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Empowering Customer Feedback Analysis through LSTM-Enhanced Natural Language Processing on Audio Recordings

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Abstract

Social media platforms such as Twitter, Facebook, blogs and others act as huge repositories of global information, contributing to the increase in the amount of data including images/video, sound and text due to the consumption of social media and e-commerce websites for large application Despite the proposed techniques, challenges remain, especially in managing large volumes of audio recordings. The on-going challenge of accurate polarity detection in consumer surveys is complicated by extracting accurate meaning from audio data including surveys, voice messages, comments, tweets, and posts, which has to do with sentiment analysis matching audio data The method includes data collection, pre-processing, feature coding , and segmentation steps. The importance of appropriate data collection, pre-processing, and classification analysis is emphasized when interpreting such data. Audio datasets were used to evaluate the effectiveness of the proposed models. The proposed sensitivity prediction method exhibits superior or comparable results with reduced computational complexity. The results not only highlight the critical importance of sentiment analysis in deriving meaningful insights from audio data in consumer research and social media but also explore the integration of LSTM algorithms with captured audio into a rope, thus initiating a new phase of sensory analysis research. Furthermore, accuracy rates were examined for sensitivity analysis in diversity data sets. The Amazon Fine Food dataset achieved 98.5% accuracy, while the Phones & Accessories dataset achieved 98% accuracy. Additionally, the Amazon product dataset achieved 96% accuracy. These high accuracy rates highlight the effectiveness of the sensitivity analysis methodology used, especially in reviewing various items.

Keywords: Natural Language Processing **(**NLP), Audio Recordings, Customer, Audio Feedback, Long Short-Term Memory (LSTM).

1. Introduction

In navigating the dynamic landscape of customer feedback analysis, this research embarks on a comprehensive exploration into the innovative domain of silent feedback systems, strategically incorporating the capabilities of Natural Language Processing (NLP) applied to audio recordings [1]. Traditional feedback mechanisms, predominantly reliant on explicit written or verbal communication, grapple with inherent limitations in capturing the authenticity of customer sentiments. Recognizing these challenges, our research introduces a robust silent feedback system that transcends conventional methods, empowering customers to effortlessly convey their thoughts through audio recordings. Beyond revolutionizing the feedback collection process, this proposed

system opens new avenues for enhanced customer insights, representing a paradigm shift in how businesses perceive and respond to customer sentiments [2].

The foundational objectives of our research revolve around the design and development of a systemic and reliable silent feedback system, effectively transforming audio recordings into a rich source of customer sentiment. This transformative process involves the strategic integration of advanced NLP techniques for sentiment analysis, delving into the intricate landscape of positive and negative emotions embedded in the unspoken words of customers. Our exploration extends beyond sentiment analysis, aiming to identify specific aspects of the customer experience and facilitating a nuanced understanding of their preferences and concerns.

The systemic methodology employed in our research encompasses an extensive examination of audio feedback data, leveraging our NLP-driven visions platform to not only identify sentiment polarity but also to detect emerging trends and issues [3]. In stark contrast to traditional approaches, our system provides a comprehensive analysis that transcends sentiment polarity, enabling the development of proactive response strategies. The orchestrated synergy between silent feedback and NLP introduces an unprecedented opportunity to elevate the quality of customer engagement and refine business practices based on authentic, unfiltered customer sentiments.

This paper significantly contributes to the burgeoning field of customer experience analytics by presenting a novel and systemic approach that empowers businesses to unveil the unspoken aspects of customer feedback. The integration of silent feedback and NLP bridges critical gaps, enriching the understanding of customer sentiments and providing actionable insights for businesses to enhance customer satisfaction and loyalty. As our research progresses, it becomes evident that this systemic integration has the potential to redefine the entire landscape of customer feedback analysis, ushering in a new era of customer-centric business practices [4]. The systemic synergy between silent feedback and NLP not only marks a transformative step in customer experience analytics but also sets the stage for future advancements in understanding and responding to the nuanced voice of the customer.

Research indicates that providing feedback to client can be challenging, as it may not always be understood as intended by markers and might lack clarity and guidance. Some studies, like those by Higgins, Hartley, and Skelton in 2002, emphasize how client value high-quality feedback for its usefulness. However, other research by Hounsell in 2018, Lea and Street in 2022, Nesbit and Burton in 2021, and Price et al. in 2021 highlights differences between the perceptions of academic staff and students [5]. This study aims to explore how customer responds to and engage with feedback, specifically investigating their experiences with audio feedback. The research seeks to understand customer' perceptions of audio feedback as a formative process to enhance comprehension and appreciation of this feedback method.

