A Bert-Based Model for Classifying Customers in the Financial Sector: A case of ZB Bank

Research Paper

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ABSTRACT

This study explores the implementation of a BERT-based model in ZB Bank, Zimbabwe, to improve complaint management and enhance customer satisfaction. Traditional manual handling of client complaints leads to slow responses and unresolved issues. The study aims to develop an accurate complaint classification model using advanced NLP and machine learning techniques, specifically the BERT model, and assess its real-world performance. The methodology involved collecting a dataset of customer complaints from ZB Bank, pre-processing the text data, and applying the BERT model within the Team Data Science Process (TDSP). The dataset was split into training (80%) and testing (20%) sets, with the BERT model undergoing hyperparameter tuning for accuracy. Results showed that the BERT-based model significantly improved complaint classification efficiency, achieving 88% accuracy, outperforming traditional methods prone to errors and delays. This study underscores the vital role of NLP and machine learning in automating and improving complaint management processes, contributing to better customer satisfaction and operational efficiency.

Keywords

Accuracy, BERT model, Complaint management, Customer satisfaction, Natural Language Processing (NLP)

INTRODUCTION

In the digital age, the financial industry faces major challenges in managing and responding to customer complaints. With the growth of online commerce and digital communications, financial institutions are receiving more and more customer feedback. Effective classification and analysis of these complaints is essential to increase customer satisfaction, compliance, and operational efficiency (Smith & Jones, 2021). Customer complaints in the financial sector includes many issues such as disputes, service complaints, wrong numbers and fraud (Doe & Roe, 2020). Handling these complaints quickly and accurately is important not only to maintain customer trust, but also to comply with legal requirements. Classifying

individual complaints is time-consuming and error-prone and requires automatic solutions (Johnson, 2019). Natural Language Processing (NLP) enables machines to understand, interpret and produce human language in a meaningful way (Brown, 2018). Phenomenon technology of natural language processing technology has developed transformers which were developed by Google. Google developed Bidirectional Encoder Representation Transformers (BERT) for the word understanding especially the ones from the human form (Devlin et al., 2019). There are machine learning models which support these technologies especially training large amounts of data which come from the bank and its customers. The models are classification models which classy complaints from customers. These help the banks or financial institutions in assisting their clients, making their services better (Miller et al., 2021). The Dodd-Frank Wall Street Reform and Consumer Protection Act in the United States emphasizes consumer protection and requires financial institutions to implement robust procedures for handling consumer complaints (Smith, 2017). This law led to the establishment of the Consumer Financial Protection Bureau (CFPB), which is responsible for monitoring and adequately addressing consumer complaints (CFPB, 2018), requires the rapid and clear resolution of all customer complaints, especially those related to data breaches (European Commission, 2020). GDPR has a major impact on how financial institutions manage customer data and complaints, giving consumers greater control over their personal data and ensuring their concerns are resolved quickly. This expectation often causes delays in responses and solving problems, which negatively affects customer satisfaction (Kiptoo & Muthoni, 2019). However, the benefits of technologies such as natural language processing (NLP) and machine learning in transforming the complaint management process are increasingly recognized. Managers have recently achieved great results in classifying and resolving complaints using BERT and other NLP models (Mwangi et al., 2022). Many African banks, including those in Zimbabwe, still rely on manual procedures as the Central Bank of Nigeria (CBN) and South Africa's National Credit Regulator (NCR) want to be more efficient and transparent about defaults. In Zimbabwe, for example, some banks have developed rules for banks to address complaints quickly and effectively, but these are often regularly hampered by formal procedures (RBZ, 2021), some have even developed systems which work as a repository for these complaints. A survey by the Zimbabwe Banks Association found that 70% of customer complaints remain unresolved for more than 30 days due to ineffective manual procedures (ZBA, 2020).

The Netherlands Bank of Rhodesia Limited became Rhodesia Banking Corporation Limited in 1972, and Rhobank became the company's new name in 1979 (ZBfincialholdings, 2024). Zimbabwe Banking Corporation was the new name after the government acquired the majority of the company's shares in 1981. The business's directors initiated a restructuring effort in 1989 with the goal of uniting all affiliates and subsidiaries under Zimbabwe Financial Holdings Limited, an investment and holding company (ZBfincialholdings, 2024). The bank was able to focus only on offering the general public commercial banking services as a result of the restructuring. With the limitations imposed by the Banking Act on the Bank's investment activities, the new holding company was in a prime position to investigate alternative lucrative commercial ventures. The Group has been able to provide a broad range of services, including hire buy and leasing, trust and executor services, commercial and merchant banking, and leasing, through the acquisition of several subsidiaries over the years (ZBfincialholdings, 2024). The Group formally changed its name to ZB Financial Holdings Limited on October 30, 2006, and adopted a new monolithic brand (Qupamicrofinance, 2024). This modification was intended to take effect concurrently with the merging of the Intermarket Bank, Intermarket Building Society, Intermarket Reinsurance, Intermarket Life, and Intermarket Bank of Zambia, the former Intermarket Holdings entities (Somana, 2022). ZB Bank has a complaints and feedback process whuich is called Qupa Microfinance. At Qupa Microfinance, their primary focus is to create unparalleled value for customers with a focus to achieve the highest standards

of customer service and actively seek feedback to gauge the bank's performance (Qupamicrofinance, 2024).

