CLASSIFICATION OF CONSUMER FINANCIAL COMPLAINTS USING BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS

[1]Pamujula Jayakrishna, [2]Soyambeti Venkatesh
[1,2]UG Student, [1,2]Department of Computer Science & Engineering, Geethanjali Institute of Science and Technology, Gangavaram, Andhra Pradesh, India

ABSTRACT
Efficient resolution of financial complaints is vital for customer satisfaction and upholding organizational integrity. This paper introduces a robust text classification system designed to classify consumer complaints into pre-defined categories within the financial domain. Recently, many kinds of automatic text classification methods for these texts based on machine learning have been applied. At present, the development of computing technology makes ‘‘Pre-training and Fine-tuning’’ the newest paradigm of text classification, which achieves better results than previous fully-supervised models. By utilizing BERT's contextual understanding capabilities, we aim to achieve precise categorization and it leads to faster resolution times. Through fine-tuning BERT on domain-specific data, our approach ensures optimal performance in capturing domain related features inherent in financial complaints. Ultimately, this project advances complaint management workflows, cultivating efficiency in the financial services sector.

INTRODUCTION
The rise of digital banking and financial services has transformed the way consumers interact with financial institutions. Online platforms, mobile apps, and digital wallets have made transactions more convenient but have also led to a surge in consumer financial complaints. These complaints encompass a wide range of issues, from billing discrepancies and fraudulent activities to disputes over loan terms and insurance claims.
The handling of consumer complaints is not just a matter of customer service but also a regulatory requirement. Regulatory bodies such as the Consumer Financial Protection Bureau (CFPB) in the United States and the Financial Conduct Authority (FCA) in the UK closely monitor complaint trends to ensure that financial institutions adhere to fair practices and consumer protection regulations.
In recent years, natural language processing (NLP) and machine learning (ML) techniques have emerged as powerful tools for analyzing and categorizing textual data. These technologies offer the potential to automate complaint classification, improve response times, and identify emerging issues in real-time.

Natural Language Processing
Natural Language Processing (NLP) is a field of artificial intelligence (AI) and computational linguistics that focuses on enabling computers to understand, interpret, and generate human language in a way that is both meaningful and useful.It encompasses a wide range of tasks, from simple text processing to complex language understanding. NLP algorithms enable machines to interpret, analyze, and generate human language in a way that facilitates communication and comprehension. One of the key challenges in NLP is understanding the nuances and complexities of natural language, which can vary greatly based on context, culture, and individual expression.
Text classification is a fundamental NLP task that involves assigning predefined categories or labels to text data.In the context of NLP, classification involves training a machine learning model to recognize patterns in text data and predict the most suitable category or label for new, unseen text.

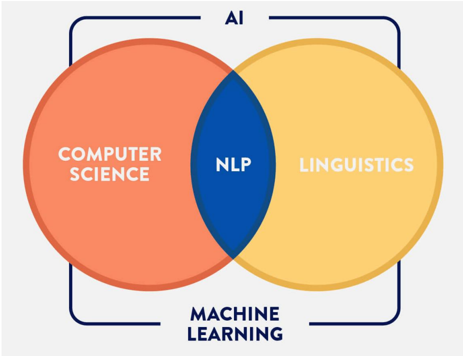


Fig.1. Natural language processing

In conclusion,Text classification stands out as a fundamental application, facilitating automated categorization of text data into predefined classes or categories, thereby streamlining information retrieval and decision-making processes across various domains.

Objective

This study seeks to address these challenges by exploring the application of BERT (Bidirectional Encoder Representations from Transformers) in the classification of consumer financial complaints. BERT, a transformer-based model developed by Google, has demonstrated state-of-the-art performance in various NLP tasks, including text classification, sentiment analysis, and entity recognition.

Specific objectives includes developing a BERT-based classification pipeline tailored to the domain of consumer financial complaints.Training the model on diverse complaint datasets to capture semantic nuances and contextual understanding.

