Bank Consumer Complaint Classification

A Natural Language Processing (NLP) Capstone Project

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Executive Summary

Project Goal: Use NLP to simplify and accelerate customer complaint classification, reducing submission time and complexity with an intuitive interface.

Model Selection: BERT chosen after evaluating models like Multinomial Naive Bayes, SVM, Logistic Regression, Random Forest, and ExtraTrees. BERT achieved a *Macro F1-score of 0.85*, *Weighted F1-score of 0.89*, and *89% accuracy*, providing balanced and reliable classifications.

Deployment: *Deployed on Hugging Face with a Streamlit interface*, allowing customers to input complaints. Classified results are sent via *Africastalking's SMS API* to both customers and relevant support teams for quick response.

Future Improvements: Implement feedback loops for retraining, optimize complaint-specific categories, and expand notification channels to enhance accuracy and adaptability.

Outline

- Project Overview
- Business Understanding
- Data Understanding & Preparation
- Modeling & Evaluation
- Deployment & Application
- Conclusion and Recommendations

Project Overview

Goal: Simplify and streamline customer complaint classification using NLP to minimize survey questions and enhance the submission process.

Objectives:

1. Train an NLP model for accurate complaint categorization.
2. Reduce complaint logging time and improve user experience.
3. Enhance bank responsiveness with faster, precise complaint handling.

Approach: *Data preparation:* handling missing values, duplicates, and applying TF-IDF and scaling; *Model training:* Multinomial Naive Bayes, SVM, Logistic Regression, Random Forest, ExtraTrees, and BERT; BERT with **Macro F1-score: 0.85**, **Weighted F1-score: 0.89**, **Accuracy: 89%** selected.

Deployment and Application: Deployed on Hugging Face with a Streamlit interface; Complaints are classified in real-time and routed via SMS to the appropriate support team and the customer.

Business Understanding

- **Problem Statement**:
  Financial institution customers face frustration due to complex complaint submission processes, including redundant chatbot questions and lengthy navigation. A streamlined system is needed to reduce steps and improve efficiency.

- **Root Causes**:
  - Complex navigation and cumbersome menus.
  - Inefficient chatbots with redundant questions.
  - Lack of personalized pathways for different complaint types.
  - Limited use of data to streamline the process, leading to repetitive requests.

- **Key Stakeholders**:
  - **Customers**: Need a quick, simple way to submit complaints.
  - **Customer Support Teams**: Require efficient categorization tools to resolve issues promptly.

Data Understanding & Preparation

Dataset Source: Consumer Complaints Dataset from the US Consumer Financial Protection Bureau (CFPB), sourced from Kaggle.

Complaint Categories:

1. Credit Reporting
2. Debt Collection
3. Mortgages and Loans
4. Credit Cards
5. Retail Banking

Key Details:

- ~162,400 records with varying narrative lengths.
- Imbalanced data: 56% of complaints focus on credit reporting, requiring tailored strategies for balanced classification.

Data Understanding & Preparation

Exploration Highlights:

- Removed unnecessary columns and handled missing values.
- Retained 37,735 duplicate entries due to their positive impact on model performance.
- Addressed class imbalance (notably in the credit reporting category) through stratified splits and SMOTE.
- Text length analysis revealed a right-skewed distribution, with most narratives under 1,000 characters.

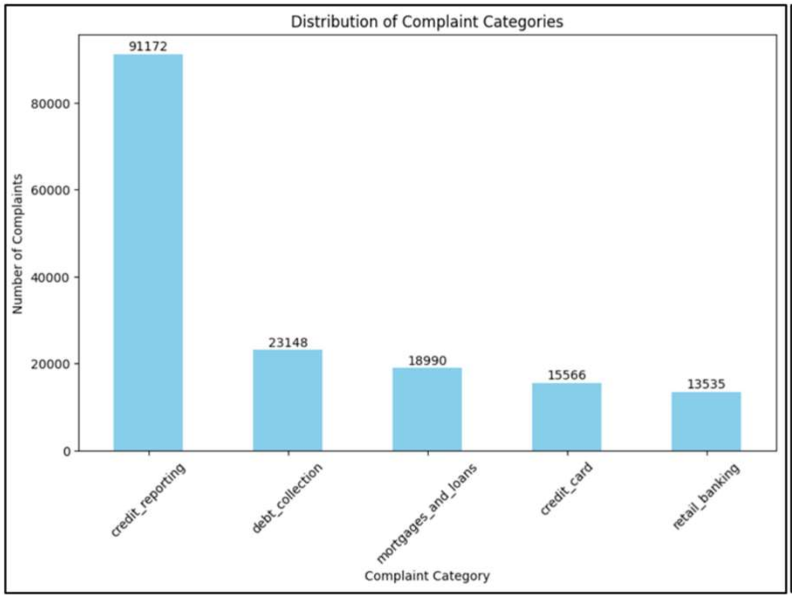
Preprocessing Steps:

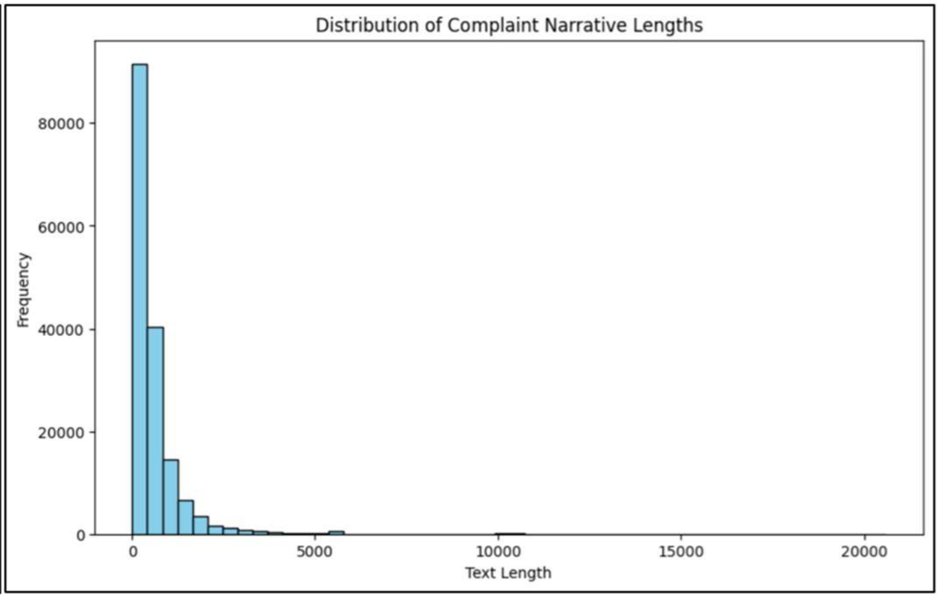
- Standardized text (lowercasing, removing special characters, handling whitespace).
- Tokenization, stop word removal, and lemmatization to clean and normalize text.

Data Transformation:

- Applied TF-IDF for weighted feature representation.
- Used MinMax scaling for feature standardization.
- Created balanced and optimized train-test datasets for modeling.

