Opinion Mining and Sentiments Analysis Based on Customer's Comments on the X Platform: A Case of a Selected Bank in Zimbabwe

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Abstract

This study explores the development of an opinion mining and sentiment analysis system targeting customer comments on the X platform for a selected bank in Zimbabwe. Utilizing Natural Language Processing (NLP), the system classifies sentiments into positive, neutral, and negative categories, aiming to enhance customer satisfaction by addressing the identified sentiments. The research employs a design science methodology, focusing on constructing an effective and sustainable system. Key findings indicate that 90% of the participants found the system effective, with a 100% reliability score and 70% cost-effectiveness score. The system's ability to analyse unstructured data demonstrates its potential in improving decision-making processes for the bank by providing insights into customer sentiments. Future recommendations include the implementation of multi-linguistic analysis and real-time sentiment polarity assignments to enhance performance. The study underscores the importance of leveraging social media data to understand customer opinions and improve service delivery, positioning sentiment analysis as a critical tool for customer relationship management and business intelligence.

Keywords—Sentimental Analysis, X, Opinion Mining, social media, Customer feedback

I. Introduction

Over the years, Opinion Mining and Sentiment Analysis have become very active areas of research. Furthermore, Opinion Mining and Sentiment Analysis evaluate different users' opinions, attitudes and emotions toward entities, individuals, issues, events, topics, and products. Sentiment Analysis along with Opinion Mining are two processes that aid in classifying and investigating the behaviour and approach of the customers concerning the brand, product, events, company and their customer services (Neri et al., 2012). Opinion Mining using Social Media platforms is still in its infancy, although there is a growing interest for several reasons. Opinions are of paramount importance because they are key influencers of people's behaviour. Also, Social Media such as X, has made it very easy for users to share opinions, interests and ideas on the internet platform and make them visible worldwide. Looking at the statistics provided by X social media, users or clients that are active monthly range at about 316 million, and on average, about 500 million tweets are sent daily on X (Internet Live Stats, 2024). This yields an unprecedented amount of user opinions on several products, services or political events. In the past years, an organisation had to conduct surveys to get the opinions of users or voters.

Social Media platforms give access to large amounts of user opinions. For the first time in human history, a huge volume of opinionated data is now available on social media on the internet. Opinion mining using data from social media platforms has been used in many domains. It has been used to find out about a company's online reputation through reviews, to detect new trends from comments, to analyse user intents and to gain knowledge. Opinion mining using Social Media (SM) data poses many challenging problems which makes it a very interesting area of research. Social media platforms like X or Facebook have gained high attention from many researchers as they allow people to share and express their opinions about topics and post messages across the world in a simple way (Alayba et al., 2017).

Customer complaints accumulate day by day and a branch manager cannot attend to all of them at once. Some of these complaints are handled through phone hotlines. However, through the emergence of the X platform, some customers end up using this platform for quicker response and traceability of quarries rather than relying on telephone conversations. Phone hotlines do not generate an audit trail of conversations and customers queue to see the branch manager thereby taking time and leading to decreased customer satisfaction.

There are several reviews and comments which are difficult to analyse manually on social media. Since opinions are subjective, one opinion is usually not enough for an application and a collection of opinions needs to be analysed. X Sentiment Analysis (XSA) tackles the problem of analysing tweets in terms of the opinions they express from person to person (Giachanou and Crestani, 2017). Using opinion mining and XSA, a large amount of data can be collected and analysed, and there is no need to select a sample.

The objectives of the paper were to:

- Design and implement a framework for identifying key factors in user-generated content on X classifying opinions as positive, neutral and negative.
- Identify client's satisfaction with provided services through opinions analysis.
- Evaluate the accuracy of tweet mining and sentiment classifications

II. Literature Review

There are a plethora of ways in which social media data can be used, this can include optimizing customer data to improve sales, brand awareness, and market surveys among others. To manage customers and improve customer image, companies can leverage artificial intelligence techniques such as Data Mining, Machine Learning, Decision Trees, and Neural Networks among other techniques to improve company image. The task of opinion mining is to retrieve nuggets of data from textual data to determine useful information that can be used by companies and government organisations.

There are a variety of algorithms and models that can be employed for Opinion Mining and Semantic Analysis such as Natural Language Processing and Supervised Learning with techniques such as the Lexicon-based approach, Naive Bayes Classifier, Support Vector Machines and Decision Trees among others (Al-Qablan et al., 2023; Gupta and Agrawal, 2020; Md Suhaimin et al., 2023; Neo, 2023), and there is no single Machine Learning model that is appropriate to every opinion mining problem. The same holds also for sub-problems like mining X data. These systems are also expensive to purchase and hence there is a need to develop heritage-based solutions for use in the Zimbabwean context and thereby promote local solutions. The following section discusses opinion mining and related work on sentimental analysis related to banks or mobile network operators.