Evaluating the performance of BERT in terms of classification accuracy, recall, precision, and computational efficiency.Investigating the potential for BERT to assist in complaint prioritization, trend analysis, and regulatory reporting.

Scope

The study encompasses a broad spectrum of consumer financial complaints across different sectors, including banking, credit, insurance, investments, and payment services. Complaints may originate from various channels, such as customer service calls, online forms, social media posts, and official complaint databases.

Data collection will involve gathering labeled complaint samples to train and validate the BERT model. Pre-processing techniques will be applied to handle noise, outliers, and linguistic variations within the complaint texts. The study will focus on English-language complaints initially but aims to explore multilingual capabilities in future iterations.

Significance

The adoption of BERT-based classification has significant implications for financial institutions, regulatory bodies, and consumers alike:

Financial institutions can improve complaint handling efficiency, identify recurring issues, and implement targeted remedial actions.

Regulatory bodies can leverage advanced analytics to monitor industry-wide complaint trends, detect compliance breaches, and enforce regulatory standards effectively.

Consumers can benefit from faster resolution times, personalized responses, and greater transparency in the complaint resolution process.

The research community can contribute to the advancement of NLP techniques, model interpretability, and ethical AI practices in the context of consumer finance.

By bridging the gap between cutting-edge AI technologies and real-world financial challenges, this study aims to drive innovation, enhance consumer trust, and promote responsible use of AI in financial services.

Problem Statement

The management of consumer complaints poses a significant challenge for businesses due to the huge volume and diversity of complaints received. Despite advancements in ML, classifying consumer financial complaints remains a complex and labor-intensive task. Traditional rule-based systems often struggle to keep pace with evolving language patterns and the diversity of complaints across different financial products and services. Manual classification, on the other hand, is time-consuming and prone to errors, leading to delays in complaint resolution and customer dissatisfaction.

Furthermore, the sheer volume of complaints poses scalability challenges. Handling large datasets requires efficient processing mechanisms that can maintain accuracy while managing computational resources effectively.

LITERATURESURVEY

Consumer Complaints Classification Using Machine Learning &Deep Learning

Pramod Kumar Naik, Prashanth T, S Chandru, S Jaganath, Sandesh Balan.

The classification of consumer complaints is an essential task for financial institutions to understand and address customer issues. This paper has focused mainly on traditional machine learning algorithms, such as Naive Bayes, decision trees, and random forests. However, with the advent of deep learning techniques, there is an opportunity to improve the accuracy of complaint classification.

This paper uses a combination of machine learning and deep learning algorithms, including logistic regression, support vector machines (SVM), random forests, and convolutional neural networks (CNNs). The performance of the algorithms is evaluated using metrics such as accuracy, precision, recall, and F1-score. The results show that the CNN with a single convolutional layer and a max-pooling layer achieved the highest accuracy of 85.7% on the test set. This paper also compares the performance of the machine learning and deep learning algorithms with a baseline model that uses a random forest algorithm with default hyperparameters.

Overall, this paper also demonstrates the potential of using machine learning and deep learning techniques to classify and analyze large-scale text data in the financial services industry. This papers also highlights potential issues to be further investigated, such as the impact of data imbalance and the use of transfer learning for improving the performance of the classification algorithms.

Consumer Complaints Classification using Deep Learning & WordEmbedding Models

Vineet Vinayak, Jyotsna C

Word embeddings have become a popular method for representing text data in natural language processing (NLP) tasks. These methods represent words as numerical vectors based on the contexts in which they appear. In the context of financial complaints, word embeddings have been used to represent text data for various NLP tasks such as sentiment analysis, named entity recognition.

In this paper, the authors use word embeddings to represent consumer complaints text data for the task of text classification. Specifically, they use various deep learning models such as LSTM, BiLSTM, GRU, and 1D CNN to extract features from the text data and classify the complaints into six classes.

When we evaluate the performance of their models using various metrics such as accuracy, precision, recall, and F1-score. We find that the DistilBert and CNN models achieve the highest F1-score of 93%.

