Githublink: https://github.com/sathishkumarsk2005

TITLE:GUARDINGTransactionswithAI-PoweredCreditCardFraudDetectionand Prevention

1:ProblemStatement:

Creditcardfraudisasignificantissueforfinancialinstitutions, merchants, and consumers globally. With the increasing volume of online and offline credit card transactions, the potential for fraudulent activity has also risen. Traditional fraud detection systems, relying on rule-based algorithms, often fall short in identifying new and sophisticated fraudulents chemes. This challenge is exacerbated by the vast number of transactions that must be processed quickly, the evolving nature of fraud tactics, and the need for real-time detection without negatively impacting legitimate user experiences.

To address this, there is a need for advanced, AI-powered credit card fraud detection and prevention systems that can adapt to emerging fraud tactics while minimizing false positives and optimizing the transaction experience for legitimate users.

2. ProjectObjectives

- Buildamachinelearningmodelthatcanreliablydetectfraudulenttransactions.
- Utilizesupervisedandunsupervisedlearningtechniquestodevelopaclassification model capable of differentiating between legitimate and fraudulent transactions.
- Trainthemodelusinglabeleddatasetswithbothfraudulentandnon-fraudulent transactions.
- Implementanomalydetectiontechniquestoidentifyemergingfraudpatternsthat have not yet been encountered in historical data.

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3:FlowchartoftheProjectWorkflow
|Start
|DataCollection&Integration|
|-Collecttransactiondata|
|-Integrateexternaldatasources(e.g.,deviceinfo,geolocation)|
|DataPreprocessing
|-Datacleaning&normalization|
|-Featureextraction&selection|
|ModelSelection
|-ChooseappropriateMLmodels(e.g., supervised, unsupervised, RL)|
|-Selectalgorithms(e.g.,decisiontrees,SVM,deeplearning)|
|ModelTraining&Evaluation|
|-Splitdataintotraining&testingsets|
|-Trainmodelonhistoricallabeleddata|
|-Evaluatemodelperformance(precision,recall,F1-score)|
|-Hyperparametertuning
|-Cross-validationforrobustness|
|-Adjustforfalsepositives/negatives|
|Real-TimeFraudDetection|
|-Deploymodelforreal-timescoringoftransactions|
|-Assignfraudriskscoretoeachtransaction|
|ActiononFraudulentTransactions|
|-Flagsuspicioustransactions|
|-Sendalertstocustomersorinstitutions|
|-Initiateverificationprocessifnecessary|
|ContinuousLearning&FeedbackLoop|
|-Monitormodelperformance(e.g.,falsepositives,detectionaccuracy)|
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-Updatemodelwithnewfraudpatternsanddata
-Retrainmodelperiodicallyforcontinuousimprovement
Compliance&Security
-Ensureprivacy(GDPR,PCI-DSS)
-Dataencryptionandsecurestorage
End
4. DataDescription
DatasetName:StudentPerformanceDataSet
Source: UCIMachineLearningRepository
TypeofData:Structuredtabulardata
 RecordsandFeatures:395studentrecordsand33features(numeric+categorical)
TargetVariable:G3(finalgrade,numeric)
StaticorDynamic:Staticdataset
 AttributesCovered:Demographics(age,address,parents'education),academics (G1,
G2, study time), and behavior (alcohol consumption, absences)
 DatasetLink:https://github.com/sathishkumarsk2005/Projectphase2.git
5. DataPreprocessing
1. DataCollection
Thefirststepinpreprocessingistogathertherawtransactiondata. This typically includes:
• TransactionFeatures:
o TransactionID
o Cardholderdetails(userID,cardnumber,etc.)
o Merchantdetails(merchantID,merchantcategory,location,etc.)
o Transactionamount

- o Transactiontime(timestamp)
- o Transactiontype(online,offline,etc.)
- o Devicedetails(deviceID,IPaddress)
- o Geolocation(latitude,longitude)

2. DataCleaning

Data cleaning involves handling missing values, removing duplicates, and dealing with any inconsistencies or errors in the raw data.

Actions:

- MissingValues:
- o Handlemissingdatapointsusingtechniqueslikeimputation(mean,median,or mode) or dropping rows/columns with excessive missing values.
- 6. ExploratoryDataAnalysis(EDA)
- UnivariateAnalysis:
 - Mean, Median, Mode
 - StandardDeviation&Variance
 - Min&Max
 - Histograms, BoxPlots, DensityPlots
- Bivariate&MultivariateAnalysis:
 - Correlationmatrix
 - ScatterplotsofG1vsG3andG2vsG3
 - Groupedbarcharts
- KeyInsights:
 - G1andG2arethestrongestindicatorsofG3

- MorestudytimecorrelateswithhigherG3
- Studentswithmorefailuresorabsencestendtoscorelower

7. Feature Engineering

Transaction-BasedFeatures

- TransactionAmountDifferences:
 - o Amountvs. Average Transaction
 - o Formula:TransactionAmount-AverageTransactionAmount
- 8. ModelBuilding
- AlgorithmsUsed:
 - LinearRegression
 - RandomForestRegressor
- ModelSelectionRationale:
 - LinearRegression:interpretableandfast
 - RandomForest:robusttooverfitting,handlesmixeddatatypeswell
- Train-TestSplit:80%training,20%testing
- EvaluationMetrics:
 - MAE,RMSE,R²Score
- 9. VisualizationofResults&ModelInsights
- FeatureImportance:BarplotsfromRandomForest
- ModelComparison:MAE,RMSE,andR2forbothmodels
- ResidualPlots:Predictionerrorsvs.actualgrades

- UserTesting:IntegratedmodelintoGradiointerface
- 10. ToolsandTechnologiesUsed
- ProgrammingLanguage:Python3
- NotebookEnvironment:GoogleColab
- KeyLibraries:pandas,numpy,matplotlib,seaborn,plotly,scikit-learn,Gradio
- 11. TeamMembersandContributions

Datacleaning:(B.THIRUPATHI)

- Mean, median, or mode imputation for numerical features
- Modeimputationforcategoricalfeatures

EDA:(M.SENTHILKUMAR)

- Classimbalanceawareness
- Biasdetection

Featureengineering:(S.SATHISHKUMAR)

- Averagetransactionamountperuser
- Transactionfrequency

Modeldevelopment:

- Algorithmselection, handling classimbalance
- Performancemetricsanalysis