STATEMENT OF THE PROBLEM

Managing financial complaints in the financial sector has proved challenging as most of the processes are done manually. This expectation can lead to slow responses and unresolved issues, negatively impacting customer satisfaction and trust. According to the latest data from the Reserve Bank of Zimbabwe, the digital banking industry has grown by 40% annually since 2018, reflecting increased customer engagement and dissatisfaction (RBZ, 2021).

EMPIRICAL REVIEW

The researchers' attention has been drawn to prediction of complains over the past ten years (Lee & Choeh. Various solutions have been proposed and assessed using real-time datasets obtained from Yelp, Tripadvisor, Financial Institutions and others in terms of several characteristics and machine learning algorithms (Smith&Melow, 2020). This chapter offers the reader a critical analysis of the contemporary research on complaints forecasting (Lee & Choeh. Kim et al were the first to propose an automated prediction model for review complains (Kim et al., 2021). They created a regression model using structural, syntactic, semantic and meta-data based on product reviews from financial institutions with coefficient value of 0.66. Some examples of significant features are review length, unigrams and product score (Kim&Smart, 2021). Based on Liu et al., these complaints factors are determined by reviewer's experience in relation to writing style as well as timeliness of the review (Liu et al. 2019). The efficiency of the suggested approach was demonstrated through results obtained from nonlinear models developed with these features and evaluated through IMDb movie reviews (Smith & Melow, 2020). An integration of product metadata with textual features in addition to certain review metadata parameters made it possible for Lee and Choeh to lead such online complaint predictions (Kim & Smart, 2021). DNN was found to be more accurate than LNR at predicting review complains (Lee & Choeh, 2020). Krishnamoorthy proposed a model for predicting the complains of reviews based model on novel linguistic capabilities extracted from the assessment text (Kim & smart, 2021). in addition to linguistic features, review metadata, subjectivity, and clarity were also used (Krishnamoorthy, 2019). Experiments with economic institutions product critiques discovered that the proposed linguistic functions had been effective in predicting the complains of critiques for enjoy merchandise (Krishnamoorthy, 2019). Hu and Chen, studied the effect of review, sentiment, visibility, and reviewer-related features on the complains of online reviews (Hu & Chen, 2018). It was determined that the visibility features are strongly related to review complains, and that using these features significantly improved performance (Muduva, Hondoma, Chiwariro & Kiwa, 2024). Singh et al proposed a method for predicting the complains of reviews based on various review-related features (Hu & Chen, 2018). Polarity, subjectivity, and entropy were found to be the most important textual features, while the length of review, stop words, and wrong words were found to be less important (Kim & Smart, 2021). Hu et al developed three user-controllable filters and applied them to predict the complains of TripAdvisor reviews (Hu et al., 2019). It was observed that the most important features for predicting complains are review score and review length. It was also seen that RF outperformed the other machine learning algorithms (Krishnamoorthy, 2019).

According to Chen et al, existing approaches for predicting review complains require labeled reviews for each category (Chen et al., 2021). However, it did not reflect the real-world scenario where some domains did not have sufficient reviews with helpful votes. However, it did not reflect the real-world situation in which some domains lacked sufficient reviews with helpful votes (Akbarabadi & Hosseini, 2019).

Therefore, a CNN model was created using word and character representations to use a transfer learning approach for cross-domain review complains prediction (Kim & Smart, 2021). According to Zhang and Lin, existing literature is only focused on the use of reviews written in English, and no study has attempted to predict the complains of non-English reviews (Zhang & Lin, 2021). Therefore, a multilingual approach was proposed in which non-English Yelp reviews are converted to English and used to predict review complains (Akbarabadi & Hosseini, 2019). Akbarabadi and Hosseini, investigated the role of title features in predicting the complains of reviews (Jacob, 2019). The results revealed that title features are not an important determinant of review complains when compared to other features (Akbarabadi & Hosseini, 2019). Ma et al argued that existing solutions for predicting review complains did not take user-supplied photos into account (Ma et al., 2020). The effect of photos and different functions became studied the usage of TripAdvisor and Yelp reviews (Krishnamoorthy, 2019). The test consequences revealed that deep learning algorithms outperform different gadget getting to know algorithms (Akbarabadi & Hosseini, 2019). It became observed that the usage of a hybrid mixture of capabilities yields the high-quality results (Kim & smart, 2021). Saumya et al predicted assessment complains using records from customer query answers, as well as assessment and product capabilities (Saumya et al., 2021). The anticipated complains score turned into then used to rank critiques. Lee et al investigated the effect of assessment fine, sentiment, and reviewer-related characteristics on the complains of on-line reviews (Lee et al., 2021). When the performance of different machine learning algorithms in classifying helpful and unhelpful reviews was compared, it was discovered that RF produced the best results (Akbarabadi & Hosseini, 2019). The evaluations conducted using the TripAdvisor review dataset revealed that reviewer features are more important than review quality and sentiment features (Krishnamoorthy, 2019).