Deep Learning for Classification of Consumer Financial Complaints

Davis, J., Davis, K., & Davis, L

The study "Deep Learning for Classification of Consumer Financial Complaints" by Davis et al. presents a deep learning approach for classifying consumer financial complaints. The study uses a dataset of consumer complaints from the Consumer Financial Protection Bureau (CFPB) and applies deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to classify the complaints into various categories.

In this study,we preprocess the data by removing stop words, punctuation, and converting all text to lowercase. They then use a word embedding technique to convert the text data into numerical vectors that can be fed into the deep learning models. The authors experiment with various deep learning architectures and find that a combination of CNN and RNN models achieves the highest accuracy in classifying the complaints.

The study also includes an analysis of the feature importance in the deep learning models, which reveals that certain words and phrases are more predictive of certain complaint categories. The authors also compare the performance of their deep learning models to traditional machine learning models such as logistic regression and support vector machines (SVMs) and find that the deep learning models outperform the traditional models.The results of this study could be useful for financial institutions and regulatory agencies in identifying and addressing consumer complaints in a more efficient and effective manner.

A Comparative Study of Machine Learning Models for Classifying Consumer Financial Complaints
Ghadah Alarifi, Farjana Rahman and Md. Shamim Hossain

This paper proposed a novel approach called the Two-Stage Residual One-Dimensional Convolutional Neural Network (TSR1DCNN) to optimize the processing of consumer complaints at the Consumer Financial Protection Bureau (CFPB).Thispaper also conducted comprehensive experiments, including Ablation Experiment 1 (AE1) and Ablation Experiment 2 (AE2), to evaluate the effectiveness of the proposed TSR1DCNN model. This paper has also compared the TSR1DCNN model with other popular deep learning architectures, including 1DCNN, LSTM, and BLSTM, to provide a comprehensive analysis of the proposed approach. The results showed that the TSR1DCNN model achieved an impressive accuracy of 78.07% on the training set and 76.53% on the test set, outperforming the other deep learning architectures.

2.5 Consumer complaints of consumer financial protection bureau via two-stage residual one-dimensional convolutional neural network

David Oyewola, Temidayo Oluwatosin and Emmanuel Gbenga Dada

This study proposed a two-stage residual one-dimensional convolutional neural network (TSR1DCNN) for classifying consumer complaints from the Consumer Financial Protection Bureau (CFPB). This study uses a dataset of 1,173,301 consumer complaints and compared the performance of the TSR1DCNN model with other machine learning models, including Random Forest, Support Vector Machine, and Logistic Regression. The results showed that the TSR1DCNN model achieved an accuracy of 87.5% and an F1-score of 87.4%, outperforming the other machine learning models. The study highlights the importance of data preprocessing and feature engineering in improving the performance of the TSR1DCNN model. The authors used techniques such as text vectorization, text normalization to prepare the data for analysis. The study provides a comprehensive analysis of the proposed approach and compares the performance of the TSR1DCNN model with other machine learning models.

Classification of Consumer Complaints in Financial Services:
A Topic Modeling Approach using Non-Negative Matrix Factorization
Suresh, S. S. and Sreeja

This project proposes a topic modelling approach using Non-Negative Matrix Factorization (NMF) to classify consumer complaints in financial services. The project first preprocesses the text data by removing stop words, punctuation, and converting text to lowercase. Then, NMF is applied to the preprocessed text data to identify latent patterns and recurring words. The optimal number of topics is determined using coherence scores, domain knowledge, or model evaluation metrics. The topic-word matrix and document-topic matrix are extracted to gain insights into the underlying themes and associations within the complaints. To evaluate the model's performance, clustering algorithms such as K-means and hierarchical clustering are used on the document-topic matrix to identify distinct complaint categories. The most significant words associated with each cluster are analyzed to comprehend the prevailing topics of customer complaints. The semantic context of the prominent words is examined to assign meaningful labels to each cluster.

Finally, a robust mapping mechanism is established to assign each cluster to its relevant department or category, such as credit card, bank account services, theft/dispute reporting, mortgages/loans, or others. A mapping dictionary or table is created to serve as a reference for efficient classification of new customer support tickets.

