# Bank Customer Complaint Classification

## A Natural Language Processing (NLP) Project

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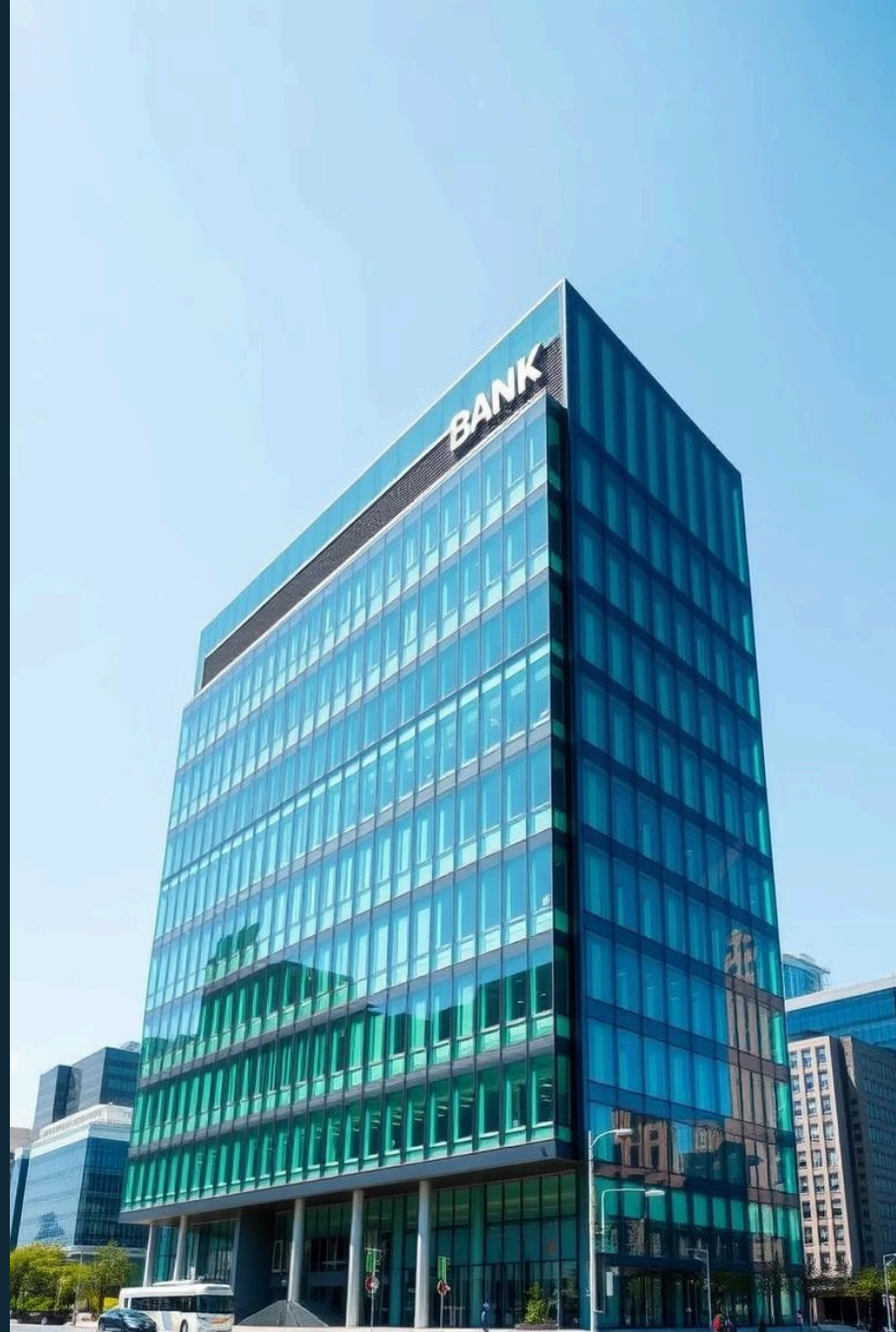


