An Intelligent Method for Collecting and Analyzing Voice Reviews to Gauge Customer Satisfaction

Nail Khabibullin
Sayt Tech Ltd, London, UK

***Abstract*—Customer loyalty and customer satisfaction are premier goals of modern business since these factors indicate customers' future behaviour and ultimate impact on the revenue and value of a business. The customers' reviews, ratings, and rankings are a primary source for gauging customer satisfaction levels. Similar efforts have been reported in the literature. However, there has been no solution that can record real-time views of customers and provide analysis of the views. In this paper, a novel approach is presented that records, stores, and analyzes the customer live reviews and uses text mining to perform various levels of analysis of the reviews. The used approach also involves steps like void-to-text conversion, pre-processing, sentiment analysis, and sentiment report generation. This paper also presents a prototype tool that is the outcome of the present research. This research not only provides novel functionalities in the domain but also outperforms similar solutions in performance.**

Keywords—Voice reviews; customer satisfaction; text mining; sentiment analysis

I. Introduction

Every business in the modern world aims to increase its revenue streams, which ultimately builds its value proposition. A typical approach used to achieve this aim is to ensure customer satisfaction. The more a customer is happy with the product or service of a business company, the higher the satisfaction level of that customer will be. Customer satisfaction level is a short-term goal of a business, but it drives a way to ensure a customer's loyalty which is a long-term goal of a business. Customer loyalty is very critical for a business since a loyal customer gives more and more revenue to a business [1]. The higher level of customer loyalty helps in achieving customer retention. Customer retention ensures that a customer is highly loyal to a business product or a service and will buy that product or service again and again. Such loyal customers also recommend a business to their family and friends which ultimately increases the customer network of a business. Conclusively, a business highly depends upon the satisfaction of its customers.

It is established that customer satisfaction is critical for a business and to achieve this goal a business firm has to continuously assess the satisfaction level of its customers. However, assessment of its customer satisfaction has been a challenge in the recent past. A business firm can use various tools to assess the satisfaction level of its customers such as surveys, interviews, customer online reviews, rankings, and ratings [2]. Various websites record users' rankings and ratings for particular products or services and that can be a source of measuring customer satisfaction. However, such rankings and ratings-based data provide shallow reflections of customer's views. However, modern businesses need deep insights into customer's views and that can be achieved through analysis of customers' online reviews, surveys, and interviews [3].

The customer reviews recorded in the last five or ten years for a particular product on a website can be useful for insightful data analysis and measuring customer satisfaction [4]. However, a few issues with such website reviews-based data can be availability, reliability, relevance, integrity, and transparency. Hence, the results of such datasets can't be authentic and can't present a true picture of the customers' satisfaction. Conventionally, customers' reviews are collected through paper questionnaires, typing-in forms, and online review services (such as those used by TripAdvisor, Trustpilot, and many others). However, such existing technologies require registration and typing, which makes it time-consuming and complicated for the customers. To identify the key reasons why people do not record their reviews, a survey of 400 respondents was conducted in October 2021. The results of this survey is shown in Fig. 1.

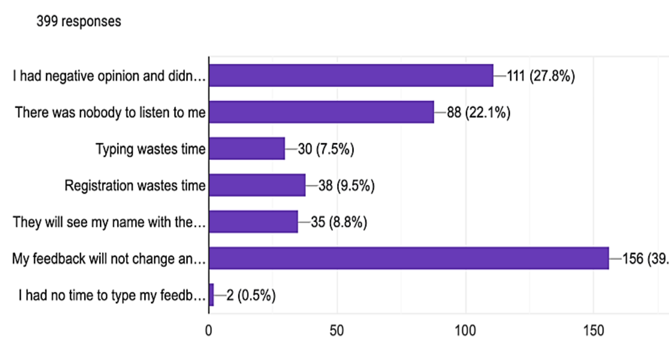

Fig. 1. A survey results to check why people don't record their reviews.

According to the survey, 27.8% do not give feedback if an opinion is negative. 22.1% responded that there is nobody to listen. In addition, respondents complained that typing wastes time (7.5%), and registration wastes time (9.5%). In the additional survey, 130 of 402 responses (32.3%) stated that they would give feedback if it was anonymous. The majority of the respondents figured out that such systems should be easy to use and anonymous.