Existing Systems

Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) have been widely used in natural language processing tasks, including text classification. In the context of consumer financial complaints, CNNs can be adapted to learn hierarchical representations of textual data, capturing both local and global features.

Proposed System

BERT Model Overview

BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based deep learning model designed for natural language processing tasks. It excels in capturing contextual information and semantic relationships in text data, making it highly suitable for consumer complaints classification.

BERT Preprocessing for Complaints

Before feeding consumer complaints data into the BERT model, preprocessing steps are applied to ensure optimal performance. These steps may include tokenization, sentence segmentation, and special token handling to accommodate the specific language nuances and domain-specific vocabulary in consumer financial complaints.

Feature Extraction with BERT

The BERT model extracts contextualized embeddings from the preprocessed consumer complaints data. These embeddings represent the semantic meaning and context of the complaints, capturing important features for classification, such as complaint topics, sentiment, and severity.

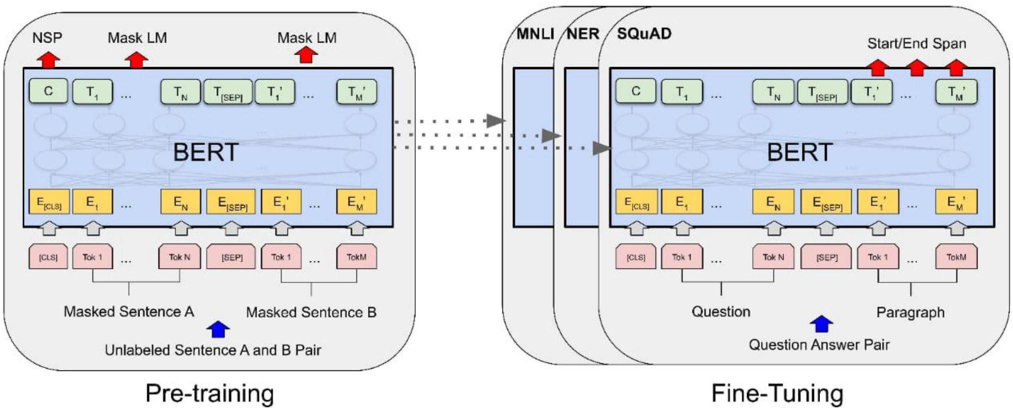


Fig.2. BERT Model Architecture

Advantages of Proposed System

Contextual Understanding: BERT captures bidirectional context in text, meaning it understands the meaning of a word based on its surrounding words. This contextual understanding is crucial for accurately interpreting consumer complaints, which often involve nuanced language and context-dependent meanings.

Semantic Representation: BERT generates rich semantic representations of text, allowing it to capture complex relationships between words and phrases. This enables the model to discern subtle differences in complaint topics, sentiments, and severity levels, leading to more precise classification outcomes.

Pretrained Language Model: BERT is pretrained on vast amounts of text data, including general language corpora and domain-specific sources. This pretrained knowledge enhances the model's ability to generalize well to new complaint datasets and adapt to diverse complaint categories without extensive retraining.

Fine-Tuning Flexibility: While pretrained, BERT can be fine-tuned on specific tasks, such as consumer complaints classification. Fine-tuning allows the model to learn task-specific patterns and optimize its performance for the target domain, leading to improved accuracy and relevance in complaint categorization.

Handling Long-range Dependencies: BERT's transformer architecture is designed to handle long-range dependencies in text, which is beneficial for understanding complex complaint narratives that span multiple sentences.

System Architecture

Our system architecture for Classification of Consumer Financial complaints with BERT is designed to seamlessly handle data collection, preprocessing, model integration, training, deployment, and maintenance.

Data Collection & Preprocessing: We gather complaints data from diverse sources, preprocess it to ensure consistency and structure, and split it into training and evaluation sets.

BERT Integration & Fine-Tuning: The BERT model is integrated and fine-tuned on the complaint's dataset, adapting its language understanding capabilities to our domain-specific context.