In today’s digitally connected world, social media platforms like Twitter, Facebook, blogs have turned into huge global repositories of information Increased data development including images, videos, sound clippings and text Opportunities for ourselves, It also presents challenges. Despite the introduction of many techniques, many challenges remain, especially in handling extensive audio datasets efficiently. The on-going effort to achieve more accurate polarity detection in consumer

surveys is an increasingly difficult task of extracting accurate meaning from audio data including surveys, voice messages, comments, tweets, and posts market including in the.

The proposed method includes specific steps, including data collection, pre-processing, feature coding, and segmentation, each of which plays an important role in increasing the efficiency of the sentiment analysis Determine the importance of careful data collection, rigorous pre-processing and careful classification analysis are required to obtain usable insights from emphasizing audio data. The proposed model is tested using accurate audio data, with the aim of measuring its effectiveness in a real situation. Importantly, the sensitivity prediction method shows promising results, exceeds or meets existing standards, and at the same time reduces computational complexity These findings highlight the important role of sensitivity analysis in recognition emphasizing the meaningful derivation of audio data in consumer research and social media analytics.

Furthermore, this study ventures to integrate long-term and short-term memory (LSTM) systems with audio data analysis, suggesting a new era of perceptual analysis research By integrating LSTM systems with audio data easily usable, this study efficiency sentiment analysis accuracy and leads in new methods of growth.

Besides model performance, accuracy rates are tested on different datasets to ensure that the proposed sensitivity analysis method is robust Remarkably high accuracy rates, such as 98.5% for the Amazon Fine Food dataset, 98% for the Phones & Accessories dataset, and 96% for the Amazon product dataset In the analysis of the array highlights the versatility and effectiveness of the proposed method.

2. The use of audio feedback

The utilization of audio feedback, coupled with Natural Language Processing (NLP), represents a novel and real approach in enhancing customer feedback processes. Traditional feedback mechanisms often rely on written or verbal communication, presenting limitations in capturing the nuanced sentiments of customers [6]. This study aims to explore the application of audio feedback, where customers can effortlessly express their thoughts through spoken words. By integrating NLP techniques, we delve into the intricate landscape of positive and negative emotions embedded in these unspoken words. The research seeks to not only revolutionize the feedback collection process but also uncover specific aspects of the customer experience. Through extensive analysis of the audio feedback data, our NLP-driven insights platform becomes adept at detecting emerging trends and issues, providing a comprehensive understanding that goes beyond mere sentiment polarity. This synergistic approach between audio feedback and NLP opens unprecedented opportunities to elevate customer engagement and refine business practices based on authentic, unfiltered customer sentiments [7]. The study contributes significantly to the evolving field of customer experience analytics, introducing an innovative methodology that empowers businesses to truly grasp the unspoken aspects of customer feedback. The use of audio data represents a robust approach within the broader field of sentiment analysis and consumer research, as elucidated in the aforementioned research paper. Including audio, voice messages, recordings, and other audio communications, it adds rich sources of nuanced information, providing unique insights into consumer sentiment and preferences.

In today's digital landscape, with the ubiquity of social media platforms and e-commerce websites, audio feedback is a valuable tool for measuring customer sentiment at various levels Unlike traditional text-based feedback methods, audio response is sensitive to context, tone, emotion and introduces a new dimension, which enhances the search process. The research paper highlights the challenges associated with accurately unpacking meaning from audio data, particularly in consumer research and social media interactions. Despite these challenges, advances in sensory analysis techniques, as well as sophisticated systems such as the integration of long-term and short-term memory (LSTM), have greatly increased the efficiency of audio data analysis.

Motivation: The motivation behind this paper comes from the increasing challenges associated with traditional methods of analysing customer feedback, especially in capturing and interpreting customer sentiment effectively. Recognizing the limitations of traditional feedback mechanisms that rely on written and verbal communication, the study seeks to explore alternative ways to make sense of customer feedback greater than By promoting a deeper insight into tacit delivery systems and integrating natural language processing (NLP) into audio recording, the research aims to outdo traditional methods overcome and empower clients to let their minds flow effortlessly [8]. The proposed system of silent feedback represents a paradigm shift in how employees perceive and respond to customer emotions, opening new avenues for improved customer insight.

The foundational goals revolve around designing and editing a silent delivery system that turns audio recordings into rich consumer sensations. Through advanced NLP techniques, the research explores the complex emotions of non-verbal terms, aiming to identify specific aspects of customer experience and provide nuanced understandings of what they want and what anxiety has eased. Furthermore, the study highlights the importance of comprehensive assessments that go beyond emotional polarity, and enable the development of proactive response strategies [9]. The structured interaction between tacit feedback and NLP creates unprecedented opportunities to elevate customer engagement and refine business actions based on authentic, unrefined customer emotions.