This paper presents an intelligent idea of capturing the views, reviews, and feedback of customers and clients of a business, performing real-time analysis of these reviews, and showing results to the business in the form of a report. The outcome of such real-time analysis can be more accurate, relevant, transparent, and reliable. To achieve this goal, a multi-faceted approach is designed in this research. One facet of this research is to design hardware that is capable of recording customers' live voice reviews and storing these on cloud storage. The second facet of this research is recognition of speech with vocabulary specific to the hospitality business. The third facet is a text mining-based approach that can do sentiment analysis of the data stored in the cloud. The fourth facet was to design a device that is energy efficient so that it can function for several weeks on one battery charge, and it should be compact so that it may be easy to handle.

The rest of the paper is divided into a set of sections. Each section develops a part of the research. Section II discusses the outcome of the literature survey and reports the major contributions in the literature that are similar to the presented research. Section III describes the used approach and its working in detail. Section IV explains the implementation details of the tool. Section V represents the results of the work. Discussion and conclusion is given in Section VI and Section VII respectively.

II. Related Work

A literature survey was conducted to find out the similar contributions reported in the literature. This section discusses the outcome of the literature survey and reports the major contributions in the literature that are similar to the presented research. In literature, not many such works were found. A few of the works that were found had their limitations in both software and hardware. One of such contribution was sentiment analysis of speech using acoustic features and lexical features [5]. In this work, speech data was taken to identify intensified sentiments of customers from their recorded product reviews. However, in this work neither a real-time data analysis was done, nor a supporting hardware tool was introduced.

A contribution was made that attributed to the analysis of voice reviews. In this work, a customer had to record his voice reviews and send them online to the business server. The server processed the received voice review using a fuzzy logic approach [6]. However, in this work, it is difficult for customers to record their reviews and send them online which results in a very low number of reviews on the server. Secondly, the quality of recorded reviews was a major concern since customers were not taking care of recording quality and background noise. A few other attempts have been made to do sentiment analysis of voice reviews such as in study [7], where voice reviews were directly parts-of-speech (POS) tagged and further processed to identify respective sentiments in a voice note. However, again this work was quite limited since the voice quality and noise in the voice were not considered in the design and implementation of the approach. However, the quality of voice notes is of prime importance to accurately extracting the text from the voice and then identifying the true sentiments of customers from their voice notes.

After the detailed literature survey, it was found that a few methods and approaches that partially address this issue of voice note-based sentiment analysis have been presented but each of these approaches has their respective limitations. A few such limitations are difficult modes of recording and submitting customer reviews, low-quality and noise-based recordings of voice, and proper reporting methodology. In addition, none of the existing works store voice notes and other related data on the cloud which questions the availability and transparency concerns of the sentiment analysis performed. In addition to this research gap in the literature, there are no similar tools available in the market. Other solutions in the market collect feedback and reviews use smartphones or tablets resulting in low-quality and noise recording. Some other solutions use text feedback that does not provide deep insights into the customer feedback. In addition, giving voice feedback is faster and less laborious than typing and registering text feedback.

To address the above-mentioned research gap, there is a need to design and devise a specific hardware device for collecting voice feedback from customers with high-quality. Our hardware tool for collecting voice feedback is unique (no similar devices are available). Smartphones and tablets can perform similar functions such as recording, analysing, and storing voice feedback. However, they are more expensive ($200-$1000). There is a need for cheap and low-cost solutions. Another issue with smartphones and tablet-based solutions is their battery life which is much lower i.e. 1-3 days. Here, a better, easy-to-use device is required that has a long battery life of up to two to three weeks. Moreover, there is a need for a device that is small-sized and much more compact than a smartphone for easy and frequent use and has a more robust design.

III. Used Approach

A lexicon-based approach is designed for voice review mining that initiates with a recording of speech-based customer reviews and then further analyses these reviews to identify the customer's satisfaction. The use approach starts with the recording of the quality speech of a customer. The recorded speech is converted into text for analysis. Meanwhile, the recorded speech data is stored in a cloud. The text reviews are pre-processed to remove noise. The typical steps like tokenization, filtering, stop word removal, and stemming are applied. The pre-processed text is forwarded to the text analysis module. Then sentiment analysis module analyses the sentiment of the reviews using steps like subjectivity classification, sentiment detection, and sentiment score calculation. This sentiment score is forwarded to the sentiment classification module that classifies a review. The final step is to generate a customer satisfaction report based on the output of the sentiment classification step. A framework for the used approach is shown in Fig. 2.