1. Opinion Mining/Sentiment Analysis

Information sharing through X has increased and most users actively share their personal ideas and information publically using text or pictures. This information for a researcher is a gold mine to dig out valuable information for strategic decision-making (Younis, 2015). Most people review others' opinions and openly convey their views, agreeing or disagreeing with the argument. For example, asking clients about a bank's customer service, and looking over public reviews of a product before it is launched. X is an online social networking site and contains a large number of active users who enthusiastically share their thoughts and reviews on posted tweets. These reviews, written by the users, express their sentiments towards the topics tweeted. Fishing out sentiments embodied in the user's written opinions helps in understanding the overall view of people at large determining whether the event is positive, negative or neutral and is called opinion mining or sentiment analysis. X is considered a very important platform for data mining by many researchers. The X platform contains more relevant information on particular events with hashtags that have been followed and accepted by many popular personalities (Hemalatha et al., 2014).

2. Handling of Grievances and Opinions in Banks

In the banking sector, the branch manager is responsible for the resolution of complaints or grievances of customers. The bank manager is responsible for ensuring the closure of all complaints received at the branches. It is the foremost duty of the bank manager to see that the complaints are attended to and solved completely to the customer's satisfaction. If the customer is not satisfied, then there should be a provision for alternative ways to resolve the complaints. If the branch manager fails to solve the problem, the case is referred to the 'divisional office' for guidance. Similarly, if the 'divisional office' finds it difficult to solve the problem, such cases may be referred to the nodal officer (Uppal, 2010).

3. How Banks Use Social Media for Opinion Mining

Banks use social media awareness to generate pricing paradigms for loans, services and other banking products with available information in the public social domain, such as Facebook, X, and other social networking sites (Sumathi and Sheela, 2017). Using Opinion Mining and Sentiment Analysis helps make an information system for classifying the bank's loan price analysing customer satisfaction, automatically responding to customers, risk analysing through social media and creating strategies to improve wherever companies fail. The researchers explored Opinion Mining and Sentiment Analysis concept in a local bank in Zimbabwe.

4. Applications of Opinion Mining and Sentimental Analysis

Opinion Mining offers a way into the thoughts and feelings of the public, allowing businesses to improve the customer experience, perform competitive research, and understand the opinions of the public at large. Opinion Mining and Sentiment Analysis applications are social media analysis, brand awareness, customer feedback and market research. The speed at which opinions or views move on social media is astonishing. Thinking how often for example Omega Bank business is mentioned on social media. It is impossible to monitor social media mentions manually. Machine Learning tools allow researchers to perform social listening and social media Opinion Mining constantly, and in real-time so that one never misses a mention. Opinions about brands and products offered on X as a social media platform are often truthful because the user feels compelled to offer them. Facebook has a character limit of 63,206, it is one of the best platforms where individuals air their views. X has a limited number of tweet characters of 280 for each tweet (Gligorić et al., 2020) and use of hashtags between words which facilitates processing and quick search. This has attracted the researchers to analyse X data for this research.

Open Dover is a web service that performs sentiment analysis tagging on any piece of text provided. The user provides the content to be analysed and the content is returned as feedback with sentiment tags and negative or positive appraisal of the whole file. To analyse, Open Dover makes use of a knowledge base of opinion words, domain-related words and intensifiers and distinguishes between context-dependent and context-independent opinion words. In addition, Open Dover tries to identify some commonly used domains and evaluates a piece of text taking into consideration these domains. Unfortunately, the result is not always as expected, since there is a limit on the available domains ready to be used.

Hemalatha et al. (2014) show an approach for pre-processing X-row data following simple steps and demonstrate how to prepare the data for training using Machine Learning. This approach eliminates unnecessary data or text such as slang, abbreviations, URLs, and special characters from the linguistic data and also reduces the size of the dataset which is fast to analyse. Mercha and Benbrahim, (2023) discussed different approaches for sentiment analysis using the Machine Learning technique and Lexicon Based approach. The case study compared sentiment analysis for three different products and brands using Naive Bayes Algorithm as a baseline classifier, which shows significant results or output with accuracy for product safety on the market.

