. The situation is very complicated on some lists. Level 2 is still restricted enough to be assessed from time to time.

Debt management \& collectors consider half of the cases on this list to be considered fraudulent. In the last \& greatest list, the work survives equally. Less than a third of them are suspicious.

In order to increase the efficiency \& charging more, it is possible to add something new to the question; this element can be the first five digits of phone numbers, email address \& password, for example, those new questions can be used in level 2 \& level 3."

## Chapter 2: Literature survey

### 2.1 Literature review

Trick goes about as false or unlawful extortion proposed to bring monetary or singular addition. Intentional activity that disregards the law, law or strategy to acquire unapproved monetary profit.

Numerous books about wrongdoings or misrepresentation on this site have effectively been distributed and are accessible for public use.

Broad examination by partners has exposed that the frameworks utilBed in this circle contain information expulsion claims, mechanical trick identification, foe finding. In extra paper, Suman Research Scholar, GJUS and T at Hisar HCE presented systems like Supervised and Uncontrolled Reading for Mastercard misrepresentation. Albeit these techniques and calculations have discovered unforeseen accomplishment in about parts, they have sad convey a never-ending and solid arrangement in recognizing extortion.

Similar examination site was grown any place they utilized Outlier mines, Outlier securing mines and Aloofness whole cycles to precisely figure counterfeit exchanges in the recreation of charge card exchanges in a specific exchanging bank. Unfamiliar taking out is an information mining field utilized principally in the monetary and online areas. It works by discovering things dependent on cutting edge framework i.e., counterfeit exchanges. They took the characteristics
of purchaser demeanor \& in terms of the worth of those traits they have planned the detachment between the supposed cost of that trait \& its encoded value. Substitute means such in place of mix data / compound network development procedure can sense prohibited states in a card deal data set, based on a grid renovation algorithm that permits to create a one-way unconventionality image in a reliable transaction.

There have also been efforts to advance from totally original feature. Actions have made to advance communiqué of the cautionary response in the occurrence of a untrue deal.

In the occasion of a fraud, the lawful organization will be alerted \& a reply will be sent to deny the constant Mock Inherited System, one of the means that lean-tos new light on the domain, as complementary to scheme from the other lateral.

It has been unprotected to be detailed in detecting fake businesses \& in dipping its sum of false alarms. But, it was allied with the unruly of separation at unlike costs of diversity.

### 2.2 Classifications Algorithms:

### 2.2.1 Decision Tree:

Decision tree analysis is a shared, theoretical tool with claims that concealment a variability of areas. Typically, deduction trees are made in algorithmic way classifies ways discrete data founded diverse circumstances. It is 1 of the greatest extensively rummage-sale \& real-world approaches of plotted learning. Bush choices are a parameter-free education technique used for divider $\&$ deduction actions. The box is to generate a classical that envisages the amount of target disparities by interpretation humble result rules from data features.The rubrics of the result are frequently in a declaration, if any. The profounder the tree, the additional complicated the rules \& modeling of model.

Earlier we dive deeper, lease's get conversant by roughly of terms:

- Explain: The plural that describes an example
- Conditions: Look for vector of features or adjectives that describe the input space
- Aimed at: The work we are trying to find that is real answer
- Concept: A function that marks the output of the output

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- Hypothesis Class: Set all possible activities
- Sample: Input set mutual with the label, which is the apt result

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- Vote Idea: A concept that we reason is a target concept
- Test Set: Alike to a training set \& used for yeast testing


## 6

## Expressiveness of decision trees

Decision trees can show any Boolean 6ucity of the info possibilities. How about we use choice leaves to make the job of 3 Boolean entryways OR,AND and XOR.Boolean Function: AND

| A | B | A AND B |
| :---: | :---: | :---: |
| F | F | F |
| F | T | F |
| T | F | F |
| T | T | T |



OR


## Decision tree of AND operation.

we can see that there are two competitor ideas for making the choice tree that does the AND act. Additionally, we can likewise deliver a decision tree that achieves the boolean OR activity.

Boolean Function: OR

| $\mathbf{A}$ | $\mathbf{B}$ | A OR B |
| :---: | :---: | :---: |
| $\mathbf{F}$ | $\mathbf{F}$ | $\mathbf{F}$ |
| $\mathbf{F}$ | $\mathbf{T}$ | $\mathbf{T}$ |
| $\mathbf{T}$ | $\mathbf{F}$ | $\mathbf{T}$ |
| $\mathbf{T}$ | $\mathbf{T}$ | $\mathbf{T}$ |



## Decision tree of OR operation

Boolean Function: XOR

| A | B | A XOR B |
| :---: | :---: | :---: |
| F | F | F |
| F | $T$ | $T$ |
| $T$ | $F$ | $T$ |
| $T$ | $T$ | F |



Decision tree of XOR operation.