The working of each step of the used approach as shown in Fig. 2 is described in the following text.

A. *Quality Speech Recording*

The bustling ambiance of restaurants introduced a significant hurdle for maintaining the integrity of voice recordings amidst substantial background noise. The question at the heart of this challenge was how our voice recording system—comprising both advanced microphone technology and sophisticated algorithms—could effectively distinguish and capture the speaker's voice alone. Given that the pre-existing technologies fell short of meeting the demands of our specialized handheld device, it became imperative to devise a tailored solution. Our journey to this solution involved extensive experimentation with a variety of microphone systems, alongside the creation of a bespoke algorithm aimed at filtering out ambient noise, which necessitated precise adjustments to achieve the desired sound clarity.

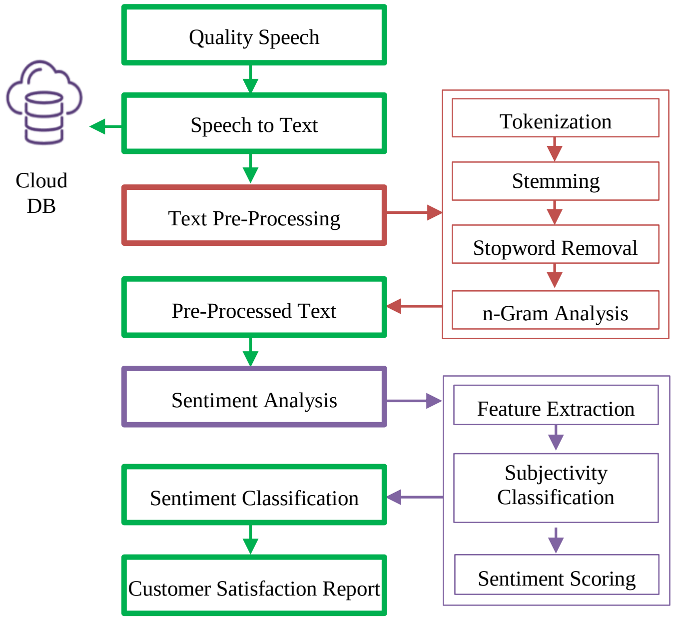

Fig. 2. The approach used for voice review mining.

The method to address background interference was multifaceted, requiring various adjustments like:

- Selection and positioning of the microphone,
- Determination of the optimal voice recording codec,
- Modification of a speech-to-text algorithm to exclude background noise.

Off-shelf offerings of microphone technologies capture all sounds indiscriminately, including undesirable background noise. Our initial trials with analog microphones proved unsatisfactory, leading us to explore digital microphones equipped with MEMS technology. This exploration culminated in the selection of the INMP441, notable for its digital output, omnidirectional pickup pattern, and 24-bit I²S interface, which emerged as the superior option. Subsequent experiments focused on identifying the microphone's optimal placement within the device to ensure unimpeded and unaltered sound capture.

Another pivotal aspect was choosing the appropriate audio codec for efficient compression and transmission of the voice recordings. Despite the availability of over fifty codecs, ranging from lossless to various compressed formats, initial tests with the lossless WAV format were hampered by its prohibitive file size for a compact device. Conversely, compressed formats like MP3, while smaller in size, failed to facilitate effective background noise removal when processed by cloud software. Ultimately, the FLAC codec, with its 16000Hz sample rate, 16-bit depth, and mono lossless format, was identified as the optimal solution.

B. *Speech-to-Text Conversion*

The next and most challenging step was refining a speech-to-text algorithm that is capable of accurately recognizing speech while filtering out background noise effectively. However, our initial attempts with Google's speech-to-text API and subsequent filtering algorithms did not meet our standards for accuracy. However, persistent efforts for modification and customization of Google's APIs eventually led to a breakthrough in achieving exceptional voice recognition performance in noisy environments. In this phase, the original audio and its text representation are stored in the cloud for the sake of the record.

