TVS CREDIT

e.p.i.c 5

ENRICH | PERFORM | INNOVATE | CHALLENGE

Ramaiah Institute of Technology

Team NishJay

IT CHALLENGE

#BeEPIC

Who are we?

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Manav Vikram Raithatha

Team NishJay

Ramaiah Institute of Technology

Contents

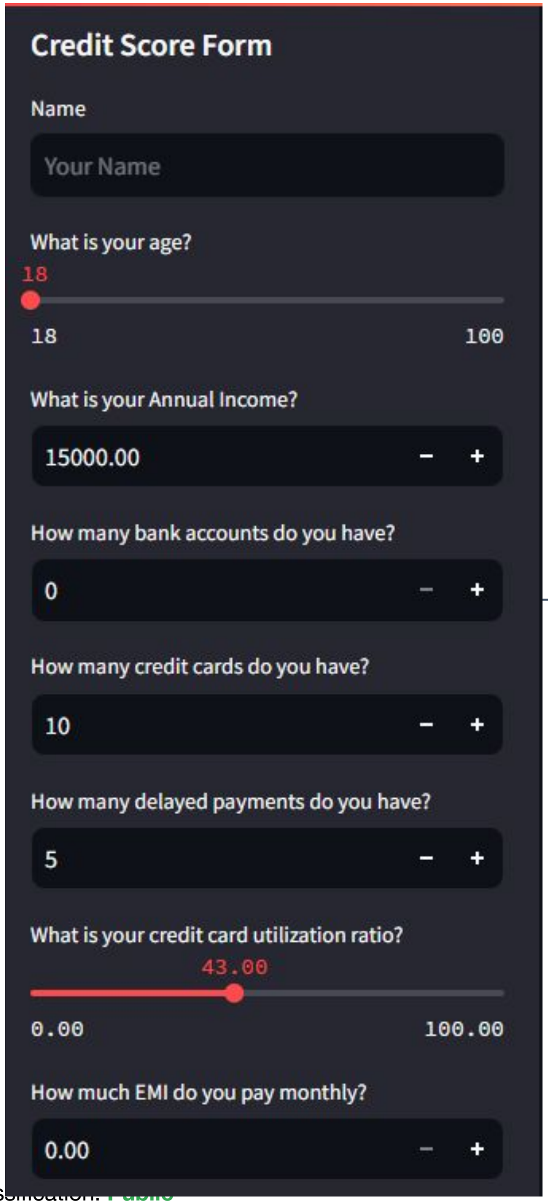
INTRODUCTION

In the ever-evolving landscape of financial services, **efficient risk assessment** is the cornerstone of responsible lending.

As technology continues to progress it is imperative that we refine our underwriting methods to adopt and **utilize the perks of the latest methods** and models.

We have developed a **sophisticated system prototype** that will evaluate the risk based on the data available from the previous customers and tell the **amount of risk** the current user carries in **failing to pay the credit** using **gradient and ensemble** learning models.

What are we doing?