Augustyniak et al. (2015) proposed a new method called "frequentiment" that robotically evaluates sentiments (opinions or comments) of the user from Amazon reviews dataset. Improving the work in this method, they developed a dictionary of words by calculating the probabilistic frequency of words present in the text and evaluated the influence of polarity scored by separating the features present in the text, each word assigned its polarity. They analysed the outcome that was produced by the unigram, bigram and trigram lexicon using a Lexicon-based approach, supervised and unsupervised Machine Learning approaches, and compared several Machine Learning methods to evaluate results in analysing the Amazon dataset. Go et al. (2009) introduced a novel approach for automatically classifying the sentiment of X messages. These messages are classified as either positive or negative for a query term. The paper describes the pre-processing steps needed to achieve high accuracy. The main contribution of this paper is the idea of using tweets with emotions for distant supervised learning. Different Machine Learning approaches have been used in this paper thus usage of unigrams and bigrams

III. Methodology

Research design is the researcher's overall view for answering the research questions or testing the research hypothesis (Beck et al., 2013). The core objective of this stage is to ensure that an operative, proficient, sustainable and reliable system is designed.

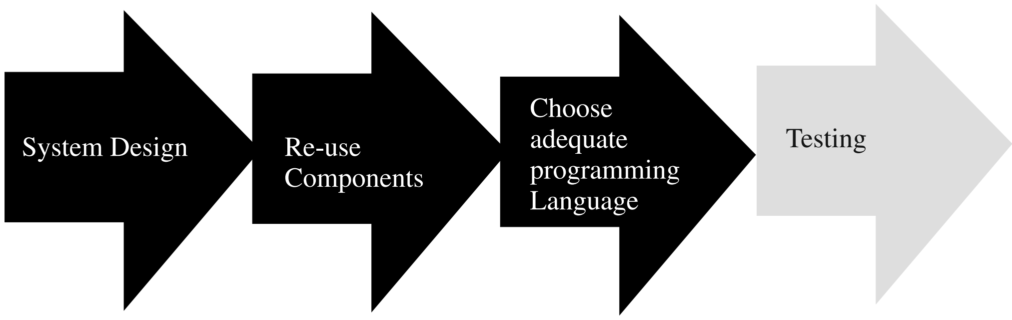

Figure 1: The design methodology and design science research methodology adopted from (A1-Qablan et al., 2023; Peffers et al., 2007)

The researchers used the build research methodology and design science methodology (Elio et al., 2011; Peffers et al., 2007) which consists of building an artefact either a physical artefact or a software system to demonstrate that it is possible. To be considered research, the construction of the artefact must be new or it must include new features that have not been demonstrated before in other artefacts (Elio et al., 2011). The methodology consists of four phases to develop the systems, which are illustrated in Figure 1 above.

Problem identification and motivation- The research problem was identified as banks have X handles that they manage in addition to helpdesk and customer care. Their handles have vast amounts of unstructured data that can be harvested to identify hidden patterns.

Define objectives for a solution- the researchers proposed objectives for the design of a prototype tool to classify customer sentiments on whether they are positive or negative. This was needed as negative sentiments have the potential to introduce negative publicity of a company since X handle is public. It was also important to examine customer tweets to determine if it was a complaint or a compliment. Functional requirements of the proposed tool were that the system should be able to mine opinions and that the system should be able to do sentiment analysis thereby classifying opinions as positive, neutral or negative and that the system should be able to automatically like tweets with specified text or hashtag thereby the system improving customer recognition.

Design development– After gathering system requirements, purposive sampling was used to determine requirements with some employees working in the customer care department, the employees were delighted by the proposed concept and they managed to review the initial prototype and concluded that the system was worth adopting since it improves customer satisfaction and helps in decision making for the bank. The researchers designed the system and considered a modular approach, which allows for simplification of system testing to increase the flexibility and reuse potential of the system. A framework was used to inform the design of the system. Figure 2 shows the proposed conceptual framework.