C. *Text Pre-Processing*

In this step, the text generated from voice was pre-processed for further analysis. Typical issues in a text are inflectional parts, group words, stop words, and other similar issues. The data has to be processed to improve its quality since the pre-processed data is considered high-quality data and it can generate quality results in terms of accuracy. Following are a few steps that are used in the pre-processing of the text data in the used approach.

1) Tokenization: Tokenization is a typical starting phase of pre-processing the text for text mining and sentiment analysis. In the tokenization phase, the large sentences are tokenized into an array of words and symbols. The tokenization is done based on spaces among the words. The following is the output of the tokenized text:

[I] [like] [two] [features] [of] [these] [products] [.]

2) Stemming: The words in the text usually have inflectional parts such as prefixes, postfixes, infixes, etc. Such inflectional parts are removed to get the original or core form of a word. For example, the word “liked” stems from the word “like”. The Porter Stemming Algorithm is the oldest and a better stemming algorithm and it is supported in NLTK. Another possible stemmer is the Lancaster stemming algorithm. Following is an example of the stemmed output:

[I] [like] [two] [feature] [of] [these] [product] [.]

3) Stopword removal: A typical piece of text has a large portion of stopwords that have no direct meanings or at least have no semantic impact on other words. Typical stopwords are ‘a’, ‘the’, ‘is’, ‘are’, and many other similar words. In text mining, such stop words are filtered before detailed analysis. Removal of stopwords from text increases the efficiency of the overall mining process. In the above-mentioned example, the stopwords such as ‘I’, ‘two’, ‘of’, ‘these’ are removed.

[like] [feature] [product]

4) n-Gram analysis: In n-gram analysis, a collection of words is identified in a sentence, A sentence can be divided into two, three, or four logical parts called bi-grams, tri-grams, and quad-grams, respectively. The identification of group words in a sentence improves the quality of sentiment analysis and text mining.

D. Pre-Processed Text

In this phase, pre-processed text is received from the pre-processing phase. This pre-processed text along with its extra information is stored in arrays so that it may get easy to process in the next phases.

E. Sentiment Analysis

This phase of sentiment analysis initiates with feature extracting and then multiple steps are performed to complete sentiment analysis.

1) Feature extraction: For sentiment analysis in the used approach, the first step is features extraction. These extracted features are used for sentiment classification. The extracted features are the number of positive words, the number of negative words, the existence of negation, and the unigram.

- A number of positive words are identified from each sentence. SentiWordNet library is used to find all the positive words and they are counted.
- A number of negative words are identified from each sentence. SentiWordNet library is used to find all the negative words and they are counted.
- The direct and indirect negations are identified in a sentence and are counted.
- Unigrams in the sentence are counted.

a) Subjectivity classification: In this step, lexicon-based analysis was performed and for this task, the OpinionFinder Lexicon [4] was used. This lexicon consists of around 2600 positive and negative words with classification. With the help of this lexicon, all the keywords in the text are labeled with positive and negative words.

b) Sentiment scoring: In this step, a sentiment score for each review is calculated. Each word is looked up in SentiWordNet [8] dictionary to retrieve its positive or negative score that is called pos_score and neg_score. For sentiment scoring, pos_score of each positive word were collected and summed as shown in Eq. (1). Similarly, the neg_score of all the negative words in a review were collected and summed as shown in Eq. (2).

$$pos\_score = \sum_{i=1}^{k} pos\_score_i \tag{1}$$

$$neg\_score = \sum_{i=1}^{k} neg\_score_i \tag{2}$$

To calculate the average positive and negative scores of a review such as pos_review_r and neg_review_r, Eq. (3) and Eq. (4) were used respectively.

$$pos\_review_r = \frac{\sum_{i=1}^{k} pos\_score_i}{n} \tag{3}$$

$$neg\_review_r = \frac{\sum_{i=1}^{k} neg\_score_i}{n} \tag{4}$$

The words with the objective score less than a given threshold are omitted. Average on review with a threshold. The pos_review_o is the sum of scores of all positive words in a review after omitting the discarded words [9]. Similarly, the neg_review_o is the sum of scores of all negative words in a review after omitting the discarded words. Eq. (5) and Eq. (6) are used to calculate pos_review_o and neg_review_o, respectively.