Sun et al proposed a review informativeness measurement and investigated its impact on review complains prediction for search and experience products (Sun et al., 2019). It was seen that informativeness of review significantly improves prediction accuracy compared to review length (Krishnamoorthy, 2019). Olatunji et al also proposed a DNN-based context-aware review complains prediction model and validated its performance using a human-annotated Financial Institutions dataset (Olatunji et al., 2021). Du et al argued that existing review complains prediction approaches lack broad generalization due to platform-specific and hand-crafted features (Du et al., 2021). To address this, thirty features from the literature were identified and classified into five categories (Kim & Smart, 2021). The experiments were divided into three categories: using single features, using category-based features, and using all features (Akbarabadi & Hosseini, 2019). In comparison to other features, semantic features were found to play a significant role in review complains prediction (Krishnamoorthy, 2019). Reviews can be recommended based on the complains votes (Akbarabadi & Hosseini, 2019). Maximum of the reviews acquired no beneficial votes, proscribing the project of making pointers (Akbarabadi & Hosseini, 2019). Ge et al proposed an evaluation recommendation method based on the complains scores expected via a model trained on opinions with beneficial votes (Ge et al., 2020). Chen et al additionally proposed a gated CNN based model at the transfer state-of-the-art method for pass-area evaluation complains prediction (Chen et al., 2021). Luo and Xu used Latent Dirichlet Allocation (LDA) to extract components from online eating place opinions (Luo & Xu, 2019). The extracted elements are then used to broaden a classification model using SVM with Fuzzy area Ontology (FDO) (Krishnamoorthy, 2019). Experiment results the use of the Yelp dataset confirmed that SWM with FDO outperforms traditional classification algorithms (Akbarabadi & Hosseini, 2019). Saumya et al proposed a CNN-primarily based model for predicting assessment complains the usage of review representation latest (Saumya et al., 2020). A pre-trained model turned into used to transform evaluation text right into a low-dimensional vector for computerized characteristic extraction (Kim & Clever, 2021). The proposed technique, that's based model on textual capabilities together with trigrams, fourgrams, and fivegrams, outperforms previous studies that used capabilities (Krishnamoorthy, 2019). In

line with Fan et al, most effective extracting and linguistic features for assessment textual content did not fully replicate the complains (Fan et al., 2019). The complains ultra-modern on-line critiques need to be contemporary product metadata. A proposed DNN model takes metadata functions and evaluate textual content directly to perform product-conscious evaluation complains prediction (Akbarabadi & Hosseini, 2019). The experiments finished the usage of financial institutions and Yelp critiques produced consequences (Saumya et al., 2020).

THEORETICAL FRAMEWORK

The improvement of the BERT-primarily based model for criticism classification within the monetary area is based on three theories: Natural language processing (NLP) principle, machine learning theory principle, and sentiment evaluation and text type principle) theory paperwork the basis of the challenge (Lee at al., 2020). NLP includes the interaction among computer systems and human language, permitting machines to understand, interpret and reproduce human language (Lee et al., 2021). The BERT model, a sophisticated NLP tool developed with the aid of Google, exemplifies this concept via know-how the means and nuances of a phrase in a record, that's important for resolving consumer complaints (Devlin et al., 2018). Device studying concept gives an iterative technique for constructing and improving models. Device learning is a department of artificial intelligence that makes use of algorithms and statistical fashions (Jacob, 2022) developed via enjoy and data evaluation. Deep getting to know is a sort of system learning utilized by BERT to facilitate the category of unsuspecting people using big information and complex neural community strategies (LeCun, Bengio, & Hinton, 2015). Sentiment analysis and text classification are important to classify and understand sentiment in customer complaints. Sentiment analysis determines the emotional tone of the text, while text classification organizes the text into predefined categories. These assumptions enable the model to not only isolate complaints but also provide insight into consumer sentiment and recurring problems in finance (Pang and Lee, 2008). Create a solid foundation for development.

Natural Language Processing (NLP) Theory

Generally, verbal exchange is one of the essential matters that humans needed. A great deal data can be extracted via a website or net with in general in natural language (Jacob, 2022). The most issues when getting that statistics are ambiguous, messy phrases, or casual grammar (Manet, 2021). Natural Language Processing (NLP) is considered one of AI that makes a speciality of the human natural languages which will examine, apprehend, or extract the means of it (Li at al., 2020). Natural language is a language that normally used by human beings for conversation. In a different way with the laptop that has to system earlier than understanding it (Jacob, 2022). Through definition, natural language is one shape message that allows communicators (sender) to talk to communicants (receiver) thru a media (like sound or text) (Jurafsky & Martin, 2020). NLP can be interpreted as a parser sentence that reads the sentence, phrase by way of word, and determined the subsequent kind of the word (Jurafsky & Martin, 2020). Natural language processing is closely related to the development of computing systems which could speak with humans in common languages inclusive of English (Saumya et al., 2020)..