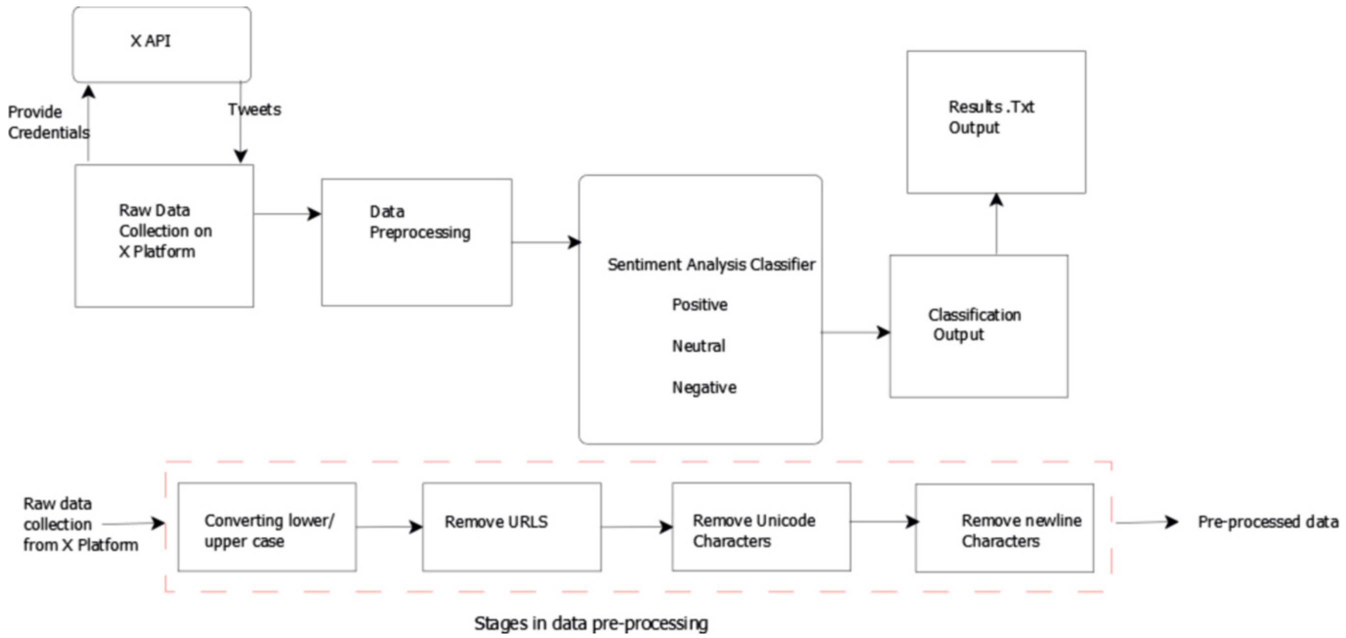

Figure 2: Framework for opinion mining for a targeted company handle

An electronic device with internet access together with X APIs was used to mine raw data from X after providing a search query as well as the number of tweets to be fetched. This raw data is difficult to analyse manually. Customer data related to a specified search query was retrieved. The tweets were pre-processed or cleaned removing special characters, URLs and other unnecessary characters. Using natural language processing, the system carried out a sentiment analysis of pre-processed data classifying comments into positive, neutral and negative thus sentiment classification. A statistical representation of the results was shown on the output box, and then a .txt file was generated with all processed classified data. The system also can test the sentiments of the provided text by simply entering the text to be tested and clicking the **text sentiment** button. It also has an X bot for automatic liking of tweets with specified text or hashtags by the admin or user.

Re-use Components – The researchers adopted already available components that were free for instance in the use of libraries for the different modules that were already available from previous systems related to the proposed system. This saved system development time. The user requirements were modelled as shown in Figure 3.