$$pos\_review_o = \frac{\sum_{obj\_score_i < \theta} {}^{i \in r}\, pos\_score_i}{n} \tag{5}$$

$$neg\_review_o = \frac{\sum_{obj\_score_i < \theta} {}^{i \in r}\, neg\_score_i}{n} \tag{6}$$

The sentiment of a review S_r is determined by the higher value between pos_review_o and neg_review_o. Eq. (7) defines the calculation of S_r.

$$S_r = \begin{cases} positive\ if\, pos\_review_o > neg\_review_o \\ negative\ if\, neg\_review_o \leq neg\_review_o \end{cases} \tag{7}$$

F. Sentiment Classification

For final sentiment classification, a few existing solutions were tried for sentiment analysis and speech-to-text such as Google API, AssemblyAI. However, these existing models were not efficient enough to perform better. However, by using the information given in Section III(E), these models were modified and trained using Machine Learning and AI, so they can recognise speech in a noisy environment. The language models specifically were used for the hospitality industry (hotels, restaurants, etc.). A labeled dataset was used to train the ML classifiers. In our approach, binary classification was used such as in positive and negative classes [10]. Various algorithms were used such as Decision Tress (DTs), Support Vector Machine (SVM), Naïve Bayes (NB), Logistic Regression (LR), and Random Forrest (RF).

G. Customer Satisfaction Report

In the final step, a customer satisfaction report is generated that disseminates the results of the sentiment analysis performed in the previous steps for a set of reviews submitted by the customers for a day, week, or month.

IV. Implemetation Details

A new and unique hardware device has been developed to collect voice feedback and reviews. A prototype has been manufactured. The prototype has been tested in a real environment.

It is operated by a single button only. Press and speak to record voice feedback (LED is on). Release button – send to a cloud (LED blinking). The various models of the devised hardware are shown in Fig. 3.

A. Key Functionalities of the Device

- Power up the device in <1sec after pressing the button.
- Record and filter voice in a noisy environment.
- Compress, store, and send voice feedback to a cloud through Wi-Fi.
- Repeat sending the file if the Wi-Fi connection is unstable.
- If the battery is low – signal with LED to charge.

a) version 2 b) version 3 c) version 4

Fig. 3. Various versions of the design of the hardware.

B. Firmware Development

The firmware development for our handheld device, specially tailored for efficient power management and rapid activation, required a comprehensive setup involving several key components. The printed circuit board (PCB) is shown in Fig. 4.

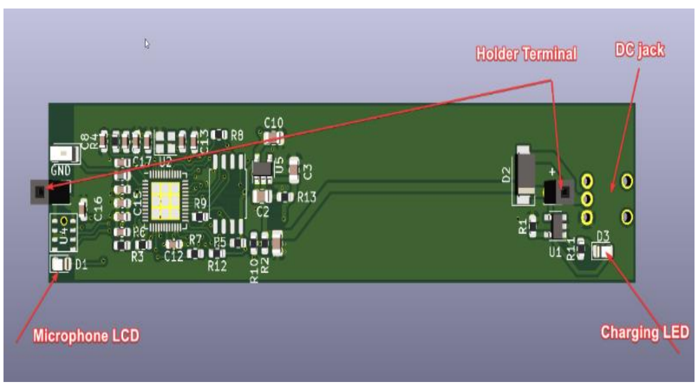

Fig. 4. The printed circuit board (PCB) for the system.

Toolchain for ESP32: The initial step in our firmware development was to establish a toolchain that would allow us to compile code specifically for the ESP32 microcontroller, the heart of our device. The ESP32, chosen for its low power consumption and Wi-Fi capabilities, necessitated a toolchain that could translate our high-level code into machine language understood by the microcontroller. We utilized the Xtensa GNU toolchain, which is specifically designed for the architecture of the ESP32, enabling us to develop efficient and optimized code for our device's specific requirements.

1) Unique characteristics

- The device can operate for several weeks on one battery charge.
- The quality of the sound recording is perfect for noisy environments.
- Manufacturing price is <$10/.