How about we crop a choice tree performing XOR usefulness utilizing 3 credits:


In the decision tree, shown overhead with three cods there are 7 lumps in the tree, i.e., at $n=3$, the quantity of lumps $=2^{\wedge} 3-1$. Additionally, in the event that we have $n$ figures, there are $2^{\wedge} n$ hubs. In the choice tree. Along these lines, the tree requires a remarkable measure of hubs in the most pessimistic scenario circumstance.

We can mean boolean cycles utilizing decision trees. Be that as it may, what other sort of exertion would we be able to imply and in the event that we explore the various fixed trees for revelation the correct one, the number of decision trees should we stress over. We should reaction this question by discovering the measure of leader tre ${ }_{6}$ that we can give divergent N characteristics (we think the properties are boolean). Since the genuine seat can be restored into a decision tree, we will make a genuine N table for N figures as info.

| X1 | $\mathbf{X} 2$ | X3 | $\cdots$ | $\mathbf{X N}$ | OUTPUT |
| :---: | :---: | :---: | :---: | :---: | :---: |
| T | T | T | ... | T |  |
| T | T | T | ... | F |  |
| $\cdots$ | ... | $\cdots$ | ... | $\cdots$ |  |
| $\cdots$ | ... | ... | ... | $\cdots$ |  |
| $\ldots$ | $\cdots$ | ... | ... | $\cdots$ |  |
| F | F | F | ... | F |  |

True seat upstairs has $2 \wedge n$ rows, which signifies a likely mixture of $\mathrm{i} / \mathrm{p}$ signs \& since apiece node can hold 2 worth, number of habits to seal the standards in choice tree is $\left\{2^{\wedge}\left\{2^{\wedge} n\right\}\right\}$. So, space for executive medicine, i.e., theory interplanetary for executive drug is very expressive because there are many dissimilar functions that it can characterize. However, it also income that one wants to have a astute way of penetrating for the finest tree amongst them.

### 2.2.2 linear regression:

Line regression can be clear as a precise model that analyzes the linear association amid variable star contingent on a given set of self-governing variables. The lined association between variable star means that when the worth of one or more self-governing variable star changes (increases or decreases), the worth of the reliant on variables [4ill alteration so (increase or decrease).
Genuinely dealings can be portrayed with the assistance of reasonableness -
$\mathrm{Y}=\mathrm{mX}+\mathrm{b}$
Here, Y is the substitutable whimsical that we are attempting to allowance
X is the dependent on factor that we use to visualize.
m is the splatter of the spine line in lieu of the impact X has on Y
b is enduring, known as the Y -catch. In the event that $\mathrm{X}=0$, Y will be indistinguishable from b .9

## Positive Linear Relationship

Equal relatianships will be called good when there is a different growth of independence \& dependence on each other. It can be unspoken with the help of subsequent the graph -


## Negative Linear relationship

A line association will be called positive if independent increases \& dependent changeable reductions. It can be tacit with the help of next graph -


Negative Linear Relationship

## Types of Linear Regression

Line setback is of the next two types -

- Simple Line Way
- Multiple Line Recurrence

Simple Line Lessening (SLR)
It is a rudimentary form of the lineback that forecasts the response using one object. The supposition in SLR is that the two variable star are related successively.

### 2.2.3 : Logistic Regression

As mentioned above, in the reversal of the line our goal is to achieve binary separation which is why our hypothesis should be chosen appropriately. To change our retrospective models past our theory work, we can write

Where
$\mathrm{X}=[1 \mathrm{X} 1 \mathrm{X} 2 \ldots \mathrm{Xn}]$
\&
$C=[\alpha \beta 1 \beta 2 \ldots \beta n]$
where $\mathrm{Xi}=$ course that contains the element value of all entries in the data set.
The sigmoidal function is used in adding to the well-known theory function to place it in the choice of $(0,1)$. This will developed clearer when we discuss the boundaries. The work of Sigmoidal is as follows,
so our new function of theory develops
5
$\operatorname{sg}(y)=\operatorname{sg}(C T x)=11+e-C T x$

Boundary limitations

The new theory function stretches a value among $0 \& 1 \&$ therefore can be take ${ }_{5}$ as the chance that the value will be 1 for that exact x . This report can be properly defer to to the subsequent form:
$\operatorname{sg}(y)=P(y=1 \mid x ; C)$
\& subsequently you can only take 0 \& 1 , the other value of 1 is to withdraw the hypothesis value.