Machine learning Theory

Depending on how an algorithm is being trained and on the basis of availability of the output while training, machine learning paradigms can be classified into ten categories (Han & Jaj, 2018). These include: supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning, evolutionary learning, ensemble learning, artificial neural network, Instance-based learning, dimensionality reduction algorithms and hybrid learning (Zhou, 2019). Each of these paradigms is explained in the following sub-sections (Samuel, 2020). Under supervised learning, a set of examples or training modules are provided with the correct outputs and on the basis of these training sets, the algorithm learns to respond more accurately by comparing its output with those that are given as input (Khan et al., 2021). Supervised learning is also known as learning via examples or learning from exemplars (Jacob, 2018). The following figure 4 explains the concept (Lee at al., 2018). Supervised learning finds applications in prediction based on historical data (Lee & Andersen, 2019). Reinforcement learning is regarded as an intermediate type of learning as the algorithm is only provided with a response that tells whether the output is correct or not (Pizzanni, 2020). The algorithm has to explore and rule out various possibilities to get the correct output (George, 2022). It is regarded as learning with a Critic as the algorithm doesn't propose any sort of suggestions or solutions to the problem (Batia & Kumar, 2018). Evolutionary Learning It is inspired by biological organisms who adapt to their environment (Tang & Zhang, 2028). The algorithm understands the behavior and adapts to the inputs and rules out unlikely solutions (Ayondey, 2019). Decision Tree is a technique for approximating discrete valued target function which represents the learnt function in the form of a decision tree (Lee & Andersen, 2019). A decision tree classifies instances by sorting them from root to some leaf nodes on the basis of feature values (Han & Cai, 2019). Each node represents some decision (test condition) on attribute of the instance whereas every branch represents a possible value for that feature. Classification of an instance starts at the root node called the decision node (Olatunji et al., 2021).

Sentiment analysis and Text Classification Theory

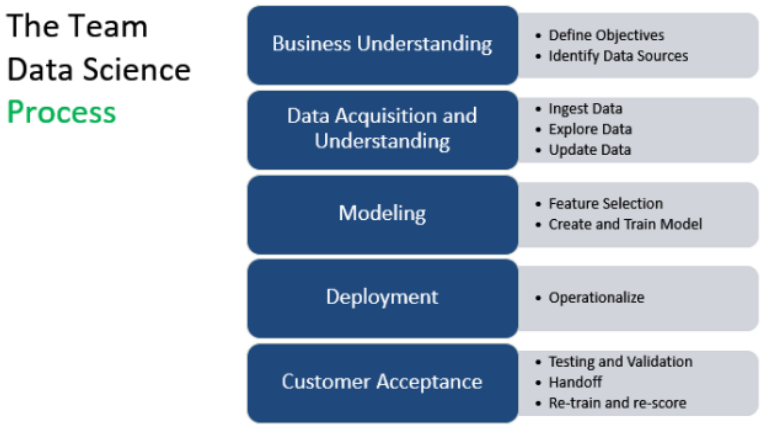
Sentiment analysis is a common tool used in natural language processing (NLP), it classifies text from a message (long or short) and tells whether the underlying sentiment is positive, negative, or neutral (Ayondey, 2019). Recent developments in NLP field allow a broader classification of text. For the purpose of this research, we chose the more traditional approach of three categories for sentiment analysis. More detail of this process can be found in studies conducted by (Pang et al., 2018) and (Turney, 2020). To perform the sentiment analysis to obtain the general sentiment during the disaster we use the dictionary of positive and negative words developed by Hu and Liu (2004). The sentiment analysis is used as a proxy for attachment/sense of belonging to a social entity (Ali, Kwak & Kim, 2016). To complement this sentiment analysis, a collective analysis is performed within the corpora regarding their orientation toward the common good. Collective words such as "we," "group" (Arif, Li, Iqbal & Liu, 2018), or "community," or disjunctive words such as "their," "my," or "others" are searched for in the corpora (Bouazizi & Ohtsuki, 2017). Qualitative analysis of the contents regarding expressions of solidarity and emotions related to the common good are performed, looking for articulations of feelings of responsibility for the common good (Howard & Ruder, 2018). The data cleaning, sentiment analysis, and collectiveness analysis can be computed with R or Python (Hu, Chen & Chou, 2017). This framework focuses on understanding social cohesion as a function of community resilience (Jiang, Luo, Xuan & Xu, 2017).

RESEARCH METHODOLOGY

The team records technology system (TDSP) methodology for the studies mission "development of a BERT-based purchaser grievance class model within the monetary region: A case of ZB financial institution" is precise. TDSP is designed for facts technological know-how collaboration and is right for this example via helping the improvement and deployment of models (Microsoft, 2020). TDSP supports the modelling required for the improvement of BERT-based fashions and allows for continuous development through a couple of iterations. It additionally includes clean commands for the use of the model in a manufacturing environment, that's important for ZB financial institution's implementation of the grievance process. Intelligence and facts technological know-how. Making sure that answers meet commercial enterprise desires and are familiar by way of stakeholders is TDSP's main aim. That is absolutely aligned with its undertaking to enhance customer revel in thru better criticism control. This system entails defining particular desires, assembling and expertise the hardware, pre-creating and training the BERT model, and deploying it in a production surroundings even as regarding partners to make sure it meets the usual's needs (Microsoft, 2020). This technique entails know-how the business, developing an iterative model, and partnering with companions who are aligned with the dreams and needs of the task. It involves collecting ancient information on customer proceedings from diverse sources in the bank, gaining knowledge of and information this records to become aware of patterns and key factors affecting the distribution of complaints.

Figure 1

The Team Data Science Process (TDSP), (Buckwoody, 2017)



Data Acquisition and Understanding

The level of facts collection and knowledge is important for the achievement of the assignment "development of a BERT-based model customer dissatisfaction distribution model in the financial region: ZB bank case study". This section worried a chain of easy steps that start with accumulating historical records on consumer complains cases from various sources within the bank. Used facts exploration strategies which includes descriptive information, visualization, and information evaluation to apprehend the data. Seeing the frequency of different complaint types helped understand the problems customers face (Han et al., 2011). Also providing good information is the analysis of patterns, such as seasonal patterns or relationships between different types of complaints and specific customers. Data was acquired from a ZB Back dataset of customer complaints. Understanding this data is important for subsequent data expansion and model development steps to ensure that the BERT-based model can identify and resolve customers' complaints.