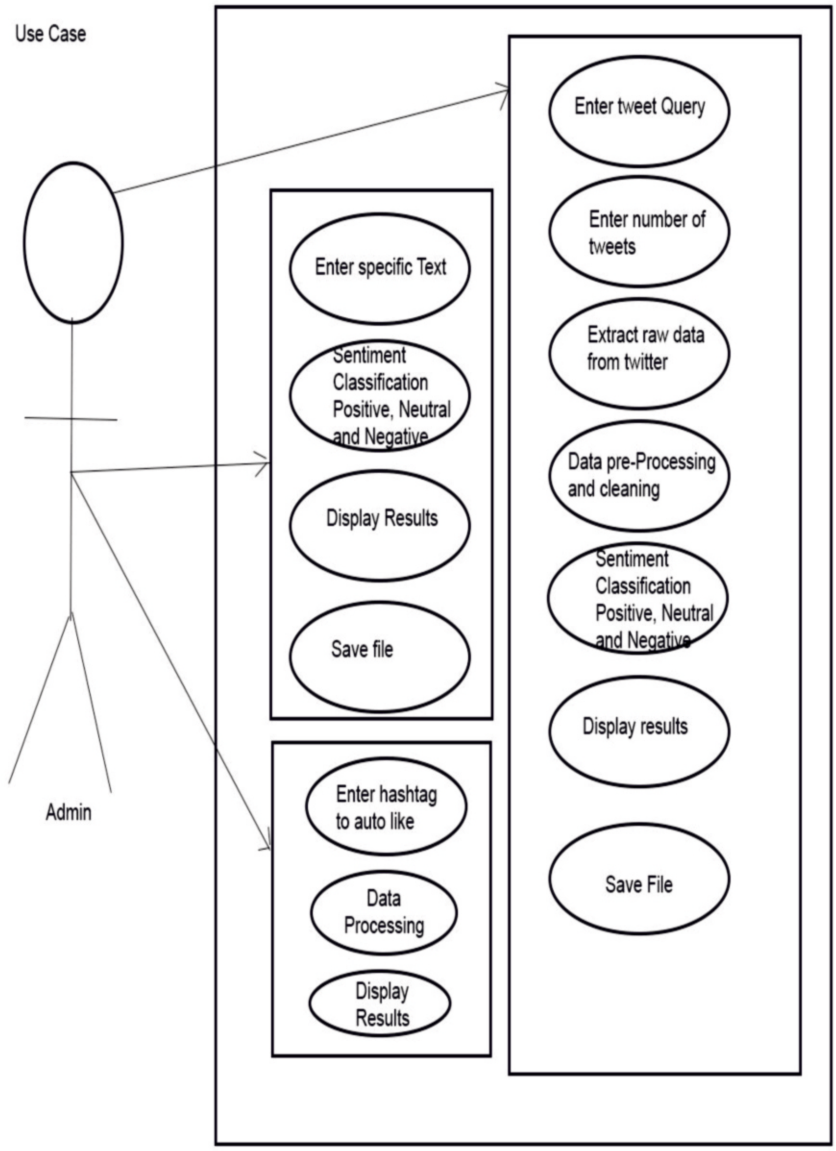

Figure 3: Use Case for modelling opinion mining for a target handle

Figure 3 describes how the system interacted with the targeted X handle for the bank. This enabled the capturing of the tweet and classification. Positive or negative sentiments were captured thereof. An electronic device with Internet access together with X APIs was used to mine raw data from X after providing a search query as well as the number of tweets to be fetched. This raw data was difficult to analyse manually. Customer data related to a specified search query was retrieved. The tweets were pre-processed or cleaned removing special characters, URLs and other unnecessary characters. Using natural language processing, the system carried out a sentiment analysis of pre-processed data classifying comments into positive, neutral and negative thus sentiment classification. A statistical representation of the results was shown on the output box, and then a .txt file was generated with all processed classified data. The system also could test the sentiment of the provided text by simply entering the text to be tested and clicking a **text sentiment** button. It also had an X bot for automatic liking of tweets with specified text or hashtags by the admin or user.

Choosing Adequate Programming Language – involved the use of a programming language that was more adequate for the building of the system. The researchers chose Python. Important factors considered in choosing a programming language to work with include required run-time speed (compiled vs. interpreted languages), expressiveness (imperative vs. functional vs. declarative languages), reliability (e.g. run-time checks, garbage collection) and available libraries.

Testing, demonstration and evaluation – This involved testing the developed system each time and the methodology required testing modules first. This way future changes can be tested when they are introduced into the system. The researchers tested the prototype and also used expert feedback to determine its usefulness. The researchers also used observation as a fundamental way of finding out about the world around them (Kabir, 2016). The researchers manually examined sample X comments to determine whether the proposed system was doing the right classification and its ability to examine people’s comments or reactions in natural settings or naturally occurring situations.

IV. Findings and Results

The need to analyse the efficiency of the developed solution arose when researchers had successfully implemented the system. Accuracy, performance and reliability were used to determine the efficiency and effectiveness of the developed solution. The developed solution's behaviour was also well observed by the researchers at different times and the outcome was recorded. Testing was of paramount importance in the development process and this section shows the tests that were undertaken and the result they produced. The testing was thus measured against the objectives and functional requirements of this research. The researchers used a pseudo-name **Omegabank** to conceal the identity of the bank under study.

1. Input of search Queries

The design interface had the capability of user input queries to search for an X handle for a target Company for example an X handle for @omegabank. This was used after the tool had incorporated an X API connection for it to be able to harvest X comments. The following discusses examples of user queries to determine whether the tool could mine X sentiments data.

Figure 4 below shows that the system was capable of allowing the user to input Search queries, number of tweets, specific text as well as hashtags for auto liking hence ensuring the system functions per requirements in this research.