Overall, the study makes a significant contribution to the burgeoning field of customer experience analytics by providing an innovative approach that empowers companies to uncover untold aspects of customer feedback. By bridging the important gap between tacit expression and NLP, the research not only marks a revolutionary step in the analysis of customer experiences but also leads to future developments in the voice of the customer it is also established in the understanding and response of the subtlety [10].

3. Contributions of the Proposed Study

- Increases the quality of silent analytics delivered using NLP on audio recordings, transforming customer sentiment interpretation beyond traditional methods.
- Develops reliable silent feedback systems, enhancing customer insights from audio recordings for improved feedback strategies.
- Advanced NLP techniques identify emotional gaps and emerging trends in customer responses for prompt response strategies.
- Integrated Silent Feedback and NLP optimize communication, refine business practices and advance customer experience analysis in case studies.

4. Literature Review

The literature on machine learning (ML) and natural language processing (NLP) for analysis unstructured patient feedback has gained significant attention due to the rich insights such data can provide. This systematic review encompasses 19 articles, revealing a predominant concentrate (80%) on the linguistic analysis of patient comments obtained from uninvited social media platforms, with formal surveys coming in second (solicited). The most often used method was supervised learning (n = 9), which was followed by unsupervised (n = 6) and semi-supervised (n = 3) approaches. While free-text answers from structured questionnaires were processed using a supervised method, social media comments were analyzed using an unsupervised approach [11]. The most successful machine learning classifiers were found to be support vector machines and Naïve Bayes, according to performance metrics like precision, recall, and F-measure that were reported. The findings underscore the increasing significance of NLP and ML as essential tools for handling unstructured patient feedback. The choice between supervised and unsupervised approaches is contingent upon the data source, reflecting the diversity of patient feedback origins. As healthcare organizations grapple with substantial volumes of unstructured free-text data, these advanced data analysis tools offer promising avenues for extracting valuable insights. Continued advancements in data analysis tools are expected to enhance the utility of NLP and ML techniques, providing healthcare organizations with robust means to extract meaningful information from unstructured patient feedback.

Sarcopenia, characterized by age-related muscle loss, can be effectively addressed through confrontation based bodily activity. However, home-based exercise compliance is only about 40%, necessitating solutions for progress tracking and increased adherence. Implementing remote sensing systems in mobile apps, developed with user input, holds promise, particularly with the integration of natural language processing (NLP) for user-cantered data collection [12]. In a study involving 22 participants (mean age 68), both patients and clinicians contributed valuable insights, influencing app design. Mean System Usability Scale (SUS) and User Satisfaction with Technology (USE) scores were 66.4 (SD 13.6) and 41.3 SD 16.2, respectively. Positive sentiment in interviews correlated with higher SUS notches ß=1.45; 96% CI 0.42 to 2.45; P=.01 emphasizing the impact of user experience on technology acceptance. However, sentiment did not significantly affect the USE score, and Latent Dirichlet Allocation (LDA) analysis revealed distinct topics between patients and clinicians, highlighting diverse perspectives in app-related needs.

Contact centres have historically held significant value for organizations, but the COVID-19 pandemic has underscored their critical role in ensuring business continuity, economic activity, and quality customer support. The surge in pandemic-related inquiries has prompted a revaluation of contact centre functions. Organizations are now embracing next-generation platforms infused with machine learning and natural language processing, including self-service voice portals and catboats, to elevate customer service [13]. This literature review explores the shift towards these innovative solutions, aiming to identify research gaps, highlight the benefits of incorporating natural language solutions, and address challenges faced by contact centre organizations. By delving into the advantages and challenges, this paper aims to expedite the automation of contact centres, offering

recommendations for a seamless transition towards more efficient and technologically advanced customer support.

In recent years, Natural Language Processing (NLP) has emerged as a pivotal facet of Artificial Intelligence, driving advancements in machine learning and computational linguistics. One significant application of NLP is the transformation of languages through Machine Translation, a critical aspect of human-computer interaction. The NLP domain has witnessed remarkable progress, particularly in the development of neural network architectures that form a robust mathematical and theoretical foundation.