Machine Learning MODEL

POOR	REGULAR	GOOD

How are we doing it - THE DATASET

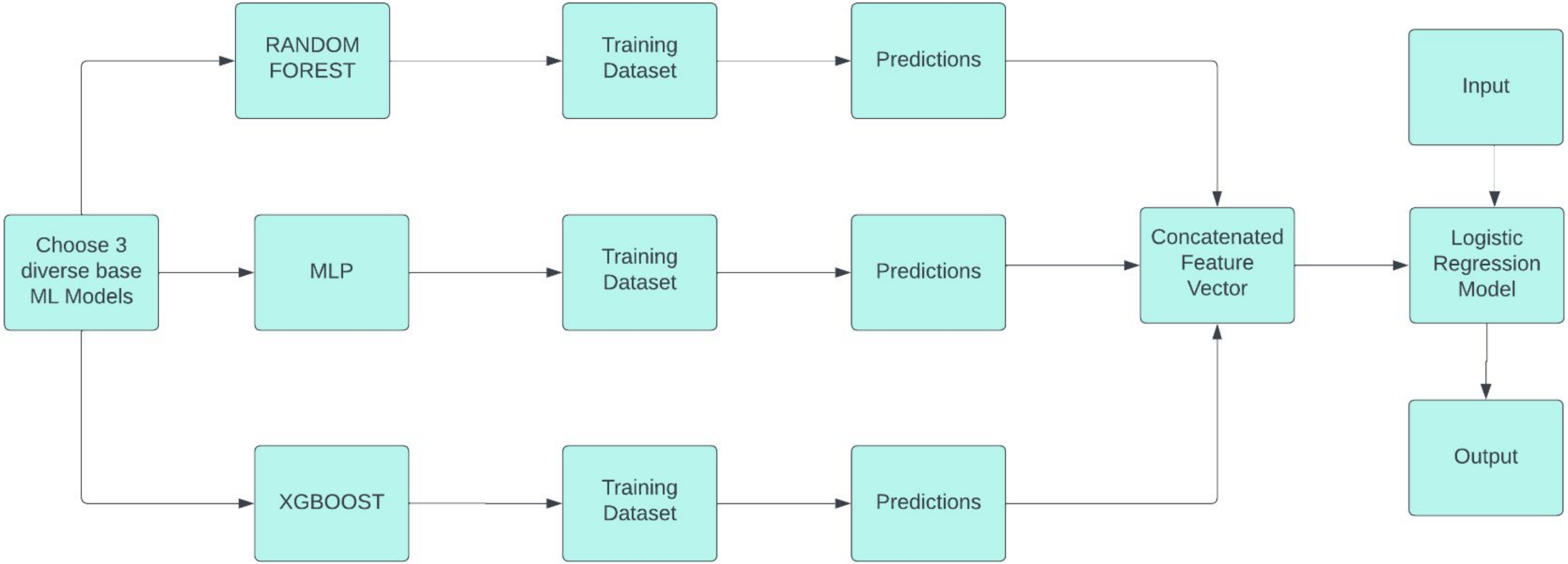
Column	Non-Null Count	Dtype
Month	100,000	int64
Age	100,000	float64
Occupation	100,000	object
Annual_Income	100,000	float64
Monthly_Inhand_Salary	100,000	float64
Num_Bank_Accounts	100,000	float64
Num_Credit_Card	100,000	float64
Interest_Rate	100,000	float64
Num_of_Loan	100,000	float64
Type_of_Loan	100,000	object
Delay_from_due_date	100,000	int64

Num_of_Delayed_Payment	100,000	float64
Changed_Credit_Limit	100,000	float64
Num_Credit_Inquiries	100,000	float64
Credit_Mix	100,000	int64
Outstanding_Debt	100,000	float64
Credit_Utilization_Ratio	100,000	float64
Payment_of_Min_Amount	100,000	object
Total_EMI_per_month	100,000	float64
Amount_invested_monthly	100,000	float64
Monthly_Balance	100,000	float64
Credit_Score	100,000	int64
Credit_History_Age_Formated	100,000	float64