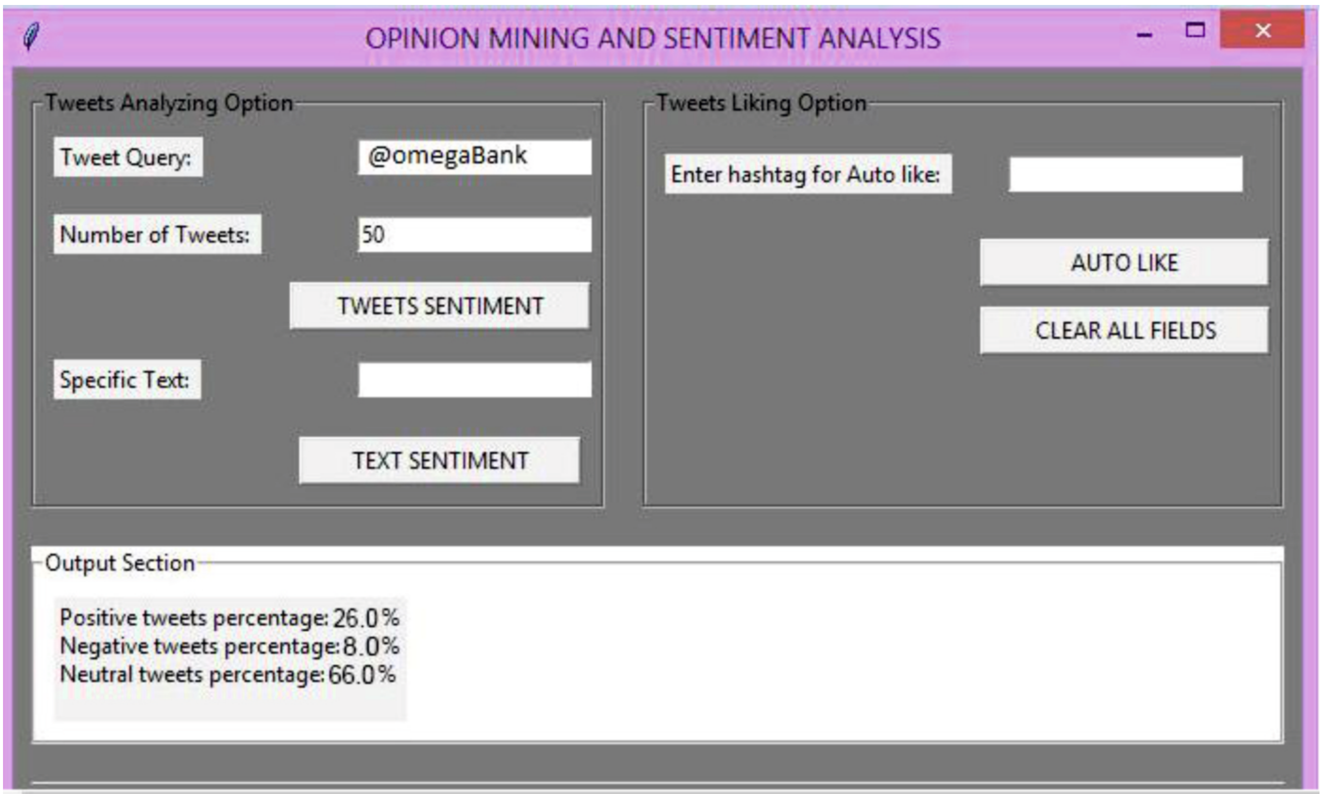

Figure 4: User Input Search Query

2. Opinion mining and sentimental analysis output

Figure 5: Shows the output of the text file of the fetched tweets

```
Tweets Analysis from Query: @omegabank
Tweets Retrieved: 50
Results:
Positive tweets percentage: 26.0 %
Negative tweets percentage: 8.0 %
Neutral tweets percentage: 66.0 %

Positive tweets:

1) 'sent a DM a msg on live chat WhatsApp early in the morning, hank you for assisting'
2) 'good day cany you check your dm'
3) 'I received my new debit card thank you'
4) 'good day can you kindly check your dm'
5) 'Switch at your own risk'
6) 'I have log onto the new square app i love it'
7) 'kindly note im following up on DM enquiry'
8) 'Kindly reply my DM'
9)'on this square app is one able to check Balance of FCA account'
10)'You are most welcome  jk'
11)'Thx so much'
12)'Wow lightining speed response thank you'
13)'Hi may kindly check your DM for our message jk'

Negative tweets:
1)'no response from you guys Very disappointed'
2)'can you please be serious for once 2 months dzanyanya jus check your dm please'
3)'How long does it take to open a corporate bank account Can this be done online Zimbabwe please respond'
4)'please we must not beg for our funds It is unfair to us ndipeiwo mari yangu veduwe My ticket number'
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Figure 5: Output of summarised X sentiments

The results shown in Figure 5 above prove that the system was effective in opinion mining and calculating sentiments. The system was able to connect to X using tweepy, pre-process data and then process sentiments of acquired information. Figure 5 above shows overall sentiment calculations grouped as positive, neutral and negative. It also shows all the comments that were mined from X following the provided search query.

3. Evaluation Measures and Results

An evaluation metric measures the performance of a classifier (Hossin and Sulaiman, 2015). Moreover, model evaluation metrics can be grouped into three types namely threshold, probability and ranking. The following discusses the outcomes of testing and evaluation of the prototype sentimental analysis tool.

4. Measuring system and performance

The performance of the system was ranked according to its ability to be able to mine opinions, and performance sentiment classifying opinions as positive, neutral and negative and producing correct results. The authors thus tested the system's accuracy in fetching tweets according to a specified number by the user to ensure the effectiveness of its functionality.

Table 1: Accuracy results of fetched tweets

Query Name	Expected tweets to be fetched	Actual tweets fetched
@omegabank	50	50
#Easybanking	70	70
Omegabank credit cards	20	15
Good day	60	60
Good evening	50	50
Omegabank POS Machine	20	20
#Easybanking	50	50
@omegabank	80	80

Accuracy = N – X / N *100

N is the total number of test

X is the number of inaccurate readings

Accuracy = (8-1)/8 *100

= **87.5%**

A sample of eight (8) tests was carried out to measure the accuracy of fetching tweets (Table 1). The authors noticed the variations in readings where as a result of the provided search query having fewer comments or reviews than requested by the user of the system, the system recorded an 87.5% tweets fetching accuracy rate.

5. Implementing system performance

Software evaluation by respondents was made in terms of performance, reliability and cost-effectiveness. Performance was the capability of the system to mine opinions and perform sentiment analysis and produce correct results. The extent to which the system could carry out its intended functions is reliability. The system produced the results with precision. It produced a text file that may be used for future reference as well as in decision-making. Cost effectiveness-to all respondents, the system was a reliable, time-saving and inexpensive way for analysing X data. This was supported by interviews and expert data. In gathering how effective the system was, the researchers distributed the system and interviewed the social media assistants who manage and handle Omegabank's social media accounts as well as interviewed a few individuals. Responses were consolidated and the results of the information gathered were measured on the effectiveness of using responses (1) Effective and (2) Not effective as shown in Table 2.