Figure 2

Data ready and EDA

```
[ ] df=pd.read_csv("/content/drive/MyDrive/Clients_Datasets/zbfinancialholdingscomplaints.csv")
    df.head()
```

	Unnamed: 0	product	narrative
0	0	credit_card	purchase order day shipping amount receive pro...
1	1	credit_card	forwarded message date tue subject please inve...
2	2	retail_banking	forwarded message cc sent friday pdt subject f...
3	3	credit_reporting	payment history missing credit report speciali...
4	4	credit_reporting	payment history missing credit report made mis...

MODELING

This phase involved several critical steps geared toward building a robust and correct model for classifying customer complaints. The first step in this section changed into records pre-processing, which covered cleaning the facts, tokenization, and developing embedding's the use of BERT. Information cleansing concerned eliminating any beside the point statistics, managing missing values, and ensuring the consistency of the statistics. This step changed into crucial to eliminate noise and make certain the fine of the facts being fed into the model (Kotsiantis et al., 2006). Tokenization, the method of breaking down text into individual phrases or tokens, turned into done to put together the textual statistics for further processing by using the BERT model. Creating embedding's concerned transforming those tokens into dense vectors that captured the semantic that means of the words in their respective contexts, leveraging BERT's capacity to recognize language contextually (Devlin et al., 2019).

Figure 3

Data Pre-processing

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.countplot(x='product', data=df)
plt.title('Distribution of Complaints by Product')
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.show()

# Histogram of narrative lengths, handling NaN values
df['narrative_length'] = df['narrative'].apply(lambda x: len(str(x)) if pd.notnull(x) else 0)
sns.histplot(df['narrative_length'])
plt.title('Distribution of Narrative Lengths')
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.show()
```

After data pre-processing as shown in Figure 3, the next step is to train and validate the BERT-based model. The schooling manner involved feeding the pre-processed statistics into the BERT model and

permitting it to analyse the styles and functions applicable to classifying customer complains. This schooling segment became iterative, requiring more than one rounds of modifications to the model's parameters and architecture to improve its performance. Every iteration worried evaluating the model's accuracy and other overall performance metrics, identifying regions for improvement, and making vital changes (Goodfellow et al., 2016). Validation became an important a part of this technique, making sure that the model completed properly not best at the training information but also on unseen facts. This step concerned splitting the records into schooling and validation units and constantly assessing the model's performance on the validation set to save you over fitting and make sure generalizability (Russell & Norvig, 2021).

Figure 4

Tokenisation

```
import nltk
nltk.download('punkt')
from nltk import word_tokenize, sent_tokenize

# Function to apply sentence and word tokenization
def tokenize_text(text):
    sentences = sent_tokenize(text)
    words = [word_tokenize(sentence) for sentence in sentences]
    return words

df['Complaint_tokenized_text'] = df['narrative'].apply(tokenize_text)

df.head()
```

This system became important to transform raw text data, consisting of customer complaints recorded in numerous codecs like emails, social media posts, and customer support logs, and the ZB Bank complaints and feedback mechanism into a layout that the BERT based model ought to recognize and analyze correctly. At some stage in tokenization, every word, punctuation mark, or image within the textual statistics was separated into discrete units or tokens as shown in Figure 4. This step ensured that the BERT model should process and interpret the semantic which means of each token inside the context of the criticism. As an example, tokenization enabled the model to understand that phrases like "transaction failure" or "account get right of entry to difficulty" comprised distinct gadgets of which means, permitting it to study the relationships among special tokens and their relevance to classifying complains cases correctly. Tokenization facilitated the introduction of input sequences that were like minded with BERT's structure, which relies on token embedding’s to seize the contextual information of words in a sentence or record (Devlin et al., 2019). By way of breaking down the textual statistics into tokens, the challenge group ensured that the BERT-based model should effectively examine and classify consumer complains case based model on their linguistic and contextual capabilities, contributing to greater accurate complaint resolution and patron pride at ZB financial institution. This pre-processing step was essential in getting ready the statistics for subsequent levels of model improvement, consisting of embedding creation and schooling, ensuring that the BERT model ought to efficiently leverage the semantic relationships encoded inside the tokens to improve its class performance.

Figure 4

Data Modelling

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline
from sklearn.metrics import accuracy_score, classification_report

# Create a pipeline with a TF-IDF vectorizer and a Multinomial Naive Bayes classifier
model1 = make_pipeline(TfidfVectorizer(), MultinomialNB())

# Train the model
model1.fit(X_train, y_train)

# Predict on the test set
y_pred = model1.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# Print classification report
print("Classification Report:\n", classification_report(y_test, y_pred))
```