# Outline

1. Project Overview
2. Business Understanding
3. Data Understanding & Preparation
4. Modeling & Evaluation
5. Deployment & Application
6. Conclusion & Recommendations

# Project Overview

## Goal

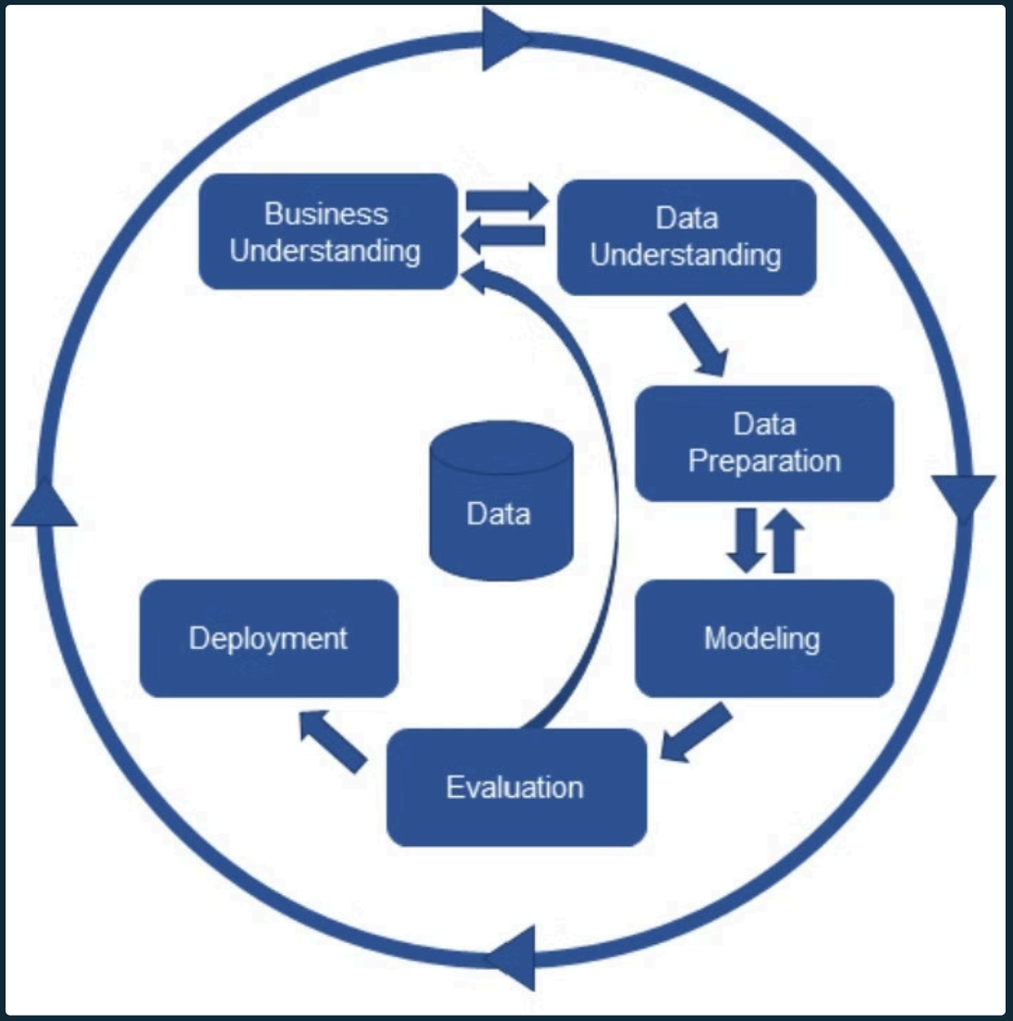
Simplify Customer complaint submission & handling.

## Objectives

1. Train an NLP model for accurate classification.
2. Reduce complaint submission time.
3. Enhance bank responsiveness.

## Methodology

Cross-Industry Standard Process for Data Mining (CRISP-DM).




*CRISP-DM*

# Business Understanding

## Problem Statement

Customers face frustration due to complex complaint submission processes.

## Root Causes

Complex navigation, inefficient chatbots, lack of personalization and limited data use.