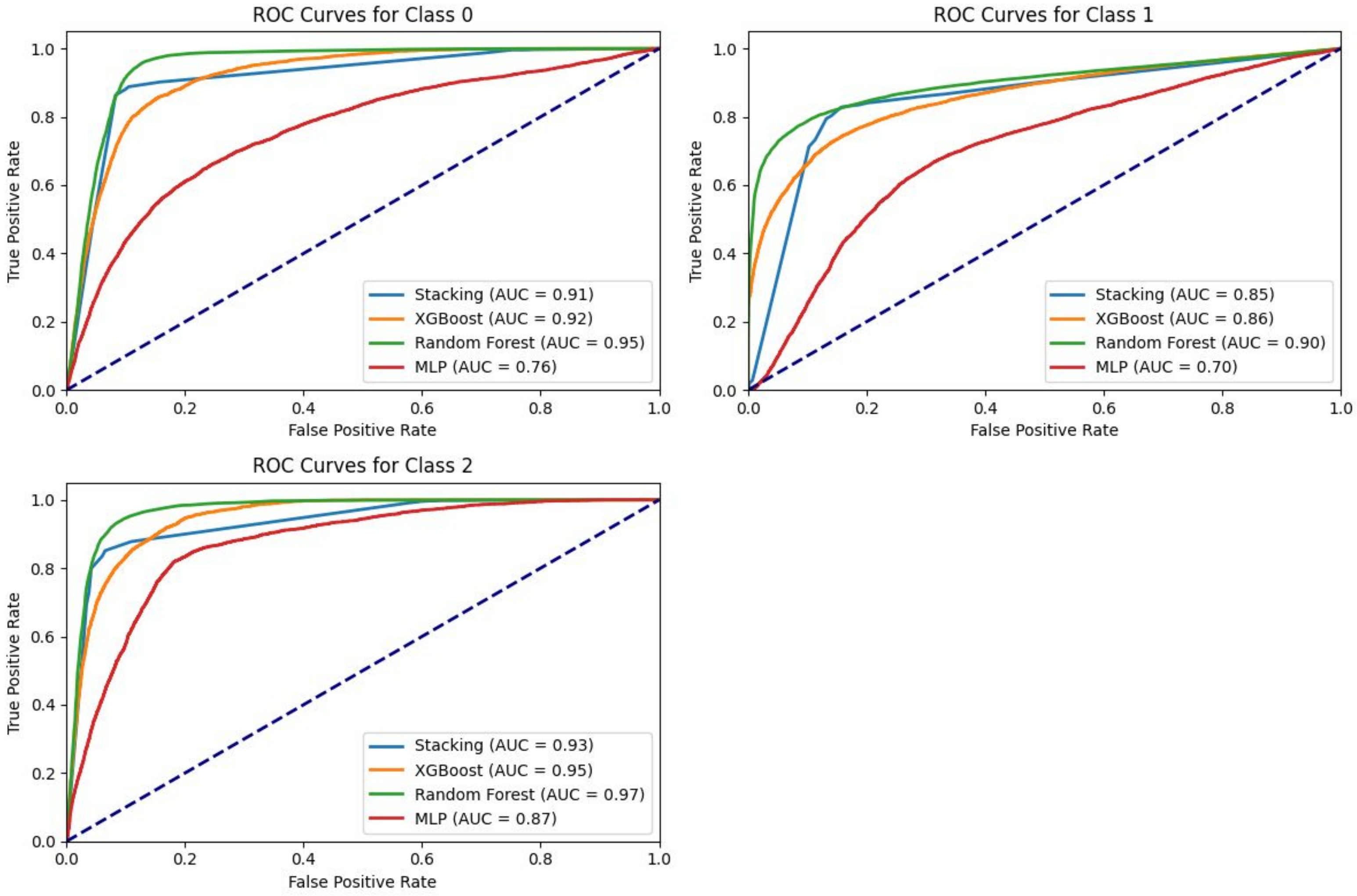
What are we using ?

- **XGBoost - "eXtreme Gradient Boosting"**
  - Combines the strengths of
    - Decision trees with
    - Gradient boosting
- **Why XGBoost?**
  - **Handles Imbalanced Data -** Majority come under “Average” category
  - **High Predictive Accuracy** - easy identification of defaulters
  - **Feature Importance -** Give importances of each parameter
  - **Regularization -** Prevent overfitting
  - **Speed and Efficiency**
- **STREAMLIT for a**
  - Simple good looking
  - User friendly
  - Interactive
  - Web frontend