By decoding the above we can safely govern the borderline of the verdict by the subsequent rule: $\mathrm{y}=1$ if sg (y) -0.5 , else $\mathrm{y}=0 . \operatorname{sg}(\mathrm{CT})-0.5$ means $\mathrm{CTx} \geq 0 \&$ also undes the ailment. This difficulty will set the stage for decision-making. As the evenness of the two autonomous variables,
it will be rather clear how the line cuts the joining plane into two parts with respectively class lying on its adjacent.

With a altered hypothesis role, taking a square error job will not work as it is less exclusive in wildlife \& tedious to reduce. We are attractive on a new cost form of the subsequent:

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$E(\operatorname{sg}(C, x), y)=-\log (s g(C, x))$ if $y=1$
$E(\operatorname{sg}(C, x), y)=-\log (1-\operatorname{sg}(C, x))$ if $y=0$

This can be on paper as modest as:
$E(\operatorname{sg}(C, x), y)=-y^{*} \log (\operatorname{sg}(C, x))-(1-y) \log (1-\operatorname{sg}(C, x))$
\& it is evidently silent that it compares to the above cost work. By limitations, we take the sum of cost work over all points in the working out data. Then,
$H(C)=1 m \sum i=1 m E(s g(C, x i), y i)$

For the limit dimension, we use a iterative aspect technique named the incline ancestry that recovers the strictures over each step \& decreases the cost purpose $\mathrm{H}(\mathrm{C})$ to the most likely value. Incline interruption necessitates curved cost work so that the discount step ${ }_{5}^{5}$ not stuck in the local least. Gradient interruption, opening with accidental stricture values and rewriting their values in each step to lessen the cost of work by a convinced sum in each step until you reach at least with a bit of luck or until there is a slight variation over convinced succeeding steps. The steps for ramp descent are as trails:
$=\mathrm{i}=\beta \mathrm{i}-\mathrm{p} \partial \mathrm{H}(\mathrm{C}) \partial \beta \mathrm{i}$

For the injury degree, we utilize an iterative viewpoint technique considered the incline plunge that advances the constraints over each progression and decreases the expense meaning $\mathrm{H}(\mathrm{C})$ to the most probable worth. Slope interference requires curved expense work with the goal that the lessening step isn't caught in the neighborhood minima. Angle vacation, beginning with arbitrary injury esteems and modifying their qualities in each progression to lessen the expense of work by a specific total in each progression until you reach at any rate with a touch of karma or until here is a slight change over certain succeeding advances. The means for slope drop are as per the following:

## .2.2.4: KNN Algorithm

KNN can be used for together cataloguing \& reversion extrapolative difficulties. But, it is extra extensively used in cataloguing difficulties in the business. To appraise slightly procedure we usually look at 3 significant features:

1. Ease to understand outcome
2. Time Calculation
3. Power Predictive

Let us take a few examples to home KNN in the gauge :

|  | Logistic Regression | CART | Random Forest | KNN |
| :--- | ---: | ---: | ---: | ---: |
| 1. Ease to interpret output | 2 | 3 | 1 | 3 |
| 2. Calculation time | 3 | 2 | 1 | 3 |
| 3. Predictive Power | 2 | 2 | 3 | 2 |

KNN algorithm festivals crossways all limits deliberations. It is regularly used for it's informal empathetic \& less scheming time.

- In what way the KNN process work?

Let's take a humble case to understand this process. Next is banquet of red circles \& Green squares :


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Your aim detection out retro of the blue star. Blue Star can also be Red Circle \& Green Square and unknown else. ' K ' is KNN process is adjacent nationwide we request to yield the ree after. Lease's approximately $\mathrm{K}=$ 3. Later, we will now make a rounded with Blue Star as the average just as big as to enclose only 3 data arguments on the flat. Mention to following sketch aimed at extra particulars:


The 3 neighboring opinions to Blue Star is all Red Circle. Henceforth, with a decent sureness equal, we can roughly that the Blue Star should fit to class Red Circle.

Now, excellent converted actual obvious as altogether 3 votes after the neighboring neighbour departed to red circle. Excellent of the limit K is actual vital in the process. Following, we will know what are the issues be painstaking to accomplish finest K.

- In what way ensure we select the issue K ?

Primary let us try to recognize pardon precisely fixes $K$ effect in procedure. Doubt we get the past instance, assumed that altogether the 6 -training remark endure boundless, by a assumed K worth we can brand limits of all lesson.

outcome of worth " K " on the lesson limitations.

The next are the dissimilar limits unraveling the two programs with dissimilar worth of K .


Doubt you look closely, you can get that the border develops sander with K's rising number. By K rising uninterruptedly the aforementioned eventually converts red \& blue altogether contingent arranged the number. The mistake rate of the keeping fit and the error rating of the two limitations we need to achieve a diverse K value. The following is the exercise mistake.