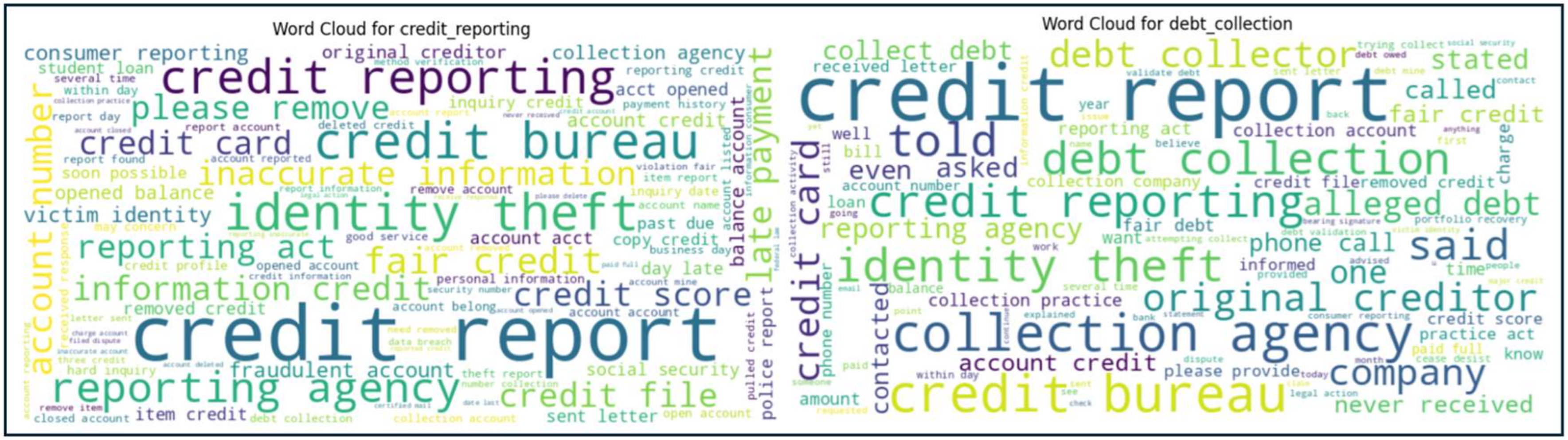
Data Understanding & Preparation





Left: *The distribution of Complaint Categories shows a class imbalance, with the credit_reporting category significantly more represented than others.* ***Right:*** *The histogram indicates a right-skewed distribution, with most narratives having fewer than 1,000 characters.*

Data Understanding & Preparation



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.

Modeling & Evaluation

Baseline Models Trained: Multinomial Naïve Bayes, SVM, Logistic Regression, and Random Forest.

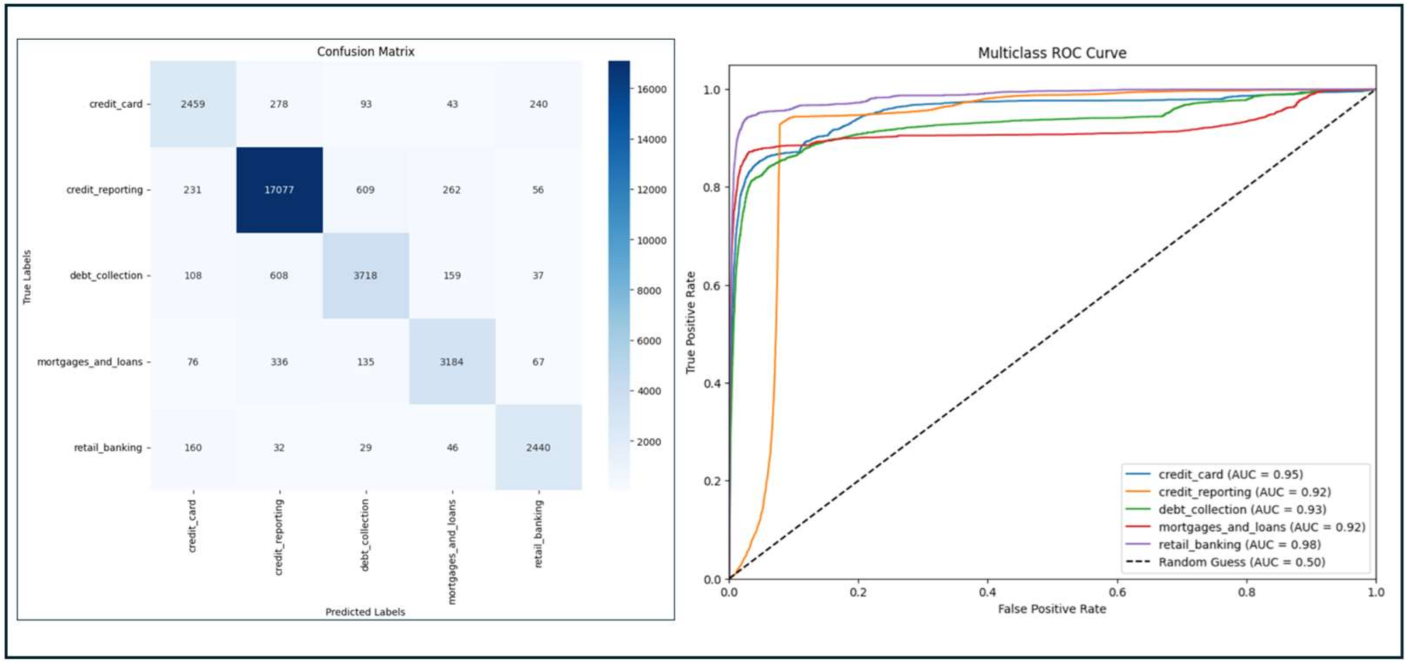
Evaluation Metrics: Focused on **Macro F1-score** (equal weighting across classes) and **Weighted F1-score** (accounts for class imbalance).