## Key Stakeholders

1. Customers and,
2. Customer support teams.

# Data Understanding & Preparation

## Dataset Source

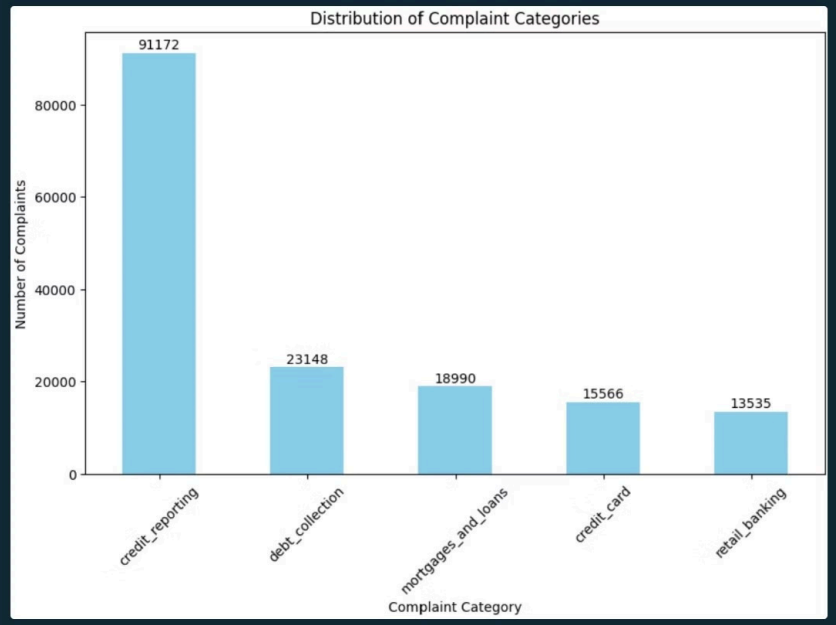
US Consumer Complaints Dataset from Kaggle.

## Complaint Categories

Five (5): Credit reporting; debt collection; mortgages, credit cards; and retail banking.

## Key Details

162,400 records, imbalanced data, and varying narrative lengths.




*The distribution of Complaint Categories shows a class imbalance, with the credit_reporting category significantly more represented than others.*

# Data Understanding & Preparation

## Exploration

Handled missing values, retained duplicates, addressed class imbalance.

## Pre-processing

Standardized text, tokenization, stop word removal, and lemmatization.

## Data Transformation

Applied TF-IDF and MinMax scaling. SMOTE also applied later for model improvement.