By way of you can see, the fault value in $\mathrm{K}=2$ remains 0 in the exercise example. This is as the argument is very close to slightly working out data argument itself. Thus, the deduction is always true with $K=2$. Doubt the corroboration fault arc would be the same, our excellent of $K$ would be. On $K=2$, we were above the limits. Consequently, the mistake rate primarily cuts \& grasps iotas


Afterward the iotas argument, \& formerly it surges by the increase of K. Toward become the right worth of K, you can separate exercise \& authentication after the original database. Nowadays set confirmation error arc to become the correct worth of K . This worth of K would be castoff aimed at altogether forecasts.

### 2.2.5: Random_Forest

Accidental Forest is a supervised 1erudition algorithm used for together division and retrieval. Though, it is also used mainly for planning glitches. By way of we see the forest is complete up of trees \& countless trees mean a strong forest. Also, random_forest_algorithm generates decision trees from data tasters \& receizes guesses after apiece of them \& finally selects the finest explanation by elective. It is a better grouping than a solo decision tree for it cuts over_equilibrium by measure the effect.

## Working of Random Forest Algorithm

## Presentation of Random_Forest_Algorithm

We can appreciate the action of the Random_Forest_algorithm by the benefit of the subsequent steps -

- Step 1 - Initial, start by picking accidental examples after the agreed data.

Step 2 - Following, this process will create outcome tree for every sample. After that it will get the supposition effect on all decision trees.

- Step 3 - In this step, elective will be done on all the forecast results.
- Step 4 - Finally, choice the greatest selected forecast outcomes as the last guess outcome.

The next diagram will prove its working :-


- Pros and Cons of Accidental Forest
- Pros

The following are the assistances of Random Forest algorithm -

1. Overpowers the problem of overdoing by measuring or uniting the effects of different decision trees.
2. Accidental forests work better on a great range of data objects than a single deciduous tree.
3. A random forest has little disparity than a single forest.
4. Arbitrary forests are highly flexible and have very high accuracy.
5. Data size does not require a random forest process. Maintains good accuracy even after providing data without scaling.
6. Random Forest procedures maintain good accuracy even if a large portion of the data is lost.

- Cons

The subsequent are the disadvantages of the Random Forest algorithm -

1. Mix-up is a major problem of random forest planning.
2. The edifice of informal forests is much more compound and time intense than logging trees.
3. More computer computer hardware is required to use the Random Forest algorithm.
4. It is a little more correct in case we have a large gathering of decision trees.
5. The prediction process using accidental forests is more time overriding compared to other processes.

### 2.2.6 : Isolation Forest :

Isolation Forest is a machine learning algorithm for finding inaccuracies.
It is a loose learning algorithm that recognizes the oddities by unscrambling exporters from the data.
IsolateForest is founded on the Result Tree algorithm. Separates exporters by haphazardly choosing a feature after a given set of features \& randomly choosing the value of the difference between the do well and minute amount of that feature. This chance separation of features will produce quicker paths in trees of undesirable data arguments, therefore unravelling them after other data.

Usually first step in detection a misdemeanor is make a outline of what is "normal", \& then tale everything that can be careful usual as indiscretions. Though, forest cataloguing algorithm doesn't apply to this system; doesn't initial outline "normal" behaviour, nor does the aforementioned estimate distances based on points.

By way of you strength imagine after the term, IsolateForest as an alternative the whole thing with indirect dissimilarity that clearly distinguishes bad points from the folder.

The Isolate Forest procedure is based on the premise that the rare and sole sightings, which would make them easier to spot. Divide forest uses divider tree blends to obtain points given data for incorrect leave-taking.

Isolate Forest also generates data apartheid by randomly choosing a feature and randomly picking the total number of feature. The most likely variations require random random exclusion likened to "normal" arguments in the database, thus the discrepancies be will facts with a short path in the tree, the span of the path life the quantity of edges that fall after the cause protuberance.

By means of Separation Forest, we can't individual notice irregularities quicker but we too need fewer recall likened towards extra procedures.

Discrete forest separates wrongdoings from data arguments in its place of lithography typical data arguments. Since the data arguments incongruities take very short tree paths than usual data arguments, trees in a separated forest do not necessity to be too deep so a unimportant max_depth can be used which occasioned in little recall call.