2) Build Tools - CMake and Ninja: To build our application for the ESP32, we employed CMake and Ninja as our primary build tools. CMake, an open-source, cross-platform family of tools, allowed us to manage the build process in a platform- and compiler-independent manner. It facilitated the generation of build configurations and was instrumental in managing the complexity of our project's architecture. Ninja, on the other hand, was used for its speed and efficiency in executing builds. It significantly reduced the building time, making the development process faster and more responsive to changes.

3) ESP-IDF (Espressif IoT Development Framework): The ESP-IDF is the official development framework for the ESP32 and ESP32-S Series SoCs provided by Espressif. It contains a rich set of APIs, libraries, and source code for common functions and features on the ESP32. This framework was crucial for our project as it provided the necessary tools and libraries for network connectivity, file system management, and power management. The ESP-IDF also includes scripts to operate the toolchain and facilitate the build process, making it easier for us to develop, compile, and flash the firmware onto the device.

4) Custom development and challenges: The customer development of the firmware from scratch was necessitated by our device's unique requirements, particularly the need to power up and initiate recording in less than a second and the optimization for energy efficiency.

We customized the ESP-IDF components and developed specific functionalities to manage the device's power states, handle audio processing, and ensure reliable Wi-Fi communication. The challenge was not only in optimizing these processes for performance but also in ensuring that they worked seamlessly together within the constraints of our hardware.

5) Iterative testing and refinement: The development of the firmware was an iterative process, involving numerous cycles of testing and refinement. This was particularly true for the components related to power management and audio processing, where real-world usage scenarios in noisy restaurant environments provided critical feedback for adjustment. The working of the developed module is shown in Fig. 5.

The firmware development for our innovative handheld device was a complex but rewarding process that pushed the limits of existing technology and required a deep understanding of the ESP32 microcontroller, the ESP-IDF, and the associated toolchain and build tools. Through customization and iterative development, we were able to overcome the significant technological uncertainties and challenges we faced in overcoming the technological challenges around energy consumption around sending review data.

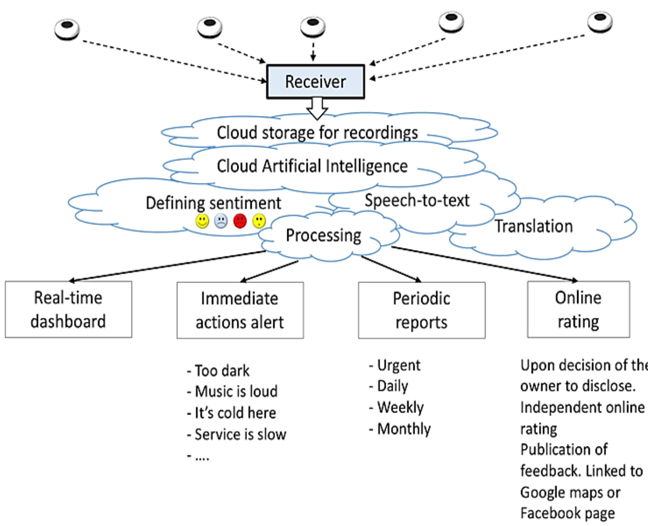

Fig. 5. Method for collecting, storing, and analysing voice reviews.

V. Experiments and Results

This section describes the experimentation details and results of the approach described in Section III. Three different datasets were collected using the device mentioned in Section IV. Each data set had a minimum of 50 reviews of various products. These three datasets were collected at different places where such as indoor, outdoor, and commercial places. The results of the experiments manifest that the results of all three datasets were almost consistent.

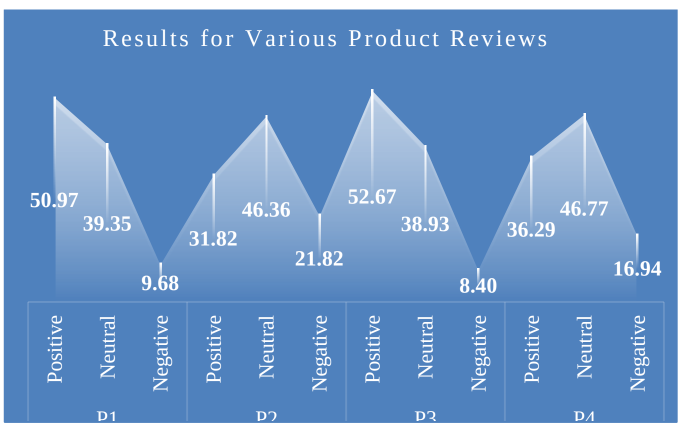

Fig. 6. Results of sentiment analysis of voice reviews for various products.