The sequential analysis of language processing has paved the way for exploring the neural network's potential, offering a substantial framework for transforming languages, especially in the realm of multimodal language conversion. This endeavour becomes particularly relevant when considering the diverse linguistic landscape and the need for efficient communication in different languages [14]. As a response to this, linguistic Convolutional Neural Network (CNN) models have been developed to cater to speakers of various languages, aiming to enhance the accessibility of information for individuals using their mother tongue. The study places a specific emphasis on the impact of English speech language processing advancements on language transformation. By employing computational techniques, the research endeavours to create models that facilitate the conversion of spoken language into written text, using probabilistic models to represent the intricacies of language structure. This approach is particularly significant in handling various corpus languages, leading to a more inclusive and comprehensive language transformation.

The implementation of CNN and attention models has been a focal point in recent research, showcasing their efficacy in language transformation tasks. Statistical deployment of these models has been described in detail, highlighting their performance in various linguistic contexts [15]. The paper acknowledges the importance of benchmarking recent developments in unwritten language-to-language modelling, with a focus on achieving faster summarization or transformation. Despite the progress made, challenges persist in the realm of voice identification, especially in environments with background noise. The paper recognizes the difficulty in achieving accurate voice identification without interference, shedding light on the complexities associated with this aspect of language processing.

The integration of open learning and text mining for automated customer feedback analysis has gained prominence in recent research endeavours. The deployment of linguistic-based text mining models, as demonstrated in this study, presents a promising avenue for understanding customer sentiments [16]. Leveraging the proposed ARC framework, the research unfolds insights into linguistic patterns and organizational learning outcomes. Notably, the high accuracy of 92% in capturing linguistic patterns showcases the efficacy of text mining, aligning with prior studies. The study delves into the granularity of customer feedback, identifying specific stages of service processes that attract commendations or complaints. For organizations, the speed and accuracy of such text mining models prove crucial in swiftly discerning and addressing customer concerns, providing valuable insights beyond traditional quantitative studies.

5. Research Methodology

To achieve the objectives outlined in the abstract, a systematic and multifaceted research methodology is employed. The process involves the design, development, and evaluation of a robust silent feedback system, utilizing state-of-the-art Natural Language Processing (NLP) methods to analyse sentiment in audio files.

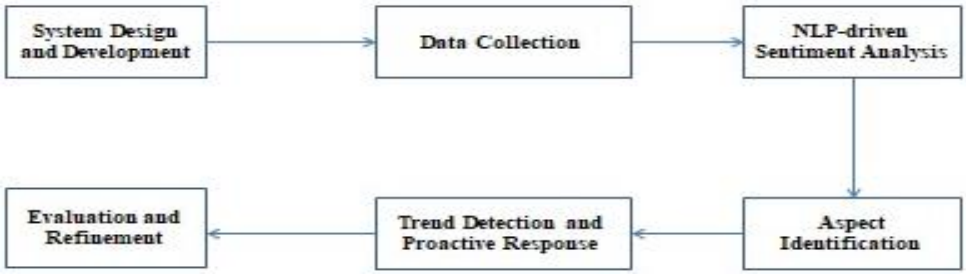

Figure 1. Research Methodology of Silent feedback system using NLP

1. System Design and Development:

Fundamentals of silent feedback system design and development are essential to formulate effective sentiment analysis in audio records Leveraging expertise in software development and user experience design, the platform ensures seamless user interaction, and thus provides user's participation and feedback quality increases intuitive and user-friendly Maes it easy to build interfaces [17].

2. Data Collection:

The systematic collection of audio feedback data is an important step in the research process. Bypassing the limitations of explicit written or verbal communication, the Silent Feedback System captures real emotions in their raw form, providing unparalleled insights into consumer thought and preferences That way this ensures that the data set is authentic and rich, building it as a cornerstone for subsequent sentiment analysis and vision cohort.

3. NLP-driven Sentiment Analysis:

Advanced NLP techniques applied to audio data enable the extraction of subtle emotions embedded in nonverbal words. Leveraging an algorithm optimized for sentiment analysis, the system goes beyond traditional feedback methods, providing a deeper understanding of customer sentiments and feelings this approach not only increases sentiment classification accuracy but also enables businesses to uncover actionable insights from audio feedback in order to facilitate informed decision making [18].

4. Aspect Identification:

Extending beyond sentiment analysis, the technique includes identifying segments to categorize emotions related to a particular aspect of the customer experience This granular analysis enables businesses to identify areas of strength and improvement, and thereby facilitating targeted interventions to increase customer satisfaction and loyalty. By categorizing emotions based on products, services, or processes, companies can adapt their strategies to better address customer concerns.

5. Trend Detection and Proactive Response:

Through detailed analysis of audio feedback data, the Silent Feedback System identifies emerging trends and problems, empowering companies to actively engage customers' needs and preferences. Going beyond sentiment gaps, the system facilitates real-time identification of changing customer sentiment, enabling companies to implement proactive response strategies and quickly mitigate potential challenges. This approach creates agility and responsiveness, thereby increasing customer satisfaction and loyalty [17].