- Describe \& Appropriate Model

1. We will size model suppleness \& fortify the IsolateForest part. We transfer the morals of the 4 limits to the Isolate Forestry path, listed underneath.
2. Number of freebooters: $n$ estimators mean the figure of speculators of the underpinning \& trees in this system, the quantity of trees to be built in the forest. This is the perfect limitation \& is elective. The evasion value is $200 / / 2$.
3. Max samples: max_samples is the quantity of examples to be strained to train each basic extent. If the max_samples exceeds the amount of models provided, all examples will be used for all trees. The default amount of max_samples is 'auto'. If 'auto', then max_samples $=\min (257-1$, n_samples $)$ :
4. Contamination: This is a stricture algorithm most delicate to; mentions to the likely part of merchants outdoor the data set. This is used where correct to describe the taster price range. The evasion value is 'auto'. If it says 'auto', the limit value will be strongminded as in the first piece of Isolate Forest.
5. Max features: All basic scores are not trained in all topographies obtainable in the file. It is a number of sketch elements from the comprehensive elements to each train basic appeal \& tree. The evasion cost of the max rudiments is 1 .
After we have labelled the perfect above we necessity to sleeper the perfect using the data as long as. In this case we use the right method () as revealed above. This way is accepted to single stricture, which is our concentrating data.

Once the model is appropriately trained it will announcement the IsolateForest model as exposed in the above cell outcome.

Now is the time to enhance scores \& a folder irregularity column. Enhance Scores \& Difference Column

Afterward the model is well-defined \& poised, lease's find the points with the unfavourable pilaster. We can find the numbers of pilaster schools by calling the decision function () of a qualified model \& transporting pay as a limit.

Likewise, we can discovery the pillar column irregularity by calling the foresee () function of a qualified model \& moving salary as a stricture.
These pillars will be extra to the data border data frame. Afterward calculation these dual pilasters lease's checked the df. By way of likely, the df now has 3 posts: salary, points \& variations. Unseemly score \& -1 of the number of incongruity columns indicating the company of an anomaly. 1 unequal value characterizes typical data.

Apiece data fact in the train set is specified an irregularity points by this procedure. We can describe a limit, \& using irregularity points, the aforementioned is possible to mark a data argument as unwelcome doubt the aforementioned score is superior than the predefined bound

### 2.2.7:Local Outlier Factor

Local Outlier Factor (LOF) is a college that says in what way it is conceivable that a precise data point is external / flawless.
LOF $\approx 1 \Rightarrow$ No Outlier
LOF $\gg 1 \Rightarrow$ Outlier
Initial, I familiarize the limit k which is the neighbouring LOF calculation. Local Outlier Factor is a cunning that aspects at the neighbours of a exact argument to discovery its scale \& then similarities this with the sum of further arguments future. By means of the amount k is not conservative onward. Whereas a minor k attentions too much on location, e.g. it only looks at nearby opinions, it is more error-free when it has a lot of
noise in the data. The big k , but, can be missed by local shops


The greatness of the red point in the direct vicinity does not differ from cramming to the fog in the higher right angle. But, it possibly stands out associated to the majority of nearby neighbours. k-distance As enlightened in k , we can familiarize k -distance which is the opinion of the argument to its neighbour kth . Doubt the k was 4 , the argument of k would be the argument of a argument to the adjoining third argument.


The red point range is designated by the red line if $k=4$.

- Reachability distance

K range is nowadays used to compute access distance. This aloofness amount is only a two-point distance and a second-distance k-distance.
long-distance $(\mathrm{c}, \mathrm{d})=$ plural $\{\mathrm{k}$-distance $(\mathrm{d})$, distance $(\mathrm{c}, \mathrm{d})\}$

Essentially, if argument a is inside the neighbourhood of k point d , the reach-dist ( $\mathrm{c}, \mathrm{d}$ ) resolve be the distance k . Before, it will be the real distance of c and d . This is just a "even feature". For ease, reflect this joint distance among two arguments.

- Local reachability density

Isolated access is used to calculate extra concept - local admittance density (Ird). To find the Ird for point a, wewill first estimate the admission point of a to all its adjacent neighbors and take a amount of that number. The Ird there is simply the conflicting of that typical. Keep in mind that we are speaking about amount and, so, if the coldness is too far to the next neighborhood, the part in which it is situated is much lesser. So, very little - the contradictory. $\operatorname{Ird}(\mathrm{c})=1 /$ (sum(reach-
$\operatorname{dist}(c, n)) / k)$
$\operatorname{lrd}(\mathrm{c})=1 /(\operatorname{total}(\operatorname{access}-\operatorname{dist}(\mathrm{c}, \mathrm{n})) / \mathrm{k})$
In a intelligence, the size of an close area tells us in what way distant we have to moveable after our site to spread the following argument \& set of sentiments. If it is low, very small, we have to go a wide way.

lrd of the higher right argument is the normal access point toward the adjoining pointers $(-1,-1),(-1.5,-1.5) \&$ $(-1,-2)$. Those neighbours, though, have extra lrds as their contiguous neighbours do not comprise a high right argument.