The designed system is based on a newly devised hardware tool that collects voice feedback and this hardware is unique in its features and functionalities. The designed system records, analyses, and sends feedback of voice review for further sentiment analysis. This section describes the results of the experiments performed with the designed system. Fig. 6 shows the results of voice reviews of various products that are classified into three classes such as positive, neutral, and negative.

The voice reviews or feedback of customers were overall accessed and overall positive, negative, and overall scores were calculated that are shown in Fig. 7.

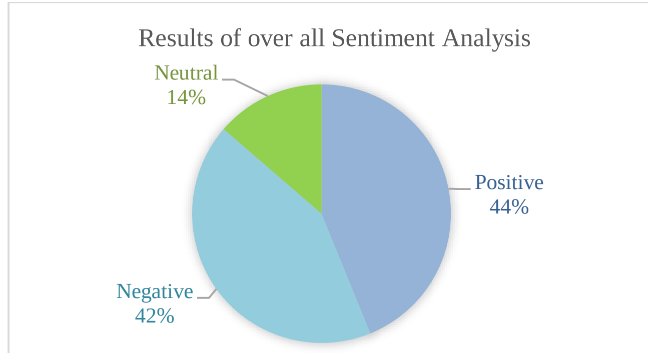

Fig. 7. Overall results of sentiment analysis of voice reviews.

In the sentiment classification phase, carious algorithms were used such as Decision Tress (DTs), Support Vector Machine (SVM), Naïve Bayes (NB), Logistic Regression (LR), and Random Forrest (RF). Here the accuracy of the classification for all classes is discussed for each ML model. Here Accuracy is the ratio between the number of true positive and true negative results to the overall test data. Fig. 8 shows the comparisons of the performance of all the used machine learning algorithms. The results of our approach are compared with the unigram based approach [12] and lexical features based approach [13].

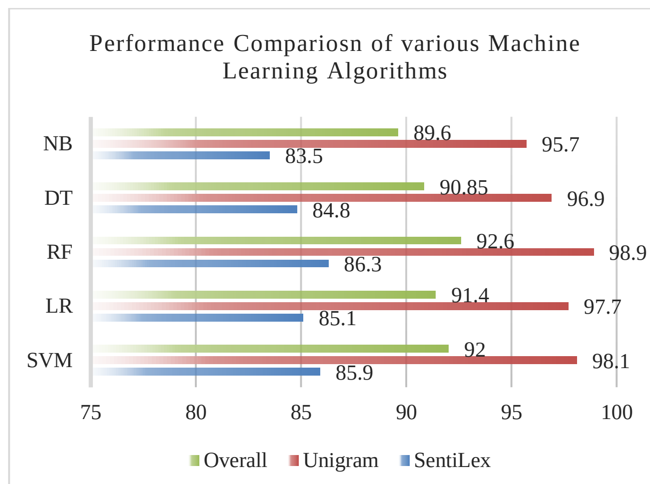

Fig. 8. Method and system for collecting, storing, and analysing voice reviews.

VI. Discussion

There are no similar tools available in the market. The hardware device for collecting voice feedback was designed and developed from scratch. It was filed for patents in the US and the UK. Other solutions in the market to collect feedback and reviews use smartphones or tablets. They use text feedback. Our solution uses voice feedback. A recent study verifies that when people were asked about their preference for typing or speaking 100 phrases, the people preferred speaking. In this study, an experiment was conducted in various languages such as English and Mandarin Chinese [11]. The study outcome was that in normal routine, speech dictation was 3.0x faster than typing in English. Similarly, in Mandarin language, it was 2.8x times faster since it takes more time to make corrections while typing.

In addition to the speed factor, it was also found that the English error rate was 20.4 percent lower while speaking. Similarly, the error rate in Mandarin was 63.4 percent lower. In this experimental study, Baidu's Deep Speech 2.0 was used for speech recognition software and deep learning. Whereas the default iOS iPhone keyboard was used for the typing test in the experiments.