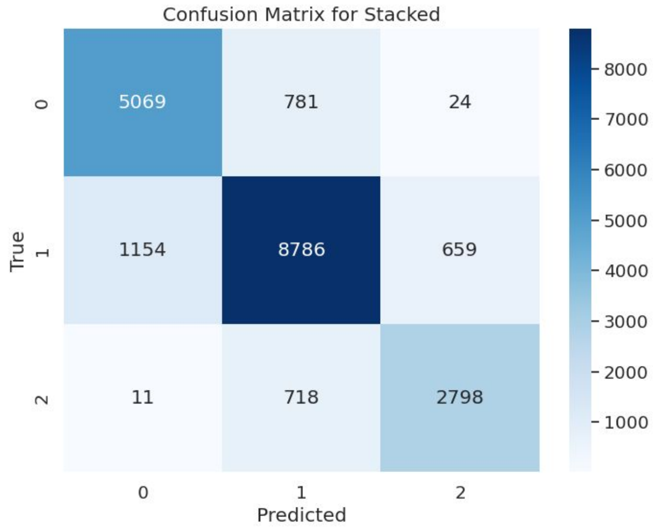
How are we doing it - THE MODEL

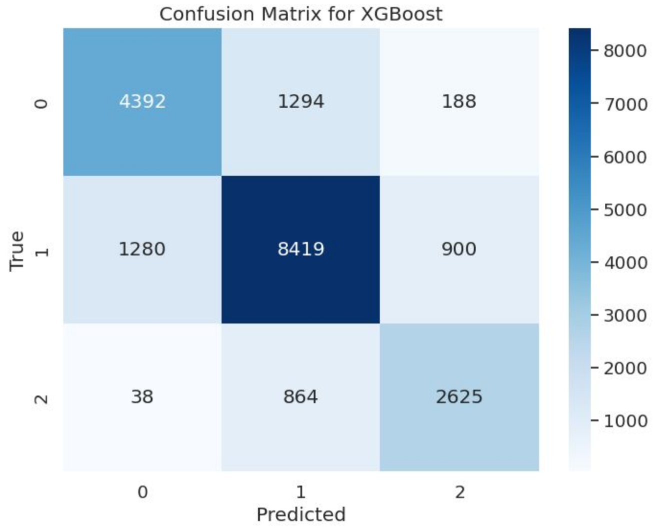


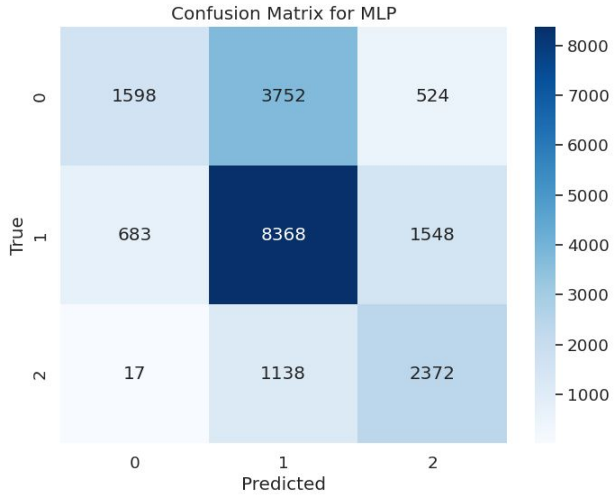
Results

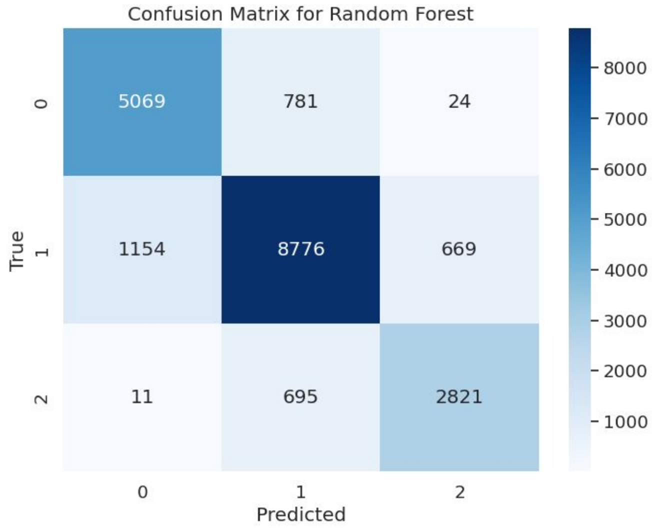

ROC Curves for Class 0
True Positive Rate
False Positive Rate
Stacking (AUC = 0.91)
XGBoost (AUC = 0.92)
Random Forest (AUC = 0.95)
MLP (AUC = 0.76)
ROC Curves for Class 1
True Positive Rate
False Positive Rate
Stacking (AUC = 0.85)
XGBoost (AUC = 0.86)
Random Forest (AUC = 0.90)
MLP (AUC = 0.70)
ROC Curves for Class 2
True Positive Rate
False Positive Rate
Stacking (AUC = 0.93)
XGBoost (AUC = 0.95)
Random Forest (AUC = 0.97)
MLP (AUC = 0.87)

Results


Confusion Matrix for Stacked
5069
781
24
1154
8786
659
11
718
2798
True
Predicted
0
1
2
8000
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for XGBoost
4392
1294
188
1280
8419
900
38
864
2625
True
Predicted
0
1
2
8000
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for MLP
1598
3752
524
683
8368
1548
17
1138
2372
True
Predicted
0
1
2
8000
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for Random Forest
5069
781
24
1154
8776
669
11
695
2821
True
Predicted
0
1
2
8000
7000
6000
5000
4000
3000
2000
1000

Results

Model	Precision	Recall	F1 Score	ROC AUC
Stacking Ensemble	0.8237	0.8284	0.8257	0.8995
XGBoost	0.7574	0.7621	0.7595	0.9065
Random Forest	0.8240	0.8303	0.8268	0.9383
MLP	0.6201	0.5780	0.5626	0.7780