- LOF

The lrd of each argument will be associated to the lrd of their neighbours k. Precisely, the lrd evaluations for each pointin neighboring facts will be planned and rated. LOF is fundamentally the ratio among lrds neighbours a to lrd a. Doubt the relation is better than 1 , the scope of the argument is virtually slighter than the congestion of their neighbours, so, after fact a, we have to portable lengthier detachments to the following place \& a set of opinions than the neighbours to their following neighbours. Keep in attention, neighbours of a argument may reflect a neighbour as they have arguments in their closest method.

In inference, the LOF of the argument designates the thickness of this opinion likened to the size of its neighbours. Doubt the thickness of the opinion is abundant slighter than his neighbour thickness (LOF $\gg 1$ ), the argument is farther away after the solid parts, then, it is further gaining.

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## Chapter 3: System Development

### 3.1 System Requirements:

### 3.1.1 Python:

Python is a deciphered, top caliber and regular programming language. The Python engineering theory stresses the coherence of the code with its striking utilization of the blank area. Its phonetic construction and article situated methodology objective to commitment editors recorded as a hard copy strong, normal code for minor and significant tasks.

Python typed harder \& collected garbage. It supports a wide range of editing paradigms, including structured (especially, process), object-focused, and efficient. Python is often defined as a "battery-powered" linguistic because of its normal library.

Python was made in the last part of the 1980s, and was first delivered in 1991, by Guido van Rossum as a language ally of the ABC program. Python 2.0 , delivered in 2000 , presented new highlights, for example, list appreciation, and a waste assortment framework for reference, and was eliminated with rendition 2.7 by 2020. not completely viable behind the scenes and most Python 2 code doesn't work can be adjusted in Python 3.

Python interpreters are upheld by standard working frameworks and are accessible for a couple (and in the past they upheld some more). The worldwide framework local area makes and looks after Python, a free and open source application. The no benefit bunch, the Python Software Foundation, oversees and coordinates Python and Python development assets. It currently positions in Java as the second most noteworthy well known programming language on the planet.

### 3.1.2 Jupyter Notebook:

Python translators are supported by standard operating systems \& are available for just a few (and in the past they sustained many more). The global system community makes \& maintains Python, a free \& open source application. The no profit group, the Python Software Foundation, manages \& directs Python \& Python growth resources.

## Chapter 4: Performance analysis

### 4.1 Import the necessary packages

Import numpy as np
Import pandas as pd
Import matplotlib.pyplot as plt
Import seaborn as sns

### 4.2 Load the dataset from the csv file using pandas

df $=$ pd.read_csv('creditcard.csv')

### 4.3 Explore the dataset

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There are 284807 Rows and 31 Columns in the dataset.

Dataset Columns

| Column Name | Column Type |
| :---: | :---: |
| TIME | フINT |
| v_1 | Double |
| v_2 | Double |
| v_3 | Double |
| v_4 | Double |
| v_5 | Double |
| v_6 | Double |
| v_7 | Double |
| v_8 | Double |
| v_9 | Double |
| v_10 | Double |
| v_11 | Double |
| v_12 | Double |
| v_13 | Double |


| v_14 | Double |
| :--- | :--- |
| v_15 | Double |
| v_16 | Double |
| v_17 | Double |


| v_18 | 月ouble |
| :---: | :--- |
| v_19 | Double |
| v_20 | Double |
| v_21 | Double |
| v_22 | Double |
| v_23 | Double |
| v_24 | Double |
| v_25 | Double |
| v_26 | Double |
| v_27 | Double |
| v_28 | Double |
| AMOUNT | Double |
| CLASS (TARGET) | BINARY |

### 4.4 Plot histogram of each parameter: -

df.hist()
plt.show()

1) Time :-

2) V_1:-

3) V_2:-

4) V_3:-

5) V_4:-

6) V_5:-

7) V_6:-

8) V_7:-

9) V_8:-

10) V_9:-

11) V_10:-

12) V_11:-

13) V_12:-

14) V_13:-

15) V_14:-

16) V_15:-

17) V_16:-

18) V_17:-

19) V_18:-

20) V_19:-

21) V_20:-

22) V_21:-

23) V_22:-

24) V_23:-

25) V_24:-

26) V_25:-

27) V_26:-

28) V_27:-

29) V_28:-

30) Amount:-

31) Class (Target):-

n
4.5 Determine number of fraud cases in dataset

N_Valid $=$ df[df['Class'] $==1]$
Valid $=\operatorname{df[df['Class']~}==0]$

O_fraction = len(N_Valid) $/$ float(len(Valid))
print (O_fraction)
print ('Fraud Cases : ',len(N_Valid))
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print ('Valid Cases : ',len(Valid))