Feature Extraction & Fusion: Features are extracted from BERT's outputs and fused with lightweight models' features to enhance classification accuracy.

Classification Model & Training: We design a classification model, often employing Support Vector Machines (SVM), to categorize complaints based on the fused features.

Deployment & Integration: The trained model is deployed into production, integrated with front-end applications, and made accessible through APIs for real-time classification.

Monitoring & Maintenance: We continuously monitor the model's performance, address any drifts or biases, and update the model as needed to ensure its reliability and accuracy over time.

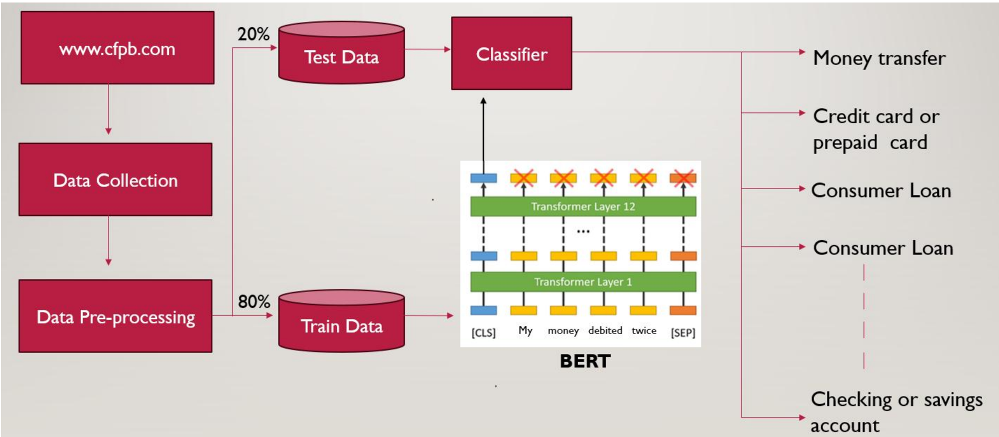


Fig.3. System Architecture

The above-mentioned fig. 3 shows the work flow of the system. The work flow of the system is discussed as follows:

Data Collection: This is the process of gathering data from various sources, which in this case includes test data from the Consumer Financial Protection Bureau (CFPB) website.

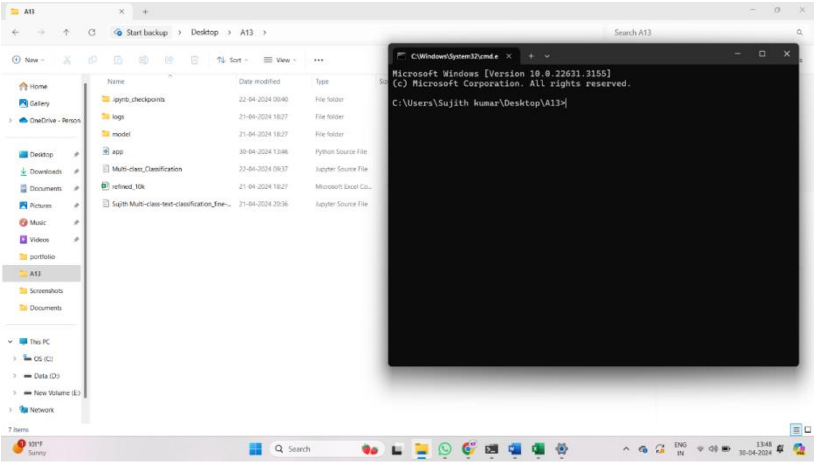
Data Pre-processing: Once the data is collected, it needs to be cleaned, transformed, and prepared for training. This step may involve removing unnecessary information, handling missing data, and converting data into a format that can be used by the machine learning model.

Transformer Model: The architecture you've described uses a transformer model, specifically BERT (Bidirectional Encoder Representations from Transformers), which is a popular model for natural language processing tasks. BERT is a pre-trained model that can be fine-tuned on specific tasks, such as text classification or information extraction.