Based on the results of this study, it is assimilated that the proposed method is better than the available methods that use typing-based reviews for customer loyalty analysis.

VII. Conclusion

This paper addresses a problem in state-of-the-art solutions for sentiment analysis used for gauging customer satisfaction. It is identified in this research that there are a few issues with such website reviews-based data can be availability, reliability, relevance, integrity, and transparency. Hence, the results of such datasets can’t be authentic and can’t present a true picture of the customers’ satisfaction. To address this problem a new device has been devised that can record customer voice reviews and can further process it using ML and produce sentiment analysis-based reports. The devised hardware tool for collecting voice feedback is unique as no similar devices are available in the market. Conventionally, smartphones and tablets can perform similar functions (record, analyze, and send voice feedback). However, they are more expensive ($200-$1000) compared to our device ($10). The battery life of smartphones and tablets is much lower (1-3 days) than our devices (20-30 days). Our device is much more compact (2-3 times smaller) than a smartphone and has a more robust design. In addition, giving voice feedback is faster than typing and registering text feedback.

As a future work, the current model of emotion recognition can be upgraded for domain-specific customers such as banking, retail, e-commerce, and others. A domain-specific system can provide improved results.

References

[1] Kang, D., & Park, Y. (2014). “Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and VIKOR approach”. *Expert Systems with Applications*, 41(4), 1041-1050.

[2] Fitri, F. S., Nasrun, M., & Setianingsih, C. (2018). Sentiment analysis on the level of customer satisfaction with data cellular services using the naive Bayes classifier algorithm. In 2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS) (pp. 201-206). IEEE.

[3] Al-Otaibi, S., Alnassar, A., Alshahrani, A., Al-Mubarak, A., Albugami, S., Almutiri, N., & Albugami, A. (2018). Customer satisfaction measurement using sentiment analysis. International Journal of Advanced Computer Science and Applications, 9(2).

[4] Khattak, A., Paracha, W. T., Asghar, M. Z., Jillani, N., Younis, U., Saddozai, F. K., & Hameed, I. A. (2020). Fine-grained sentiment analysis for measuring customer satisfaction using an extended set of fuzzy linguistic hedges. International Journal of Computational Intelligence Systems, 13(1), 744-756.

[5] Govindaraj, S., & Gopalakrishnan, K. (2016). Intensified sentiment analysis of customer product reviews using acoustic and textual features. ETRI Journal, 38(3), 494-501.

[6] Nuthakki, S., Bhogawar, S., Venugopal, S. M., & Mullankandy, S. (2023). Conversational AI and Llm's Current And Future Impacts in Improving and Scaling Health Services. International Journal of Computer Engineering and Technology 14 (3), 149-155.

[7] Swetha, B. C., Divya, S., Kavipriya, J., Kavya, R., & Rasheed, A. A. (2017). A novel voice-based sentimental analysis technique to mine the user-driven reviews. International Research Journal of Engineering and Technology.

[8] Baccianella, S., Esuli, A., & Sebastiani, F. (2010, May). Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. In LREC. Vol. 10, No. 2010, pp. 2200-2204.

[9] Kathiriya, S., Nuthakki, S., Mulukuntla, S., & Charllo, B. V. (2023). AI and The Future of Medicine: Pioneering Drug Discovery with Language Models. International Journal of Science and Research 12 (3), 1824-1829.

[10] Ghani, U., Bajwa, I. S., & Ashfaq, A. (2018). “A fuzzy logic-based intelligent system for measuring customer loyalty and decision making”. Symmetry, 10(12), 761.

[11] Weiner, S. (2016). “Stanford Study Says Speech-to-Text Is 3 Times Faster than Typing on Your Phone.” Popular Mechanics, Hearst Digital Media, 2 Sept. 2016, www.popularmechanics.com/technology/a22684/phone-dictation-typing-speed/.

[12] Dey, A., Jenamani, M., & Thakkar, J. J. (2018). Senti-N-Gram: An n-gram lexicon for Sentiment Analysis. Expert Systems with Applications, 103, 92-105.

[13] Teng, Z., Vo, D. T., & Zhang, Y. (2016, November). Context-sensitive lexicon features for neural sentiment analysis. In Proceedings of the 2016 conference on empirical methods in natural language processing (pp. 1629-1638).