# 0.0017234102419808666 <br> Fraud Cases : 49 <br> Valid Cases : 28432 

### 4.6 Correlation matrix

C_mat $=$ df.corr()
fig $=$ plt.figure()
sns.heatmap(C_mat, vmax $=.8$, square $=$ True )
plt.show()


### 4.7 Build Model

13
$\mathrm{col}=\mathrm{df}$. columns.tolist()
$\mathrm{col}=[\mathrm{c}$ for c in columns if c not in ["Class"]]
target $=$ "Class"

$$
\begin{aligned}
& X=d f[\text { columns }] \\
& Y=\text { df[target }] \\
& \text { from sklearn.model_selection import train_test_split } \\
& \text { fro }
\end{aligned}
$$

$$
38
$$

X_tr, X_te, Y_tr, Y_te = train test_split(X,Y,test_size=0.7) from sklearn.metrics import classification_report, accuracy_score from sklearn.ensemble import IsolationForest, RandomForestClassifier from sklearn.neighbors import LocalOutlierFactor, KNeighborsClassifier from sklearn import tree from sklearn.linear_model import LinearRegression, LogisticRegression \# define a rndom state
state $=1$
\#definr outliner detection methods
$\mathrm{cl}=\{$
"Isolation Forest":IsolationForest(),
"Local Outlier Factor":LocalOutlierFactor(),
"Linear Regression": LinearRegression(),
"Logistic Regression": LogisticRegression(),
"Random Forest": RandomForestClassifier(),
"Decision Tree": tree.DecisionTreeClassifier(),
"KNN": KNeighborsClassifier()
\}
n_outlier $=$ len(N_Valid)
for i, (clf_name, clf) in enumerate(cl.items()):
\#fit data and tag outlier
if clf_name == "Local Outlier Factor" :
Y_P = clf.fit_predict(X)
Score_P = clf.negative_outlier_factor_

```
1
    # reshape the prediction values to 0 for valid, 1 for fraud
                                    39
    Y_P[Y_P == 1] = 0
    Y_P[Y_P == -1] = 1
    N_E = (Y_P != Y).sum()
    # run classifcation matrics
    print (clf_name,':',N_E)
    print (accuracy_score(Y,Y_P))
    print (classification_report(Y,Y_P))
elif clf_name =="Linear Regression" :
clf.fit(X_tr,Y_tr)
Y_P = clf.predict(X)
for a in range(len(y_pred)):
    Y_P[a] = int(Y_P[a])
    # reshape the prediction values to 0 for valid, 1 for fraud
    Y_P[Y_P == 1] = 0
    Y_P[Y_P == -1] = 1
    N_E = (Y_P != Y).sum()
```

```
# run classifcation matrics
print (clf_name,': ',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "Decision Tree" :
clf.fit(X_tr,Y_tr)
Y_P = clf.predict(X)
# reshape the prediction values to 0 for valid, 1 for fraud
Y_P[Y_P == 1] = 0
Y_P[Y_P == -1] = 1
N_E = (Y_P != Y).sum()
# run classifcation matrics
print (clf_name,': ',N_N)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "KNN" :
clf.fit(X_tr,Y_tr)
Y_P = clf.predict(X)
# reshape the prediction values to 0 for valid, 1 for fraud
```

$$
\begin{aligned}
& Y \_P\left[Y \_P==1\right]=0 \\
& Y \_P\left[Y \_P=-1\right]=1
\end{aligned}
$$

N_E = (Y_P !=Y).sum()
\# run classifcation matrics
print (clf_name,': ',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "Logistic Regression" :
clf.fit(X_tr,Y_tr)
Y_P = clf.predict(X)
\# reshape the prediction values to 0 for valid, 1 for fraud
$\mathrm{Y} \_\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}==1\right]=0$
$Y \_P\left[Y \_P==-1\right]=1$

N_E $=\left(Y \_P!=Y\right) . s u m()$
\# run classifcation matrics
print (clf_name, ':',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))
elif clf_name == "Random Forest" :
clf.fit(X_tr,Y_tr)

Y_P = clf.predict( X )
\# reshape the prediction values to 0 for valid, 1 for fraud

$$
\mathrm{Y} \_\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}==1\right]=0
$$

$$
\mathrm{Y} \_P\left[\mathrm{Y} \_\mathrm{P}==-1\right]=1
$$

$$
\mathrm{N} \_E=\left(\mathrm{Y} \_\mathrm{P}!=\mathrm{Y}\right) . \operatorname{sum}()
$$