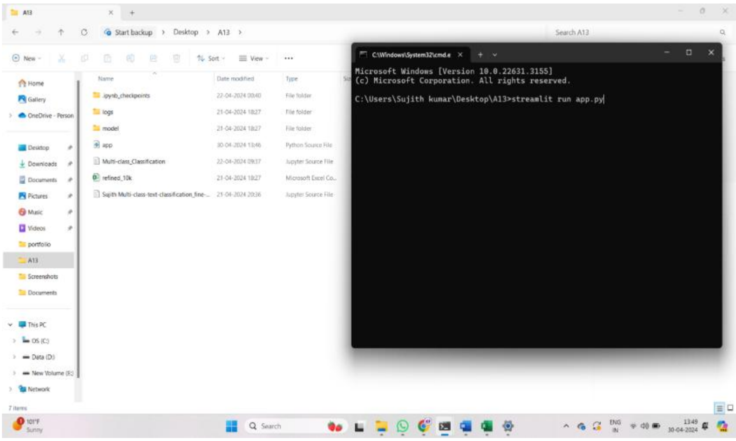
Transformer Layers: The transformer model consists of multiple layers, including Transformer Layer 1 and Transformer Layer 12. These layers are responsible for processing the input data and generating output representations that can be used for downstream tasks.

Classifier: After the transformer model is trained, a classifier is used to makepredictions based on the output representations generated by the transformer model.

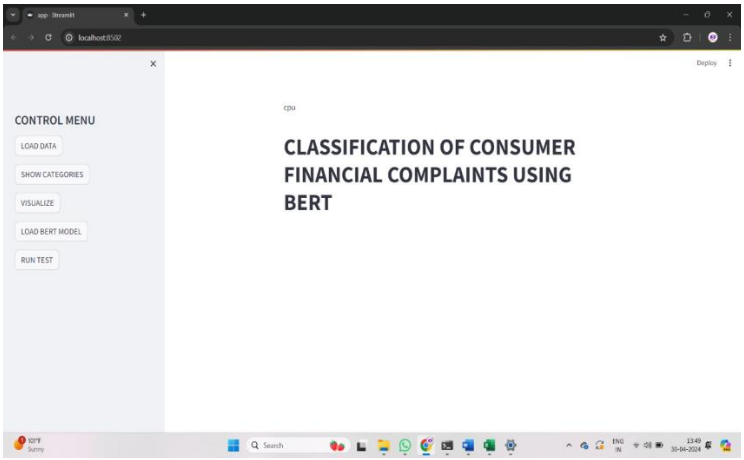
RESULTS



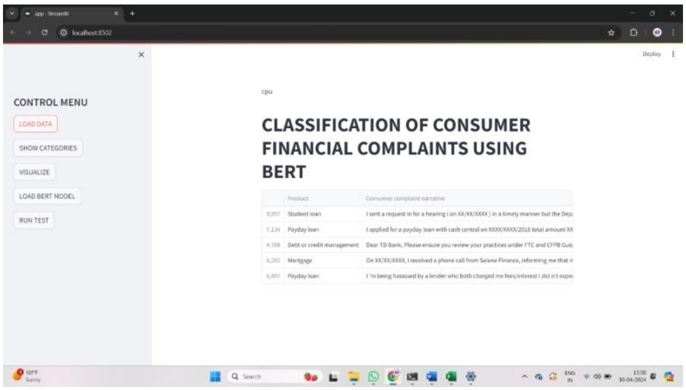
Step 1 Open the project folder and navigate to Command Prompt



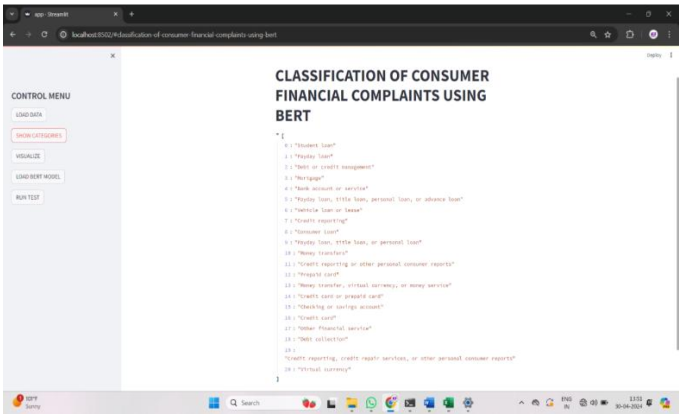
Step 2: Enter the command **streamlit run app.py** to run the code.