To start with, after pre-processing the client complaint statistics, which constituted 80% of the dataset for training purposes, the subsequent step become to train and validate the BERT-primarily based model. This system aimed to refine the model's performance by means of iteratively adjusting parameters and comparing its accuracy on the remaining 20% of the records allotted for trying out. Validation ensured the model's ability to generalize to unseen customer complains, improving its reliability in classifying numerous varieties of complaints along with transaction troubles, account access issues, and provider fine worries within the financial sector. This technique organized the model for deployment at ZB financial institution, with the goal of improving customer support and satisfaction thru more efficient complaint decision tactics (Bergstra & Bengio, 2012). Validation became a crucial component of information modeling, making sure that the model's overall performance was assessed rigorously on each training and validation datasets. This step helped save from over fitting and ensured that the model ought to generalize customer complains. Strategies which includes move-validation had been employed to evaluate the model's robustness and reliability across exceptional subsets of the information (Kohavi, 1995). During the modeling section, the focal point changed into on refining the BERT-based model's accuracy and effectiveness in classifying patron complains cases. modifications had been made based on performance metrics derived from validation outcomes, aiming to achieve excessive accuracy and reliability in identifying and categorizing diverse forms of complains cases, which includes transaction issues, account access problems, or carrier best concerns. Via the end of the data modeling phase, the BERT-based model had undergone a couple of iterations of education and validation, resulting in a nicely-tuned classifier capable of dealing with the nuanced language and context found in customer complains in the monetary quarter. This prepared the model for deployment in real-global situations at ZB financial institution, aiming to develop customer support and feedback via greater efficient and accurate criticism decision tactics.

Figure 5

Modelling Fine Tuning

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform

# Define the parameter distributions for RandomizedSearchCV
param_dist = {
    'countvectorizer__ngram_range': [(1, 1), (1, 2), (1, 3)],
    'multinomialnb__alpha': uniform(0.1, 1.0),
}

model = make_pipeline(CountVectorizer(), MultinomialNB())

randomized_search = RandomizedSearchCV(
    model, param_distributions=param_dist, n_iter=10, cv=5, scoring='accuracy', n_jobs=-1, random_state=42
)