Table 2: Effectiveness of the system

Software Criteria	Effective (%)	Not effective (%)
Performance	90	10
Reliability	100	0
Cost Effectiveness	70	30

Results in Table 2 above showed that the performance of system was accepted by 90% of the respondents however only 10% felt it was not an effective system. All the participants responded positively on reliability and were of opinion that the system was very convenient and useful. Exactly 70% of the participants thought that the system was cost effective in terms of saving time and saving money, whilst 30% felt completely different.

6. Observations from system –Service provider

This research shows the assessments of opinion mining and sentiment analysis on customer's comments, reactions through the X tweets of Omegabank posts. 10 Observations were used by the researchers to test system effectiveness and usefulness in analysing X data specifically for Omegabank posts and comments for a period of 10 days. When Omegabank social media team responds, they use the keyword **"Good day".** The researchers used this keyword to test the system as a response from service provider should be positive or neutral, if negative appears, it's a call for concern. Table 3 below shows the observed queries and the recordings taken.

Table 3: Observation for the Service Provider Tweets

Observation No	Query Name	Number of Tweets	Positive (%)	Neutral (%)	Negative (%)
1	Good day	40	22.5	77.5	0
2	Good day	30	16.6	83.4	0
3	Good day	70	17.1	82.9	0
4	Good day	100	16.0	84.0	0
5	Good day	60	16.6	78.4	5
6	Good day	100	16.0	80.0	4
7	Good day	75	18.6	81.4	0
8	Good day	20	16.9	83.1	0
9	Good day	80	19.6	80.4	0
10	Good day	70	17.7	82.3	0

The Table 3 above shows that most responses to clients by the service provider were either positive or neutral. On day 6, the researchers encountered a negative (Figure 6) and manually assessed the response.

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Negative tweets:

1) 'Good Day please we are sorry for that, share with us your account number inter bank reference and expected amount in our DMs'

2) 'Good Day clemy It will be sad to see you go Please note that your case was resolved and you can now transact using your card Nfc'

3) 'Good Day troy I am sorry you feel that way and I apologize for the delayed response Please note your DM was responded to Nfc'

4) 'Good Day I am sorry to hear that your experience with us has not met your expectations Customer sa'
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Figure 6:Sample negative response

Analysing the keyword (Good day) used by the service provider when responding to customers helped in identifying whether responses to clients were favourable and not offending when a negative comment was encountered. There was a need to manually cross-check whether the service provider had not given an unfavourable response. This helps in customer care management as a service provider

7. Observation from the system-customer side

Six-day observations were used by the researchers to test system effectiveness and usefulness in analysing X data specifically for Omegabank posts and comments for six days. When most customers respond or complain on X, they tag the targeted company so for Omegabank, they use the keyword "@omegabank". The researchers used this keyword to test the system's effectiveness and usefulness.

Table 4: Six-day observation of customer-related tweets

Observation No of day	Query Name	Number of Tweets	Positive (%)	Neutral (%)	Negative (%)
1	@omegabank	20	35.0	60.0	5.0
2	@omegabank	50	38.0	50.0	12.0
3	@omegabank	70	31.4	55.7	12.9
4	@omegabank	89	26.9	60.7	12.4
5	@omegabank	75	31.1	56.7	12.2
6	@omegabank	60	39.0	48.6	12.4

From Table 4, above it can be observed that around 10% of customer tweets indicated negative sentiments, this could be an indicator of poor service from service providers. On day three, there was a greater negative percentage 12.9%, analysing why there is a slight rise in negative comments helps to improve customer satisfaction and the service provider can easily see where it is lagging behind in making its customer care efficient. The example in Figure 7 below shows snippets of exchanges on the X platform.