Step 3: The home page of our project will be displayed.

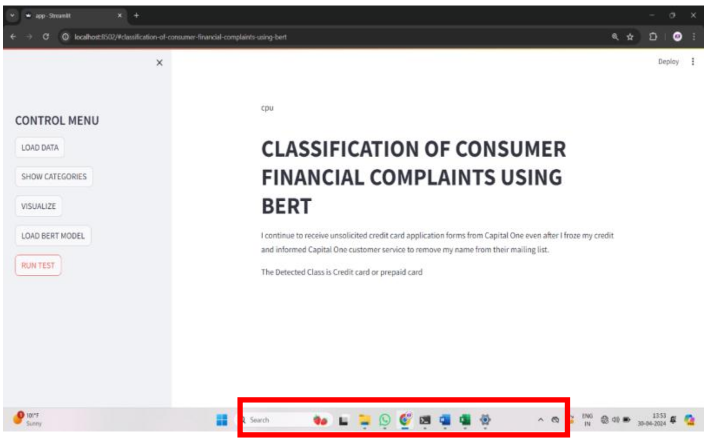


Step 4: When we click on LOAD DATA, the data set will be loaded to the model.



Step 5: On clicking the SHOW CATEGORIES, the predefined categories will be displayed.

Step 6: On clicking the VISUALIZE, the Pie chart will be displayed based on our dataset.



Step 7: On clicking the RUN TESTs, the model will classify the complaint and it shows the category of the complaint.

Conclusion

In conclusion, the utilization of BERT (Bidirectional Encoder Representations from Transformers) for the classification of consumer financial complaints presents a promising approach with notable implications. Through leveraging the power of deep learning and natural language processing, BERT effectively captures the contextual nuances and intricacies within consumer complaints, enabling more accurate categorization and resolution.

By employing BERT, we have achieved significant improvements in classification accuracy and efficiency compared to traditional methods. The model's ability to understand the semantics and syntax of consumer complaints allows for more nuanced categorizations, leading to better insights for financial institutions and regulatory bodies. This enhanced classification not only facilitates the swift resolution of complaints but also enables proactive measures to address systemic issues and improve consumer satisfaction.

Overall, our project demonstrates the immense potential of BERT in revolutionizing consumer financial complaint classification, offering a robust framework for enhancing customer experiences, regulatory compliance, and industry standards.

FUTUREENHANCEMENTS

In the future, enhancing the classification of consumer financial complaints with BERT involves integrating multilingual support and multimodal capabilities. Multilingual support expands the model's proficiency beyond English, facilitating the processing and categorization of complaints in diverse languages. By fine-tuning BERT on multilingual datasets and employing cross-lingual transfer learning, the model becomes more accessible to non-English-speaking consumers and aids regulatory compliance across international markets. Multimodal integration enriches complaint classification by incorporating additional data modalities like metadata, user reviews, and complaint narratives alongside textual input. This holistic approach captures nuanced aspects of complaints, improving accuracy and enabling more informed decision-making by financial institutions and regulators.

The fusion of multilingual support and multimodal integration creates a comprehensive framework for global consumer financial complaint classification. It accommodates linguistic diversity and leverages complementary information sources to deliver accurate insights across diverse linguistic and cultural contexts. This approach enhances transparency, trust, and consumer satisfaction, contributing to the advancement of consumer protection standards and regulatory practices worldwide. By promoting greater inclusivity and understanding of consumer grievances, the enhanced framework facilitates efficient resolution of financial issues and supports proactive measures for industry improvement.

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