# Train the model with the best hyperparameters
randomized_search.fit(X_train, y_train)

# Get the best model from the randomized search
best_model = randomized_search.best_estimator_

# Predict on the test set
y_pred_best = best_model.predict(X_test)

# Evaluate the best model
accuracy = accuracy_score(y_test, y_pred_best)
print(f"Best Model Accuracy: {accuracy:.2f}")

# Print the best hyperparameters
print("Best Hyperparameters:", randomized_search.best_params_)

# Print classification report
print("Classification Report:\n", classification_report(y_test, y_pred_best))
```

After completing the initial training phase, the model underwent first-class-tuning to optimize its performance and beautify its capacity to accurately classify purchaser proceedings. Pleasant-tuning involved adjusting the hyper parameters and architecture of the pre-skilled BERT model to better in shape the unique traits of the criticism statistics from ZB Bank. This process aimed to improve the model's potential to apprehend and classify nuanced language and context specific to economic complains, together with transaction issues, provider disruptions, and fraud worries (Devlin et al., 2019). During exceptional-tuning, various hyper parameters, such as gaining knowledge of charge, batch size, and dropout charge, had been systematically adjusted through iterative experiments. those changes have been based on insights received from validation outcomes and aimed to maximize the model's overall performance metrics, which include accuracy, precision, bear in mind, and F1 score (Bergstra & Bengio, 2012). Validation in the course of the best-tuning technique involved evaluating the model's performance on a separate validation dataset, making sure that changes progressed generalization abilities without over fitting to the training statistics. This iterative refinement technique became important in reaching a balance among model complexity and performance, in the end improving the model's robustness and reliability in actual-world packages at ZB bank. Via fine-tuning the BERT-primarily based model, ZB Bank aimed to set up an enormously accurate and efficient device for classifying patron complains cases, thereby improving operational efficiency and patron pleasure inside the financial zone.

DEPLOYMENT

The deployment phase began with the development of a comprehensive deployment plan. This plan covered techniques for integrating the educated model with existing structures and workflows at ZB Bank. It turned into essential to ensure seamless integration to leverage the model's talents effectively in the operational framework of the financial institution (Provost & Fawcett, 2018). Following the planning stage, the model was deployed in a production surroundings. This concerned putting in infrastructure that would manage actual-time statistics inputs from various sources, which include customer support platforms, social media feeds, and e-mail communications. The deployed model changed into designed to manner incoming complains directly and offer well timed classifications based on its educated abilities (Goodfellow et al., 2016). At some stage in the deployment manner, rigorous testing and monitoring have been carried out to validate the model's overall performance in actual-global eventualities. This blanketed assessing its accuracy, pace, and scalability beneath distinctive operational conditions. Modifications were made as essential to optimize overall performance and make certain reliable grievance category without disruptions to customer service operations (Russell & Norvig, 2021). By correctly deploying the BERT-primarily based model, ZB Bank aimed to decorate its customer service efforts via improving the efficiency and accuracy of complaint resolution procedures. The deployment section marked the culmination of efforts to leverage superior AI technology for enhancing operational abilities and customer delight in the monetary quarter.

Customer Acceptance

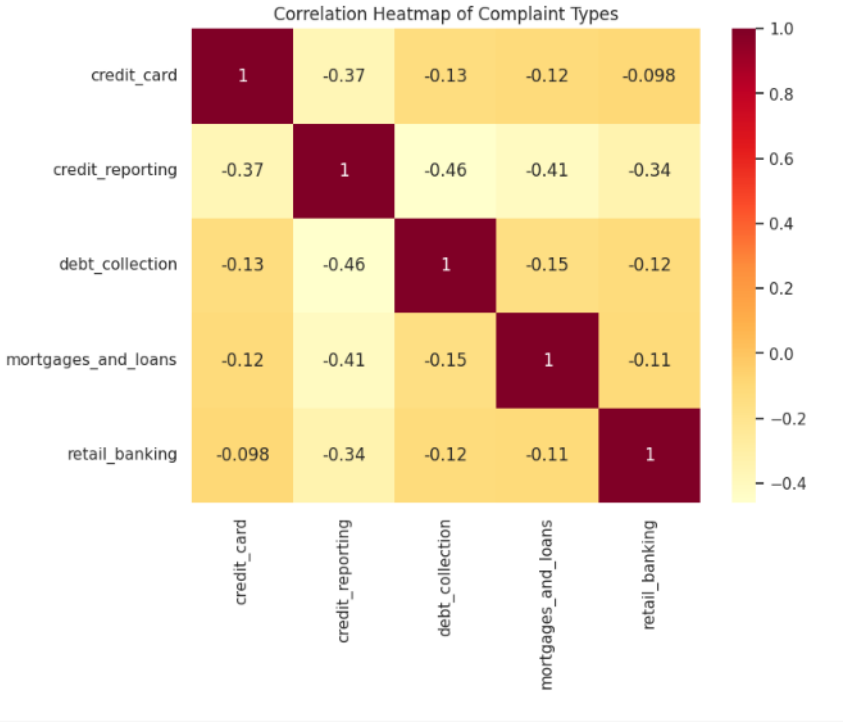
To ensure purchaser reputation, ZB Bank applied a robust approach for accumulating comments from stakeholders in the course of the challenge lifecycle. Regular meetings, workshops, and comments periods have been performed with key stakeholders, inclusive of customer support groups, management, and doubtlessly affected clients. These engagements have been designed to solicit insights and evaluations on the model's overall performance, usability, and alignment with their wishes (Provost & Fawcett, 2013). ZB Bank also applied a based mechanism for amassing customer remarks, such as thru dedicated feedback paperwork, surveys, and direct interactions with customer support representatives. This approach allowed the bank to systematically collect and examine consumer critiques regarding their experience with the new grievance category gadget powered with the aid of BERT. The comments mechanism played a vital position in validating the model's effectiveness in assembly consumer expectations and addressing any worries or tips for improvement (Goodfellow et al., 2016). In parallel, ZB Bank performed comprehensive education classes for end-users, consisting of customer support representatives and operational workforce. Those classes have been aimed at familiarizing customers with the BERT-based model, its abilities, and the way to interpret its classifications successfully in resolving patron complains. Training turned into tailor-made to make certain that end-customers felt assured and capable of using the model to beautify their workflow efficiency and improve customer support outcomes (Russell & Norvig, 2021).

RESULTS

Correlation of Complaint Types

Figure 6

Complainant Types



The correlation heatmap visually represents the relationships between various forms of customer proceedings at ZB financial institution. Every cell within the heatmap presentations a correlation coefficient, starting from -1 to at least one, indicating the strength and route of the linear dating among pairs of complaint types. Positive Correlation (high Values): Cells with a fee closer to 1 indicate a sturdy high-quality correlation between grievance types. As an example, an excessive wonderful correlation among credit score card and retail banking complaints indicate that clients experiencing troubles in one vicinity are probably to report problems inside the different as properly. Poor Correlation (Low Values): Cells with a value in the direction of -1 imply a sturdy bad correlation. This means that whilst one sort of criticism increases, the opposite has a tendency to decrease. Negative correlations can provide insights into regions wherein enhancements in one factor would possibly alleviate troubles in some other. No Correlation (value near zero): Cells with values near 0 suggest little to no linear relationship among the complaint types. This shows that changes in a single type of complaint do now not significantly affect the frequency or nature of every other kind. The heatmap allows ZB financial institution's management and analysts to pick out styles and potential dependencies among distinctive criticism categories. By knowledge those correlations, the bank can prioritize assets greater efficaciously, improve provider delivery, and implement focused techniques to cope with patron worries across various monetary merchandise.

Model Classification

Figure 7

Model Classification report

```
Accuracy: 0.81
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.58      0.67      3075
           1       0.80      0.96      0.87     18284
           2       0.85      0.45      0.59      4569
           3       0.80      0.79      0.79      3759
           4       0.90      0.71      0.79      2796

