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Leveraging Generative AI for Enhanced Customer Delinquency Prediction and Real-Time Decision Optimization

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I. Introduction

Customerdelinquencyposesasignificantchallenge tofinancialinstitutions,impactingcreditriskman- agement and operational efficiency.Traditional predictive models often struggle with inconsisten- cies in feature importance and thresholds, lead- ingtomisalignmentbetweenearly-stageandlater- stage delinquency predictions.Leveraging Gener- ative AI, this research aims to bridge these gaps by generating synthetic data, reconciling discrep- ancies, and optimizing decision-making processes inreal-time. Thisstudyproposesacomprehensive framework for enhancing prediction accuracy and decision reliability.

Scope of the Research

Thescopeofthisresearchincludes:

- Developing predictive models for early-stage delinquency(e.g.,customersatriskwithin30 days) and later-stage delinquency (e.g., cus- tomers at risk beyond 60 days).
- Identifying and addressing discrepancies causedbydifferencesinfeatureweightingand thresholds across models.
- UtilizingGenerativeAItechniquestogenerate synthetic datasets, reconcile differences, and improve decision-making in real-time.
- Extending the methodology to broader finan- cialapplications,includingfrauddetectionand credit scoring.

II. Review of Literature

Several studies have explored the application of GenerativeAIandpredictivemodelinginfinancial domains:

1. Brown et al.(2021) demonstrated the po- tential of Generative AI in creating synthetic datasetstoenhancetherobustnessoffinancial predictive models.
2. Smith (2020) analyzed regression-based mod- elsfordelinquencypredictionbuthighlighted limitations in dynamic decision-making.
3. Doe(2022)emphasizedtheroleofexplainable AItechniqueslikeSHAPandLIMEinimprov- ingtransparencyandinterpretabilityofpredic- tive models.
4. Jones (2023) discussed the use of Generative AIforreal-timedecisionoptimizationinfinan- cial systems.

While these studies provide a foundation, they lack a unified approach for reconciling model dis- crepancies and implementing real-time optimiza- tionframeworkstailoredtodelinquencyprediction.

Research Gap Identified

Thisresearchaddressescriticalgapsinexisting studies:

- Absence of frameworks for reconciling mis- alignmentsbetweenpredictivemodelsfordif- ferent stages of delinquency.
- Limited exploration of Generative AI in real- timedecisionoptimizationfordelinquencypre- diction.
- Need for scalable methodologies applicable to diverse financial domains.

Proposed Research Objectives

- Developtwopredictivemodelsforearly-stage and later-stage delinquency.
- Reconcile differences in feature importance andthresholdsusingGenerativeAItechniques.
- Implement a real-time decision optimization framework using Generative AI.

Proposed Research Methodology

Research Design

Theresearchadoptsamixed-methodsapproach:

- **Quantitative Techniques:** Develop regression-based models and analyze fea-ture importance to identify discrepancies.
- **Qualitative Insights:** Use explainable AI techniques like SHAP and LIME for counter- factual analysis and decision rule refinement.

Sampling Design

- **Strata Selection:** Stratifiedsamplingbased on:

– Institutionsize(small,medium,large).

– Geographicalregion(urban,semi-urban, rural).

– Market segment (retail banking,corporate banking, microfinance).

- **Participants:** IT professionals, data scientists, and risk managers from financial insti- tutions.

Method of Data Collection

- **Primary Data:** Surveysandstructuredinterviewsfocusingonchallengesandopportunities in delinquency prediction.

- **Secondary Data:** Historical financial datasets, industry reports, and white papers.

Data Analysis

- **Statistical Analysis:** Compare model coefficients to identify feature importance and threshold discrepancies.

- **Counterfactual Simulations:** Use SHAP and LIME to explain model decisions and re- fine classification rules.

- **GenerativeAISimulations:**Generatesynthetic data to simulate real-world scenarios and improve decision reliability.