```
Negative tweets:
1)'So in a bank queue Sam Levys A guy comes jumps the queue Worse no Covid protocols observed Upon e'
2)'Sorry sis i have same issue with my account of not reflecting amount 24th May kunogarako its worst of tym i hav'
3)'Am still waiting I think its taking long loan approval'
4)'Me too I am due for my june salary in a week and i haven t received my May salary'
5)'No such luck The usual canned response about working on it blah blah blah'
6)'how long does it take to upgrade account once I send details please respond'
7)'How long does it take till an account upgraded, respond us please, why taking long'
8)'support What s happening with Net work Poor Net work why'
9)'I think they need fewer staff silly messages and more staff fixing their mess'
```

Figure 7: Example of negative sentiments from the customer side

From Figure 7 above, the sentiments could indicate that customers were not happy with the services provided. This could impact customer retention as the customer could open bank accounts with other banks.

V. Discussion of Results

After conducting interviews and observations, the researchers were able to infer whether the tool could be used to help customer care departments or not. It would be prudent to indicate that the purpose and objectives of the system were achieved. By being able to analyse responses from the service provider side as well as the customer side, this helps to cover the gap in customer satisfaction. Responses from the service provider are not supposed to be negative as this will be poor service delivery there-by having fewer negative responses from the service provider helps to improve customer satisfaction. Analysing the customer side helps in decision-making for the service provider as they would tap into the negative sentiments to improve service provision and close gaps by improving customer retention. The researchers concluded that opinion mining and sentiment analysis on customers' comments, and reactions on the X platform will be efficient and effective in improving customer satisfaction by large data analysis.

VI. Conclusions and Reccomendations

The research aimed to develop an opinion mining and sentiment analysis system on customer opinions for targeted bank posts on X through Natural Language Processing. From the sentiment classification, it was easy to identify if clients were enjoying services and were being satisfied. From the feedback, 90% accepted the system and evaluated it as effective in its performance. System reliability scored 100% while cost effectiveness scored 70%. Observations carried out show also that the system was effective in terms of analysing unstructured data. For future work on opinion mining and sentiment analysis, it is necessary to perform multi-linguistic analysis considering different languages and real-time sentiment polarity assigned to the X data. To do so, there is a need to implement data processing algorithms on a cloud that increase the performance of sentiment analysis using Natural Language Processing (NLP) techniques. This will contribute towards real-time opinion mining and sentiment analysis in a cloud environment and will allow the business user to fetch real-time sentiment analysis for the linguistic data. Opinion mining can also be used for mining national security threats, especially in the era of fake news and parody accounts being created beyond Zimbabwe's boundaries. Other areas of opinion can be used for determining awareness of policies and regulations in e-governance issues.

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