Model Improvement:

- Tuned Random Forest for better performance.
- Applied SMOTE to balance data and trained Random Forest and ExtraTrees models.
- Explored **BERT**, which excelled due to its deep language understanding, achieving balanced and robust classification.

Final Selection: **BERT** chosen for deployment for its strong performance and suitability for NLP tasks.

Modeling & Evaluation



Left: *The BERT confusion matrix reflects good differentiation across categories, with relatively few off-diagonal errors.* ***Right:*** *The AUC-ROC curve for the BERT model demonstrates high discriminative power across all complaint categories, with AUC values ranging from 0.92 to 0.98.*

Deployment & Application

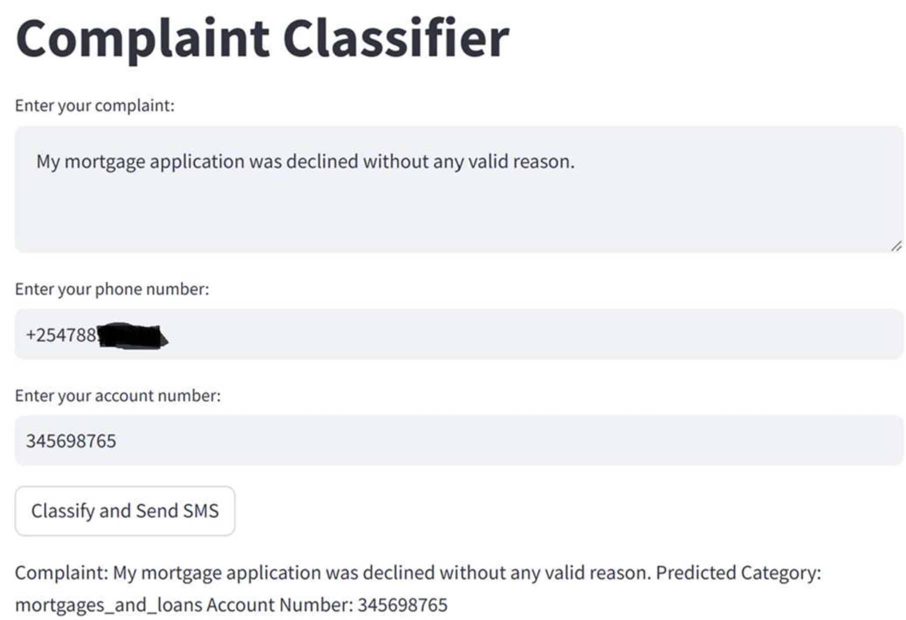
Approach:

- **User-Friendly Interface**: Built with Streamlit, allowing customers to submit complaints along with their phone and account details.
- **Model Integration**: BERT classifies complaints in real-time based on input data.
- **Automated Notifications**: Integrated with Africastalking's SMS API to notify both the support team and the customer of complaint details. SMS was chosen over email for faster delivery.
- **Deployment**: Deployed on Hugging Face for easy access via a link.
- **Future Enhancements**: Implement a feedback loop to retrain the model and improve adaptability.

Challenges:

- SMS notifications are limited to Airtel and Telkom due to restrictions on Safaricom.
- Email notifications were slower and replaced with SMS.

Deployment & Application



Snapshot of the system user interface that includes only three fields for complaint, phone number and account number.

Conclusion & Recommendations

Model: BERT chosen for its strong NLP capabilities, achieving a Macro F1-score of 0.85 and Weighted F1-score of 0.89, ensuring reliable and accurate complaint classification.

Deployment: Model integrated with Streamlit and deployed on Hugging Face, providing a seamless complaint submission experience with automated SMS notifications for quick resolution.

Insights and Impact: Streamlined complaint submission process, reduced customer friction, and improved response times by categorizing complaints and routing them to appropriate support teams efficiently.

Limitations and Future Work:

- Accuracy varies across complaint types; further tuning and data augmentation are needed.
- SMS notifications are currently limited to Airtel and Telkom networks.
- Recommendations include implementing a feedback loop for retraining, expanding notification channels, and optimizing model performance for specific categories.

Questions?

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Thank you.