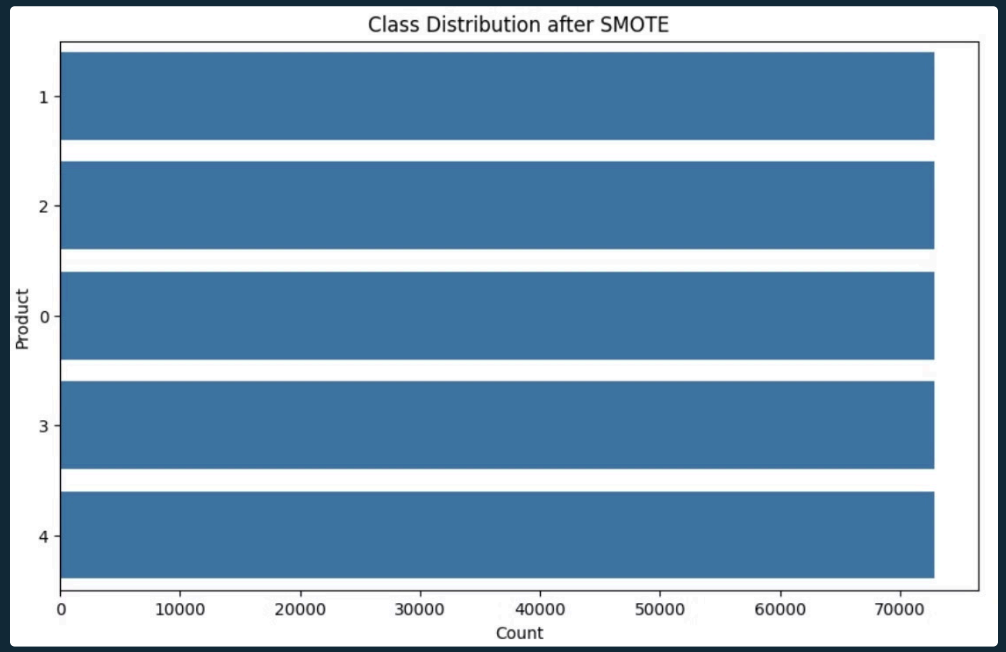

***Word cloud*** *highlighting specific terms associated with common issues for each product. Shows that customer complaints are centered around distinct themes based on the product type.*

# Data Understanding & Preparation

## SMOTE Class Balancing

**Synthetic Minority Oversampling Technique (SMOTE)**

- Perfectly balanced class distribution after applying SMOTE.
- Each product category having an equal count of samples (approximately 73,000).
- This balanced distribution helps the model learn patterns more evenly across classes.



# Modeling & Evaluation

## Models

Baseline: MNB, SVM, Logistic Regression, Random Forest.
Improved: Tuned Random Forest, ExtraTrees, BERT.

## Evaluation Metrics

Classification report, Confusion Matix, AUC-ROC curve with focus on Macro F1 **Score** supported by Weighted F1-score.

## Model Selection

BERT seleted for its balanced performance and suitability for NLP tasks.

# Modeling & Evaluation

## BERT Model Performance

**Metrics Report:**

- Solid performance.
- The **Macro F1 of 0.85** shows consistent results across classes.
- **Weighted F1 0.89** and **Accuracy** of **89%.**

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| credit_card | 0.81 | 0.79 | 0.80 | 3113 |
| credit_reporting | 0.93 | 0.94 | 0.93 | 18235 |
| debt_collection | 0.81 | 0.80 | 0.81 | 4630 |
| mortgages_and_loans | 0.86 | 0.84 | 0.85 | 3798 |
| retail_banking | 0.86 | 0.90 | 0.88 | 2707 |
| accuracy | | | 0.89 | 32483 |
| macro avg | 0.85 | 0.85 | 0.85 | 32483 |
| weighted avg | 0.89 | 0.89 | 0.89 | 32483 |

# Modeling & Evaluation

## BERT Model Performance

**Confusion Matrix:**

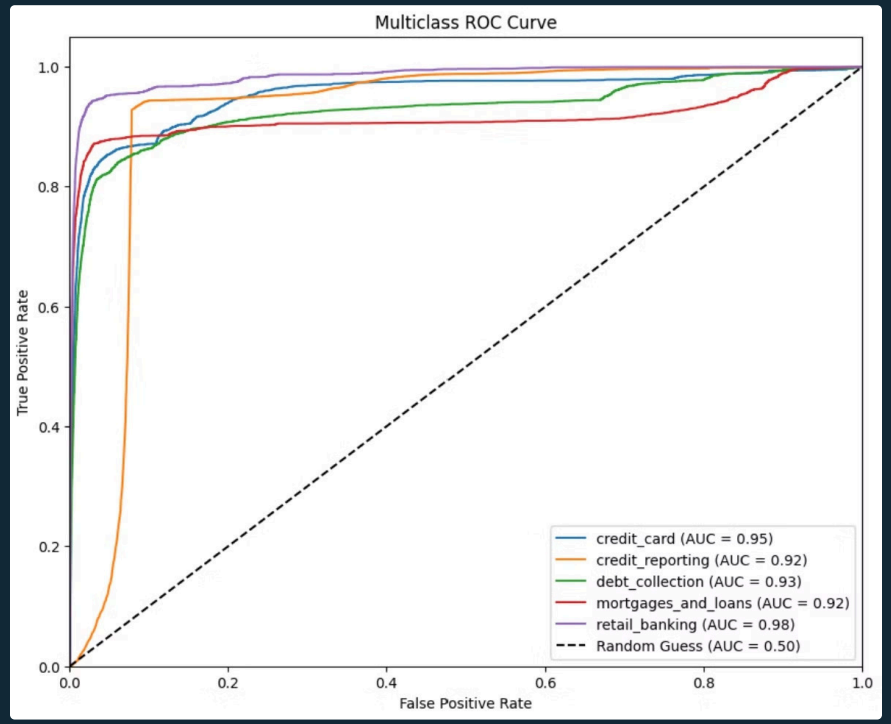
- Indicates strong classification performance.
- Some misclassification occurred between similar financial categories.
- Shows good overall differentiation.