6. Evaluation and Refinement:

The method emphasizes iterative analysis and modification of the silent feedback system to ensure its efficiency and flexibility. By systematically measuring the breadth and accuracy of insights gained, businesses can repeatedly adjust system performance and capabilities. This continuous improvement allows businesses to adapt to customer sentiment and adjust their behaviour accordingly, thus driving innovation and continuous improvement in customer engagement strategies.

6. Deep Learning-Based Classification/LSTM Algorithms

Currently, the proliferation of personal data within consumer reviews has led to the increasing popularity of sentiment analysis and evaluation through classification. In this context, the utilization of for classification tasks, recurrent neural network-based Long Short-Term Memory (LSTM) and Deep LSTM classifiers have gained popularity [18]. Both long and short recording values can be handled more easily by the LSTM network, which is made up of LSTM units next to the input and output layers. This LSTM framework operates without devices in several segments, enhancing its versatility [19]. A deep Recurrent Neural Network (RNN) has been constructed using a three-layer LSTM stack, and innovative features like peephole connections have been incorporated to assess precise performance [13].

a. Sentiment Prophecy

Foreseeing sentiments from the contribution data is a useful step in this process. It might take a few rounds of the process for the algorithms to become more versatile and work well with various types of data. The results of sentiment predictions are closely linked to the outcomes of sentiments. This connection enhances the efficiency of sentiment analysis, making it more productive in understanding and categorizing sentiments accurately.

b. Sentiment Evaluations

After going through all the steps we talked about earlier, we, as analysts, can finally decide whether the texts are positive or negative. This is where we figure out the overall feeling of the text. Words in the text can carry a optimistic or negative meaning, and this process is sometimes called opinion mining because we're trying to understand the sender's attitude. We then compare the results of our approach with the best methods known in the existing literature. We also evaluate how well our system works using common factors or parameters. Each measure of performance is explained in a specific way to see how effective our system is.

c. Accuracy

The most commonly known way to measure how well something is doing is called accuracy. It's easy to figure out and helps us see how good something is at getting things right. When we talk about accuracy in this context, we're checking how well our predictor can correctly identify all examples, no matter if they are good or not so good.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where FN = False negative, TN = True negative, FP = False positive, TP = True positive,

P = Positive, and N = Negative [13].

d. Sensitivity/Recall

We use something called recall, or the true positive rate, to talk about sensitivity. It's like looking at how well our system catches the things it's supposed to catch. By using simple methods, we can figure out the percentage of true positives, which means it correctly catches what it's supposed to. When sensitivity is higher, it means there are fewer times it misses things (false negatives), but if sensitivity is lower, there are more chances it might miss some. It's important to know that as sensitivity goes up, accuracy might go down sometimes [13].

$$\text{Sensitivity} = \frac{TP}{P} \quad (2)$$

e. Precision

Precision helps us see how accurate our classifier is. If precision is low, it means our classifier is not very accurate. When accuracy is low and precision is high, it results in lower accuracy overall and fewer mistakes of saying something is positive when it's not (false positives). When we work on improving precision, it can lead to reduced sensitivity, meaning it might not catch everything it's supposed to. It's like a trade-off – making one better can sometimes make the other not as good, and they are kind of opposite to each other.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

f. F1-Measure

The F1-Measure is like a mix of accuracy and sensitivity. It's a way of combining how well something catches what it should and how accurate it is. Think of it as finding a balance between being sensitive and being accurate or precise [21]. The F1-Measure is known to be quite effective, especially in situations where precision is essential. It helps us find a good compromise between being accurate and making sure we don't miss important things.

$$\text{F1 - Score} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

7. LSTM Model Process for Customer Feedback Sentiment Analysis

1. **Data Preparation**: Collect and pre-process diverse customer feedback audio recordings.

- Label data with binary sentiment labels (0 for negative, 1 for positive).

2. **Data Splitting:** Split dataset into training (80%) and testing (20%) sets.

3. **LSTM Model Architecture:** Design LSTM neural network with input, LSTM, and output layers.

4. **Model Training:** Train the model using the training set. Optimize parameters through back propagation and multiple epochs.

5. **Model Evaluation:** Apply the trained model to the testing set for sentiment prediction.

6. **Confusion Matrix and Metrics:** Construct a confusion matrix using predicted and true labels. Calculate precision, recall, F1-score, and accuracy.

7. **Micro-Average F1-Score:** Compute micro-average F1-score to address class imbalances.