\# run classifcation matrics
print (clf_name, ':',N_E)
print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))

8
else:
clf.fit(X)
score_pred = clf.decision_function $(\mathrm{X})$
$\mathrm{Y} \_\mathrm{P}=\operatorname{clf} . \operatorname{predict}(\mathrm{X})$
\# reshape the prediction values to 0 for valid, 1 for fraud
$\mathrm{Y} \_\mathrm{P}\left[\mathrm{Y} \_\mathrm{P}==1\right]=0$
$Y \_P\left[Y \_P==-1\right]=1$
$\mathrm{N} \_\mathrm{E}=\left(\mathrm{Y} \_\mathrm{P}!=\mathrm{Y}\right) . \operatorname{sum}()$

> \# run classifcation matrics
> Print (clf_name,',',N_E)
> print (accuracy_score(Y,Y_P))
print (classification_report(Y,Y_P))

### 4.8 Output of Bulid Models :-

1) Isolation Forest :-

Isolation Forest: 71
0.99750711000316
precision

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.28 | 0.29 | 0.28 | 49 |

accuracy
macro avg
0.64
0.64
1.00

28481
weighted avg
1.00
1.00
0.6428481
1.00

28481

## 2) Local Outlier Factor

Local Outlier Factor: 97
0.9965942207085425
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.02 | 0.02 | 0.02 | 49 |

accuracy
macro avg
0.51
0.51
1.00

28481
1.00
1.00
0.51

28481
weighted avg
1.00

28481
3) Linear Regression

44
Linear Regression: 49
0.9982795547909132
c: \users \admin\appdata\local\programs \python\python38-3: MetricWarning: Precision and F-score are ill-defined anc sion parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |

accuracy
macro avg
0.50
0.50
1.00

28481
weighted avg
1.00
1.00
0.50

28481
1.00

28481
4) Logistic Regression

Logistic Regression: 49
0.9982795547909132
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |

accuracy
0.50
0.50
1.0028481
macro avg
1.00
0.50

28481
weighted avg
1.00
1.00

28481
5) Random Forest

Random Forest: 49
0.9982795547909132
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |

accuracy
0.50
1.0028481
macro avg
1.00
0.50
0.50

28481
weighted avg
1.00
1.00

28481
6) Decision Tree

Decision Tree: 49
0.9982795547909132
precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |

accuracy

|  |  | 1.00 | 28481 |
| :--- | :--- | :--- | :--- |
| 0.50 | 0.50 | 0.50 | 28481 |
| 1.00 | 1.00 | 1.00 | 28481 |

7) KNN Classification

KNN: 49
0.9982795547909132

> precision recall f1-score support

| 0 | 1.00 | 1.00 | 1.00 | 28432 |
| ---: | ---: | ---: | ---: | ---: |
| 1 | 0.00 | 0.00 | 0.00 | 49 |
|  |  |  |  |  |
| cy |  |  | 1.00 | 28481 |
| vg | 0.50 | 0.50 | 0.50 | 28481 |
| vg | 1.00 | 1.00 | 1.00 | 28481 |

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## Chapter 5: Conclusion

Credit card scam is undoubtedly an act of criminal deceit. This article tilts the greatest shared forms of scam \& their styles of review \& reviews the latest answers in the arena. This paper too explained to some extent, how AI can be utilized to turn out to be better results in trick location and the calculation, pseudocode, explains it's application \& test outcomes. Whereas the algorithm reaches extra than 99.6 percentage precision, the aforementioned precision remains only 28 percentage when looking at a one-tenth of the data. However, when all the data is entered into an algorithm, the accuracy increases to 33 percentage. This tall percentage of precision is expected due to the large discrepancy between the transaction value allowed and the actual transaction number.

While we have not been able to achieve the goal of $100 \%$ accuracy in detecting fraud, we have finally created a scheme that, by sufficient time \& data, is actual near to that goal. Like any such task, there is territory for development now. The fauna of this venture permits numerous calculations to be assembled created 3 modules and their results can be joint to rise the exactness $\frac{3}{3}$ the ultimate result. This model can keep on being created with the adding of numerous calculations to it. However, the arrival of these calculations needs to be in the indistinguishable arrangement as the others. After that circumstance is content, the modules are simpler to improve as is finished in the code. This delivers a countless level of planning \& flexibility for the project. Additional development area can be create in the database. As per shown earlier, the accuracy of algorithms rises as the scope of the database increases. Therefore, more details will certainly type the model 3 3rther accurate in noticing scam \& cut the number of incorrect profits. But, this needs authorized provision from the banks themselves.

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