# Modeling & Evaluation

## BERT Model Performance

**AUC-ROC Curve:**

- Demonstrates high discriminative power across all complaint categories.
- AUC values ranging from **0.92 to 0.98**.
- Overall reflects a strong ability of the model to distinguish between classes.



# Deployment & Application

## User-Friendly Interface

Built with Streamlit & deployed on huggingface.

## Model Integration

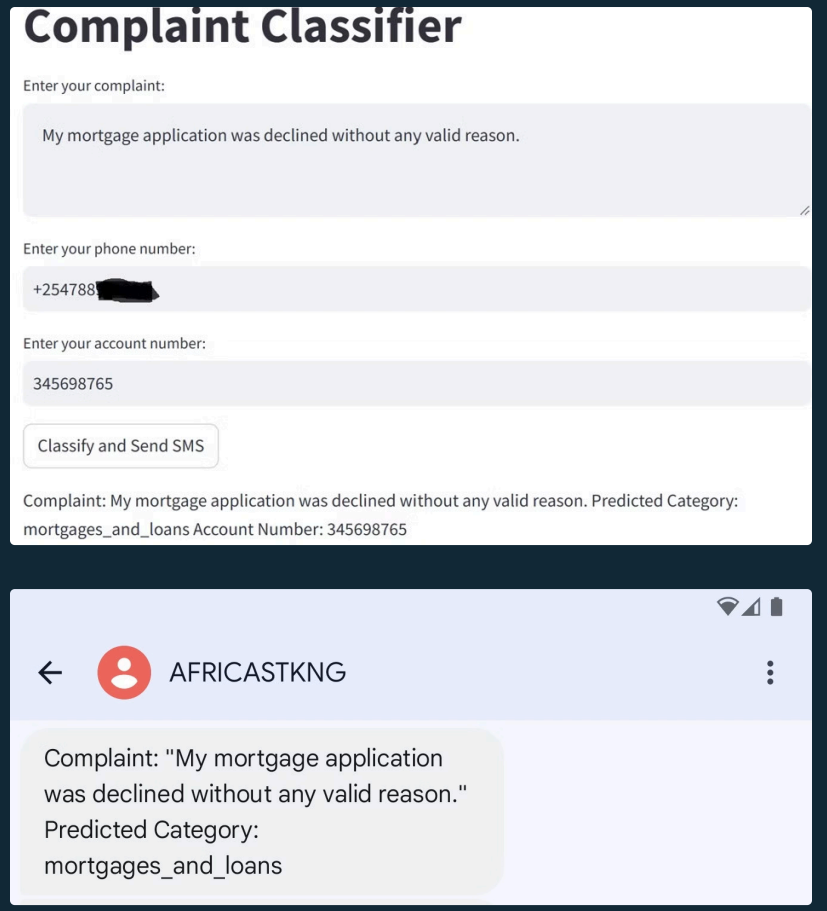
BERT classifies complaints in real-time.

## Automated Notifications

Integrated with Africastalking's SMS API, sending classified notificatioin.

## Challenges

SMS  limited to Airtel and Telkom; Email notification slow.




*Snapshot of the system simlified user interface and SMS notification received*

# Conclusion & Recommendations

## Insight & Impact

1. BERT model with robust classification accuracy trained.
2. Simple complaint submission system deployed.
3. Prompt notification for enhanced responsiveness.

## Future Improvements

- Feedback loops.
- Category optimization.
- Expanded notification channels.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# Thank you.