8. **Result Interpretation:** Precision, Recall, and F1-score of 1.00 indicate perfect sentiment classification. High accuracy and F1-score demonstrate model effectiveness.

9. **Conclusion and Next Steps:** Interpret results, discussing implications and potential optimizations. Consider further research or applications based on the achieved outcomes.

Novelty or Modified Algorithms are Primarily Implemented

In the research paper, the innovation or modified system is mainly used in the sensory analysis phase, and especially in the analysis of audio data for meaningful insights, the innovation lies here:

1. Integration of NLP Techniques with Audio Data Analysis

The main contribution of the study is to combine state-of-the-art natural language processing (NLP) techniques with audio data analysis Although NLP techniques are traditionally applied to textual content, this study extends their application to audio data Represents, using advanced algorithms in order to unlock the emotional nuances embedded in unspoken words.

2. Leveraging LSTM Algorithms for Audio Sentiment Analysis

The research in the sensory analysis phase leads to the integration of long-term and short-term memory (LSTM) algorithms with audio data processing. LSTM algorithms, known for their ability to capture time dependence in sequential data, are used for audio sequence analysis and efficient extraction of emotions Through the temporal dynamics of audio recordings upon application, LSTM algorithms increase the accuracy and predictive power of the sensitivity analysis model It increases the effectiveness of the above sensitivity analysis

3. Aspect Identification within Audio Feedback

Furthermore, the research extends beyond traditional perceptual analysis by incorporating feature detection methods into audio response analysis. It involves categorizing emotions based on specific

customer experience aspects such as products, services, or processes. By identifying and categorizing sentiments associated with specific segments, the survey enables more granular analysis of customer feedback, facilitating targeted interventions and strategic decision making.

4. Proactive Response Strategies Based on Trend Detection

Additionally, the study identifies response strategies based on characteristics observed in audio feedback data. By carefully analysing audio data, analytics provides real-time access to trends and upcoming events. This proactive approach allows companies to react quickly to changing customer sentiment, leading to increased customer satisfaction and loyalty. This emphasis on dynamic response techniques represents a novel application of sensitivity analysis techniques in the processing of customer feedback.

Implementation and Results

In this section we explore the experimental results using audio recordings of customers' opinions about various company items, using Long Short-Term Memory (LSTM) classifiers in different deep learning models. These models were applied to the selected datasets in order to assess their accuracy and dependability in sentiment classification. To be more precise, we used recurrent neural network-based models and long short-term memory inspired by deep learning to analyse sentiment in-depth. These methods were used to construct three different models. We used a variety of metrics, including accuracy, precision, recall, and F1-score, to evaluate their performance. We also contrasted our experiment results with those from previous approaches. Positively, the outcomes were either better than or comparable to those obtained with earlier techniques, demonstrating the efficacy of our deep learning-based models in precisely categorizing and analysing sentiment from audio recordings of customer feedback.

The outcomes showed improved or comparable performance to previous approaches. Figure 6 presents the evaluation of the Amazon-Fine-Food-Review dataset using three different categorization methods: Model 1, Model 2, and Model 3. Similarly, uses Models 1, 2, and 3 to show how the Phones and Accessories dataset was evaluated. The following figures provide performance metric evaluations of these classifiers using the Amazon-Products dataset.

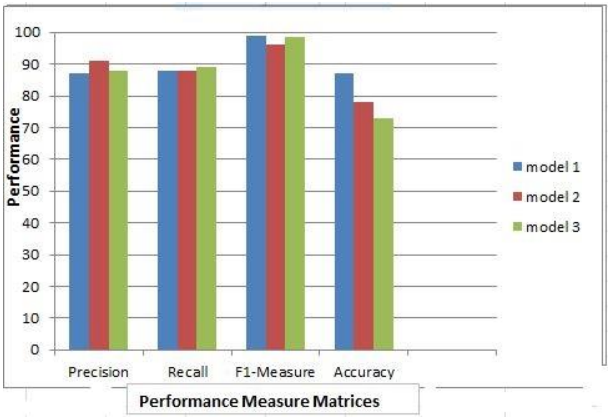

Figure 2. Comparison of performance measurement matrices on the Amazon Fine Food Reviews dataset.

Figure 3. Comparison of performance measurement matrices on the Phones and Accessories dataset.