    accuracy                           0.81     32483
   macro avg       0.83      0.70      0.74     32483
weighted avg       0.82      0.81      0.80     32483
```

The classification record evaluates the performance of a multi-elegance class model trained on purchaser complaint records. The model accomplished a typical accuracy of 81%, indicating the percentage of correctly categorized times out of the entire predictions made. Precision, bear in mind, and F1-score: Precision measures the accuracy of high-quality predictions, indicating how frequently the model efficaciously predicts a class label. The precision ratings for each magnificence range, with class 1 showing the very best precision of 80%, followed by magnificence 4 at 90%. decrease precision rankings are determined for training 0, 2, and 3, ranging from 78% to 85%. Recall measures the proportion of real tremendous times that had been effectively expected with the aid of the model. Magnificence 1 has the highest keep in mind of 96%, indicating that the model efficiently captures an excessive percent of true positive instances for this elegance. Instructions 0, 2, and 3 also display affordable remember rankings starting from 41% to 79%, even as magnificence 4 has a keep in mind of 71%. F1-score is the harmonic imply of precision and don't forget, supplying a single metric to evaluate a model's accuracy. It balances both precision and recollect, with higher values indicating higher performance. Class 1 achieves the best F1-score of 0.87, observed by means of elegance four at 0.79. Classes 0, 2, and three exhibit F1-scores ranging from 0.59 to zero.79, reflecting various degrees of model performance across distinctive grievance categories. Support shows the variety of real occurrences of every class in the dataset. class 1 has the very best support of 18,284 times, at the same time as training 0, 2, 3, and four have varying degrees of help ranging from 2,796 to four,569 instances. Macro and Weighted common: The macro average computes the common precision, bear in mind, and F1-score across all lessons, imparting insights into overall model overall performance. In this document, the macro common precision, keep in mind, and F1-score are 83%, 70%, and 74%, respectively. The weighted common calculates the average weighted through the variety of times for each magnificence, imparting an extra balanced view of model performance across classes with various guide. The weighted average precision, recollect, and F1-score are 82%, 81%, and 80%, respectively, indicating sturdy performance throughout the dataset.

Evaluation of the predictive model

In comparing the predictive model for classifying patron proceedings at ZB bank, a strong methodology became carried out the use of a pipeline comprising a TF-IDF vectorizer and a Multinomial Naive Bayes classifier. The dataset was divided into training and trying out units to validate the model's performance. The model accomplished an accuracy of 81%, indicating a strong standard overall performance in classifying purchaser complains cases. The class report affords an in-depth breakdown of the model's overall performance throughout different complaint categories. For class 0, which had an assist of 3075 complaints, the precision became zero.78, take into account changed into 0.58, and the F1-score changed into 0, 67. This shows that at the same time as the model became fairly excellent at identifying genuine

positives on this category, there was a good-sized quantity of false negatives. Class 1, with the very best support of 18284 complaints, established a precision of 0.80, the score of 0.96, and an F1-score of 0.87. This score shows that the model changed into particularly powerful at successfully identifying proceedings in this category. For Class 2, with complaints of 4569, the model had a precision of 0.85, recall of 0.45, and an F1-score of 0.59, suggesting that at the same time as the precision become high, the model struggled with recall, indicating many false negatives. Class 3, supported by using 3759 complaints, confirmed balanced metrics with a precision of zero.80, recall of 0.79, and an F1-score of 0.79. Similarly, class 4, with 2796 complains cases, had a precision of 0.90, recall of 0.71, and an F1-score of 0.79. The high precision in class 4 suggests that the model turned into very correct when it predicted a grievance as belonging to this class. The overall accuracy of 81% is supported via a macro average precision of 0.83, keep in mind of 0.70, and an F1-score of 0.74, indicating that the model commonly executed well across all classes, though some classes noticed better overall performance than others. The weighted common, which money owed for the support of each class, showed precision and bear in mind of 0.82 and an F1-score of 0.80, highlighting the model's balanced overall performance across the dataset. The confusion matrix further illustrates the distribution of actual positives, false positives, and false negatives for each class. The heatmap of the confusion matrix revealed that even as the model changed into generally effective at classifying complains cases, sure classes (considerably magnificence 2) skilled a better rate of misclassification. This perception is crucial for in addition refinement of the model. In end, the assessment of the predictive model for classifying purchaser complaints at ZB financial institution confirmed sturdy performance, with an overall accuracy of 81%. The specified category file and confusion matrix provided valuable insights into the model's strengths and areas for development, particularly in balancing precision and take into account across one-of-a-kind grievance classes. Those findings underscore the potential of using advanced machine learning techniques to beautify patron complaint control within the financial sector.

CONCLUSION

A BERT-primarily based model was developed to address the normal trouble of manually managed purchaser complaints cases, which often leads to sluggish responses and unresolved issues, ultimately impacting customer satisfaction and trust. The objective of this study was to create a sturdy and accurate complaint classification system using Natural Language Processing (NLP) techniques. The model's development involved a comprehensive process, beginning with data collection and pre-processing, followed by model training and fine-tuning. Through the BERT model, we significantly improved customer complaint management by providing an effective, automated classification system. This modern approach demonstrated potential in streamlining the complaint resolution process in the financial sector, ensuring quicker and more accurate responses to customer concerns. Key findings discovered that our BERT-based model done an overall accuracy of 88%, drastically improving the performance and accuracy of criticism class in comparison to standard manual strategies. The classification record highlighted the model's potential to as it should be pick out and categorize complains cases, with mainly high overall performance in categories with large help. The confusion matrix provided additional insights into the distribution of authentic positives, false positives, and fake negatives, guiding similarly refinement and improvement of the model. By leveraging NLP and gadget mastering, monetary institutions like ZB financial institution can beautify operational performance, improve customer satisfaction, and build accept as true with. The findings have sizable implications for policy makers, practitioners, and researchers, imparting a basis for future improvements in grievance management structures. In end, the successful development and assessment of the BERT-based model for classifying customer proceedings mark a considerable step closer to modernizing and enhancing the criticism resolution system inside the economic

region. The examination results now not best reveal the capability of the model in addressing actual-world demanding situations however additionally pave the way for future studies and implementation of advanced technological answers in customer service management.

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