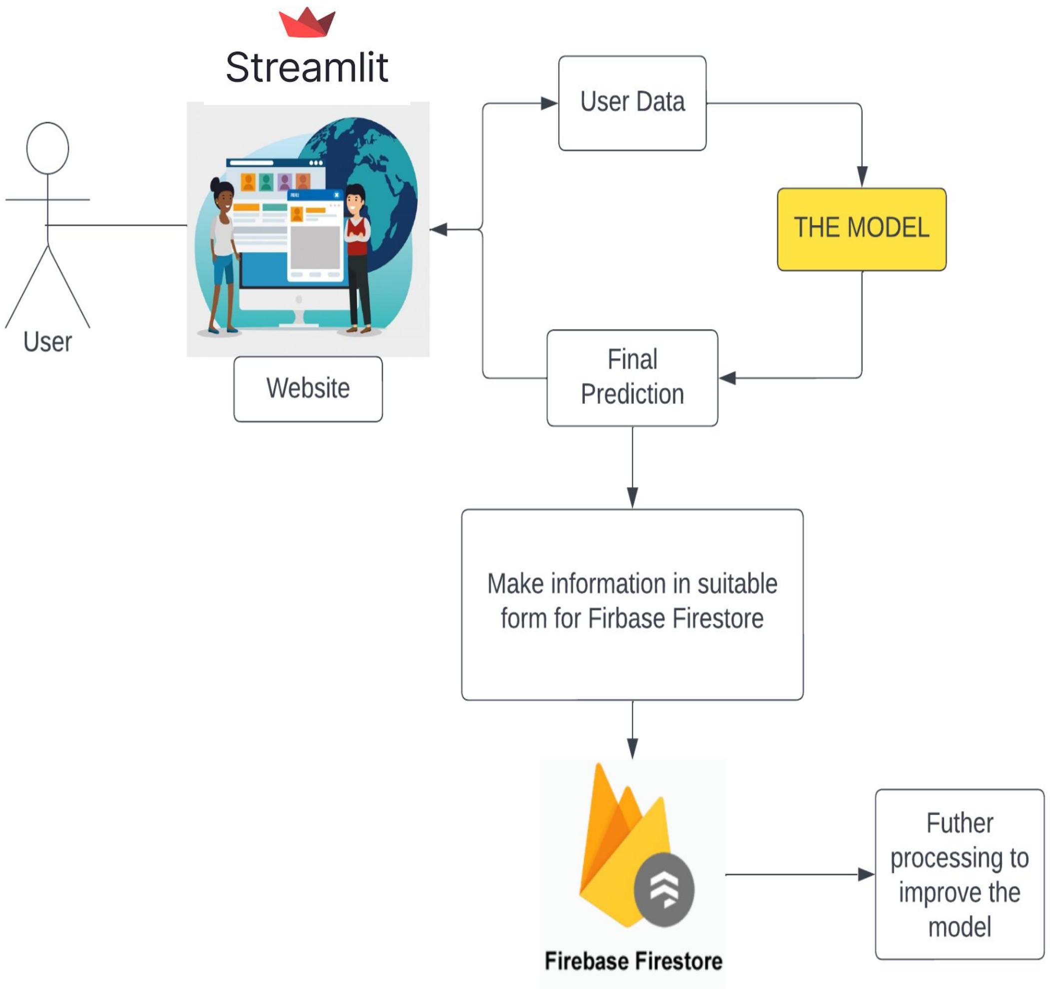
Accuracy metrics for the combination model

Model	Class 0 AUC	Class 1 AUC	Class 2 AUC
Stacking	0.91	0.85	0.93
XGBoost	0.92	0.86	0.95
Random Forest	0.95	0.90	0.97
MLP	0.76	0.70	0.87