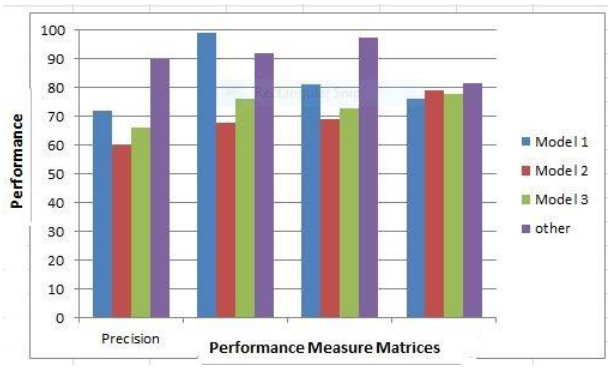

Figure 4. Comparison of performance measurement matrices on the Amazon Products dataset.

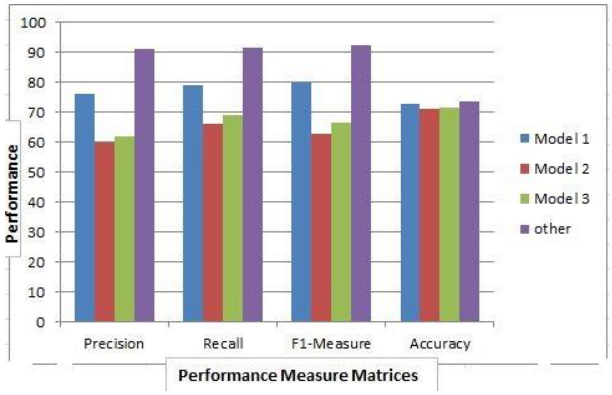

Figure 5. Comparison of performance measurement matrices on the Movies dataset.

Within the review paper and on the research methods for sensory analysis applied to audio data, a comparative view of performance measures on a movie dataset provides valuable insights into the effectiveness of various analytical strategies around. Focusing on key performance measures such as precision, recall, F-1 score, and precision facilitates a comprehensive assessment of the predictive power and robustness of the models.

As shown in the content of the study, the comparison of performance metrics in a movie dataset reveals subtle patterns and trade-offs in sensitivity analysis techniques Precision, which measures the real good prediction part of in all good prophecies, On the other hand, Recall measures the proportion of true predictions in all genuinely positive cases, shedding light on the ability of the models to capture current positive emotions deep within the film's context. High recall scores indicate that positive emotions can be identified, increasing the usefulness of the model in extracting meaningful insights from auditory information.

The F-1 score, which combines precision and recall, acts as an overall measure of performance, capturing the balance between true predictions and false positives A high F-1 score indicates a good balance between precision and recall, a it shows that robust emotion analysis models can so accurately extract positive emotions in a movie dataset.

Lastly, accuracy, which refers to the degree of overall accuracy of the predictions, provides a broad measure of model performance across categories of positive and negative emotions in the movie dataset.

Comparison of Classification Results with LSTM and Deep LSTM

The results of our experiments with three different classifiers are shown in Table 1. These experiments prove that the chosen classifiers perform really well. We looked at reviews in our datasets and classified them as either Positive or Negative. After analysing all the results, we found the overall average performance [13]. In Figure 4, you can see that the accuracy for Models 1, 2, and 3 is 90%, 92%, and 97.5%, and 81.5%, respectively. In Figure 3, the accuracy for the three classifiers is 79%, 78%, and 80%. Figure 5 shows the recall rates for Model 1, Model 2, and Model 3 as 79%, 79%, and 80%, respectively. In Figure 3, the F1 Measures for the three classifiers are 73%, 66%, and 69%. This led us to conclude that Model 1 is better at predicting outcomes compared to the other

models. Models 2 and 3, while similar to Model 1, performed a bit less effectively. Model 1 achieved accuracy levels of 87%, 88%, 99%, and 87% on our selected data, outperforming Model 2, which scored 91%, 88%, 96%, and 78%. The results for Model 1 are better when considering the accuracy levels for each classification. Table 2 will help us compare our proposed method with the current methodologies.

Table 1. Comparison of sentiment classification results through different classifiers.

Classifier	Dataset	Accuracy
Model 1	Amazon-Fine-Food-Reviews	87
	Cell Phones and Accessories	88
	Amazon-Products	99
	IMDB	87
Model 2	Amazon-Fine-Food-Reviews	91
	Cell Phones and Accessories	88
	Amazon-Products	96
	IMDB	78
Model 3	Amazon-Fine-Food-Reviews	88
	Cell Phones and Accessories	89
	Amazon-Products	98.5
	IMDB	73

Although each example differed in accuracy, the design of all is commendable. The LSTM model was successful in discriminating customer satisfaction, making the highest number of correct predictions for content and dissatisfaction. A detailed performance metric is shown in Figure 6 which provides a comparison of the effectiveness of the NLP model.