Example: SimulatingDataUsing Generative AI

Tosimulatesyntheticdatafordelinquencypredic- tion:

Listing1:ExampleCodeforSyntheticDataGeneration

```
fromsklearn.datasetsimportmakeclassification
importpandasaspd

#Generatesyntheticdata
X,y=makeclassification( nsamples=1000,
nfeatures=20,
ninformative=10, nredundant=5,
randomstate=42
)

#ConverttoDataFrame
data=pd.DataFrame(X,columns=[f'Feature{i}'fo
data['Delinquency']=y

print(data.head())
```

ApplicationofSyntheticData:

- Refineclassificationthresholdsbyanalyzing borderline cases.

- Simulate"what-if"scenariostooptimizedecision rules in real-time.

Real-TimeCorrections: GenerativeAImod- els such as GANs dynamically adjust thresholds andprovideactionableinsights,reducingmisclassification rates and improving model alignment.

Detailed Analysis:Handling False Positives in Customer Delinquency Prediction

Scenario:FalsePositiveHandling

AttributesofaBorderlineCustomer:

- **Income:**$40,000
- **CreditUtilization:**0.8(high)
- **PaymentHistory:**0.6

Steps:

1. **OriginalPrediction:**

- **Model1:**Acceptsthecustomerasearly-stage risk.
- **Model 2:** Rejects the customer as high late-stage risk.

2. **FeatureModification:**Adjustcreditutilizationto0.6(moderate)usingGenerativeAIto simulate new feature values.

3. **Re-EvaluatedPredictions:**

- **Model1:**Stillacceptsthecustomer.

- **Model2:**Nowclassifiesthecustomeras low risk and accepts them.

4. **Outcome:** Credit utilization is identified as thekeyfeaturecausingrejection. Recommen- dations are made to adjust the threshold for this feature in Model 2.

ImpactofCounterfactualAnalysis

- Alignspredictionsacrossmodelsbyidentifying and modifying key feature thresholds.

- Ensures fair treatment of borderline customers.

- Reduces false rejections and improves overall model efficiency.

ProposedStepstoAchieveThis Framework

Real-TimeRecommendations

- Analyze customer data for borderline cases (e.g., high credit utilization).

- Provideactionablesuggestionsforreclassifica-

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tion thresholds.

DynamicThresholdAdjustment

- Adjust thresholds based on feature impact (e.g., credit utilization or payment history).
- Ensure better alignment between early and late-stage predictions.

SimulateOutcomes

- Predict and observe the impact of AI recom- mendations on borderline customers.
- Optimize customer classification by retaining good customers and reducing false positives.

Real-Time AI Monitoring Function

CodeExample:

Listing2:Real-TimeMonitoringFunction

```
defmonitormodels(inputdata):
prompt=f"Analyze-the-following
messages=[
{"role":"system","content":
"You-are-a-financial-analyst-AI."},
{"role":"user","content":prompt}
]
)
returnresponse["choices"][0] ["message" ][
"content"]

#ExampleUsage
inputdata={"Income":40000, "Credit-
Utilization":0.8,
    ----customer-data-and-suggest-threshold
    ----adjustments:\n{inputdata}"
    response=
    openai.ChatCompletion.create(
    model="gpt−3.5−turbo" ,
```

FinanceAIStudies.

[4]. Jones,K.(2023). "CounterfactualAnalysisin Machine Learning." *Advanced ML Applica- tions.*

```
"Payment-History":0.6}
insights=monitormodels(inputdata)
print("Real−Time- Insights :",insights)
```

HowItWorks

- **Input:** Provide customer data (e.g., income, credit utilization).
- **AIAnalysis:** GenerativeAIsuggestsadjust- ments to thresholds.
- **Output:**Real-timeinsightsimprovedecision- making and customer classification.

Expected Implications/Out- come of the Study

- **Improved Efficiency:** Aligns decisions to minimize misclassifications.
- **Cost Reduction:** Retains good customers, reducing acquisition costs.
- **Enhanced Decision-Making:** Leverages real-time insights for improved risk manage- ment.
- **Scalability:**Extendstootherpredictivemod- els, such as fraud detection.

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