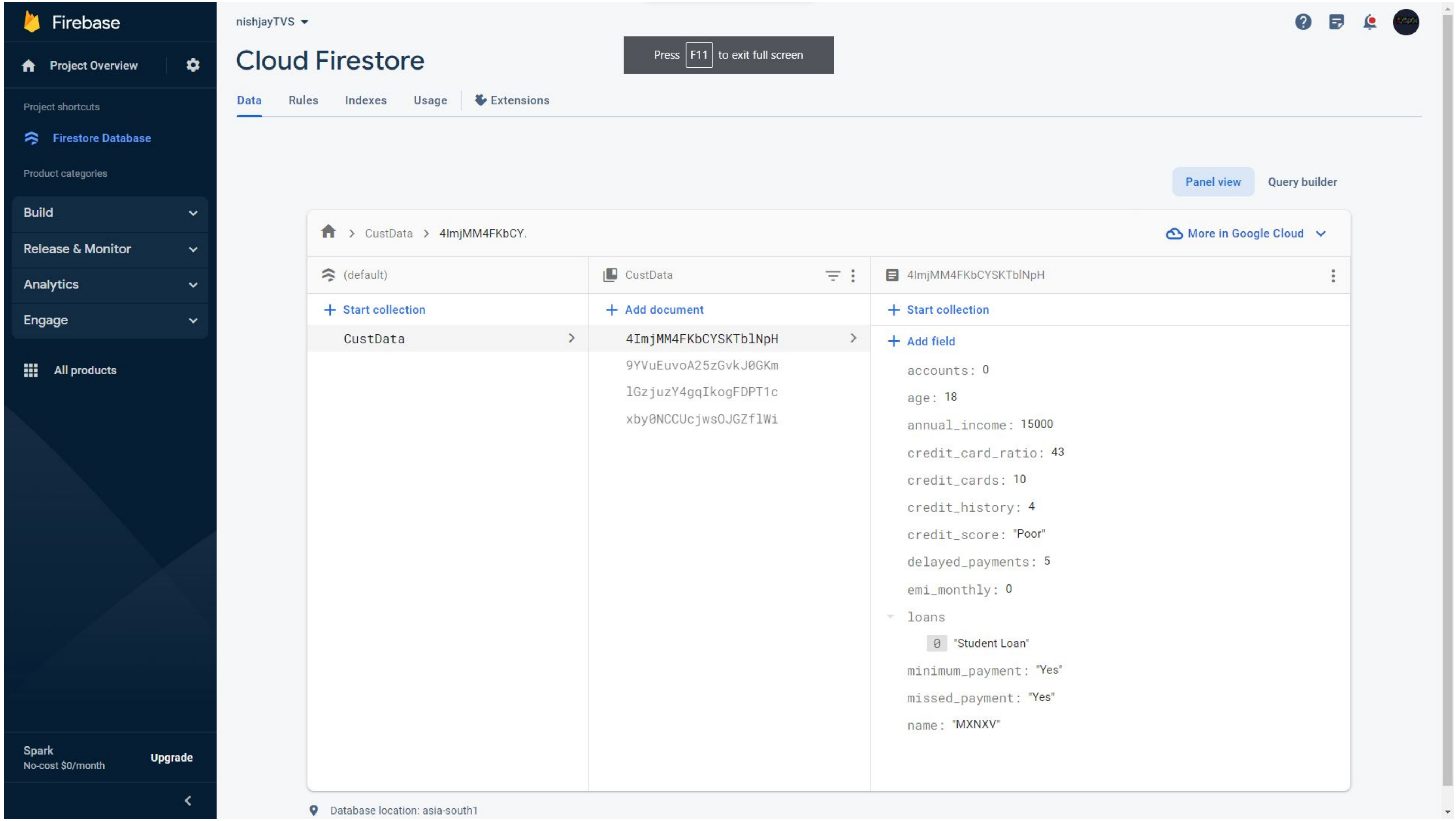
Class Wise metrics

How are we doing it - THE APP WORKFLOW

- **User Visit:** When a user visits our website, they're taking the first step towards finding their category of credit score.
- **Data Input:** The user is prompted to enter their personal details, financial history, and other relevant information. It's like painting a picture of their unique financial journey.
- **Behind the Scenes:** Behind the scenes, our sophisticated system employs cutting-edge machine learning models, as explained in previous slides, to analyze the user's input. It's like a diligent detective, examining every detail.
- **Credit Score Category:** Within moments, the user is presented with their credit score category. This is the compass guiding them towards financial opportunities.
- **Feature Importances:** But we don't stop there. We also provide the user with a breakdown of feature importances. This is like revealing the puzzle pieces that determine their creditworthiness, helping them understand and improve their financial future.