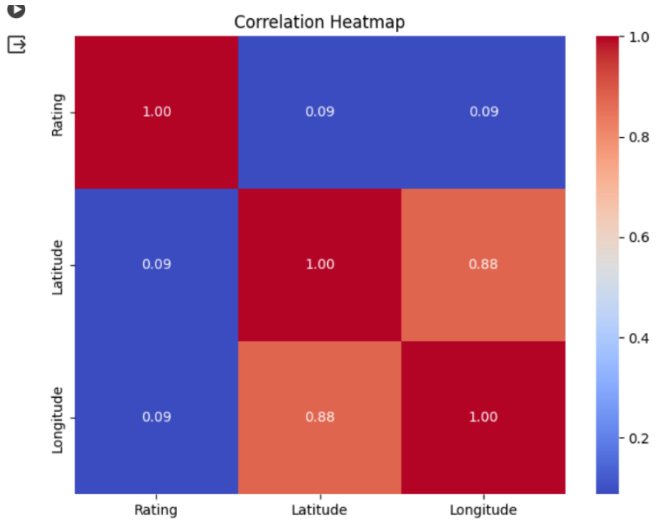

Figure 6. Confusion matrix plots of the study models: LSTM

Major Findings from the Experimental Results

In different sets of information, various models give different levels of accuracy. This happens mainly because the data can be really complicated and big. There are many things that can affect how well a trial classifier works. One big factor is pre-processing, which means getting the data ready in the right way before using it. If this step isn't done correctly, the classifier might not give the right results. Noise, which is like interference in the data, can also make the classifier not work well. Making sure the data is encoded properly is crucial too. There are different methods in the literature, and this work uses the best ones. Models can also have problems like over-fitting or under-fitting, which can really affect how well they work. To avoid this, the dataset needs to be balanced, not too small or too big. The design and features of the chosen model also matter. It's important to train any model well. Checking how well a classifier works shouldn't be based on just one try. Using something called cross-validation, where many tests are done and the average accuracy is taken, is a good way to make sure the classifier is really effective.

Comparison with Previous Work

Model 1 in the research paper shows strong performance on different datasets, with surprisingly high accuracy, recall, F1-calibration, and accuracy values for example, in the Amazon Fine Food Reviews dataset, scored 87 points % accuracy and 88% recall, which in terms of accuracy Wu-Ji (2016) do (2018) no. Overall, the models of the present paper exhibit high or comparable performance coefficients in different data sets, which demonstrate the effectiveness of the proposed method in sensitivity analysis [13-15-16].

Table 2. Comparison of performance measure matrices with previous work

Classification Models	Datasets	Precision	Recall	F1-Measure	Accuracy
Model 1	Amazon-Fine-Food-Reviews	87	88	99	87
	Phones and Accessories	91	88	96	78
	Amazon-Products	88	89	98.5	73
	IMDB	85	87	97	76
Model 2	Amazon-Fine-Food-Reviews	79	98	73	79
	Phones and Accessories	59	76	66	78
	Amazon-Products	53	81	69	80
	IMDB	93	89	98	81
Model 3	Amazon-Fine-Food-Reviews	76	60	62	91.3
	Phones and Accessories	79	66	69	91.4
	Amazon-Products	80	63	66.5	92.5
	IMDB	73	71	71.6	73.8
J.Wu and T. Ji (2016) [8]	Amazon-Fine-Food-Reviews	0.75	0.75	0.74	0.75
S. A. Aljuhani and N. S. Alghamdi [9]	Cell Phones and Accessories	0.8	0.8	0.8	0.79
H. Nguyen, A. Veluchamy, M. Diop, and R. Iqbal (2018) [10]	Amazon-Products	0.91	0.97	0.94	0.9
J. Hong and M. Fang (2015) [11]	IMDB	–	–	–	0.89

Conclusions

The study highlights the important role social media platforms play in storing vast amounts of global data including text, images, sound and video. Despite the improvements, challenges remain, particularly in maintaining comprehensive audio records and accurately differentiating between sensory differences in consumer surveys The survey uses a comprehensive approach that includes

data collection , pre-processing, feature coding, and segmentation steps Which are good robust or exhibit comparable results, especially in perceptual prediction These findings highlight the importance of perceptual analysis in the insight of understanding wom derived from audio data in customer surveys and social media emphasis. Furthermore, the inclusion of the LSTM algorithm in audio data heralds a new phase in sentiment analysis research. The analysis of accuracy levels on different data types highlights the effectiveness of the sensitivity analysis method, especially in detecting different features, thus opening the way for improved understanding and applications in audio data in sensitivity analysis

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