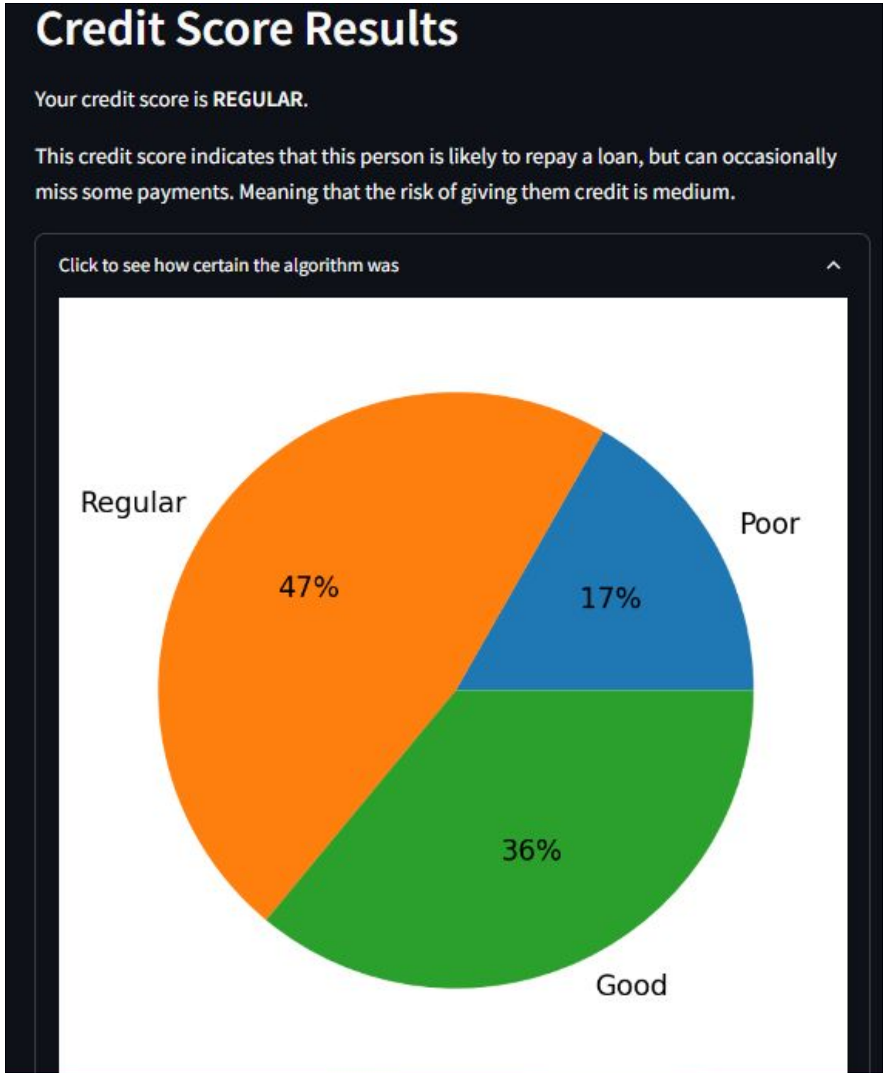


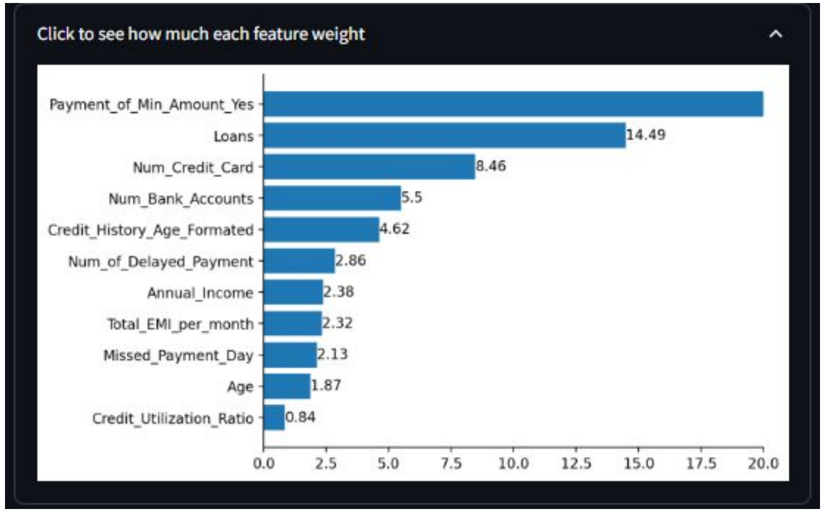
How are we doing it - FIREBASE BACKEND



Classification: **Public**

RESULTS - THE APP OUTPUT





Thank You