A

SYNOPSIS REPORT

On

"SENTIMENT ANALYSIS FOR GRIEVANCE TRACKING"

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Autonomous Institute,

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ABSTRACT

Sentiment analysis for grievance tracking leverages natural language processing (NLP) and machine learning techniques to automatically identify and interpret the emotional tone embedded in written feedback. This approach is highly beneficial for organizations managing large volumes of grievances, such as customer complaints, employee concerns, or public feedback, allowing them to process and prioritize responses more effectively. At its core, sentiment analysis involves classifying text into predefined sentiment categories, typically positive, neutral, or negative. For grievance tracking, the primary focus is often on identifying negative sentiments to flag urgent issues that require immediate attention. This enables organizations to address high-priority concerns in real time, thereby improving customer satisfaction and responsiveness. Sentiment analysis can be applied to various communication channels, including emails, social media, surveys, and support tickets, providing a comprehensive view of public sentiment across different platforms. Our project proposes the development of a grievance tracking system that incorporates sentiment analysis to enhance the speed and accuracy of feedback management. By utilizing advanced NLP algorithms and machine learning models, the system will automatically analyze incoming complaints, classify their sentiment, and provide actionable insights to stakeholders. This approach also enables the detection of recurring issues or emerging trends, allowing organizations to proactively resolve problems before they escalate. In addition, the system aims to reduce the manual effort involved in sorting and responding to grievances by automating the initial stages of analysis. This will allow human resources to be focused on resolving the most critical issues, improving both efficiency and effectiveness. Ultimately, sentiment analysis for grievance tracking represents a transformative solution that not only enhances operational efficiency but also fosters better customer and employee relations through timely and data-driven grievance resolution.

INTRODUCTION

Sentiment analysis for grievance tracking is an innovative application of natural language processing (NLP) and machine learning that aims to transform the way organizations handle complaints and feedback. In an era where customer experience and employee satisfaction are critical to business success, organizations receive large volumes of feedback from various channels, including emails, social media, customer reviews, surveys, and support tickets. Managing this influx of data manually can be overwhelming and inefficient, often leading to delayed responses and unresolved issues. Sentiment analysis, also known as opinion mining, offers a solution by automatically analyzing the emotional tone within these grievances, helping organizations understand and address concerns more effectively. Sentiment analysis involves the use of algorithms to classify textual data into different sentiment categories—such as positive, neutral, or negative. In the context of grievance tracking, the focus is primarily on identifying negative sentiments, which indicate dissatisfaction or urgent issues that require prompt attention. By leveraging machine learning models, sentiment analysis tools can quickly scan and interpret large amounts of text, providing real-time insights into the emotional state of customers, employees, or users. This automated approach ensures that critical issues are flagged for immediate action, reducing the risk of dissatisfaction escalating into larger problems. In addition to identifying urgent grievances, sentiment analysis can also uncover underlying trends in feedback, such as recurring complaints or emerging concerns that may not be immediately apparent through traditional analysis methods. By tracking sentiment over time, organizations can proactively address systemic issues, refine their processes, and improve service quality. This makes sentiment analysis a valuable tool for not only resolving individual grievances but also driving long-term organizational improvement. Our project focuses on developing a grievance tracking system that integrates sentiment analysis to enhance the efficiency and effectiveness of feedback management. In a competitive business environment, timely and effective grievance handling is essential for maintaining customer loyalty and employee engagement. Sentiment analysis offers a data-driven approach to grievance tracking, enabling organizations to respond to concerns more quickly, address root causes of dissatisfaction, and ultimately foster better relationships with their stakeholders. As a result, organizations that implement sentiment analysis for grievance tracking can expect to see improvements in both operational efficiency and overall satisfaction levels.

AIM & OBJECTIVES OF PROJECT

Aim:

The aim of this project is to develop an automated grievance tracking system that uses sentiment analysis to efficiently classify and prioritize feedback based on emotional tone. By leveraging NLP and machine learning, the system will identify critical issues in real-time, enabling faster resolution and providing data-driven insights for continuous improvement of customer and employee satisfaction.

Objectives:

- **Automate Sentiment Classification**: Develop an NLP-based system to automatically classify grievances into positive, neutral, or negative sentiments, reducing the need for manual sorting.
- **Prioritize Critical Grievances**: Implement real-time analysis to identify and flag high-priority complaints, ensuring that urgent issues are addressed promptly.
- **Improve Grievance Resolution Efficiency**: Streamline the grievance handling process by reducing manual workload, allowing faster response times and more efficient resource allocation.
- **Identify Recurring Issues and Trends**: Detect patterns in grievances over time, enabling organizations to address systemic problems and improve processes proactively.
- **Enhance Decision-Making with Data-Driven Insights**: Provide actionable insights to stakeholders, helping them make informed decisions and improve overall customer and employee satisfaction.

These objectives aim to create a robust, data-driven grievance tracking system that not only improves the efficiency of handling complaints but also enhances the quality of organizational responses. By leveraging automation and real-time sentiment analysis, the project will contribute to faster issue resolution, increased customer satisfaction, and continuous improvement in service quality.

LITERATURE REVIEW

The literature surrounding sentiment analysis and grievance tracking is extensive, reflecting the growing interest in automating feedback management using advanced computational techniques. Early studies focused on traditional methods of handling complaints, which often relied on manual sorting and categorization, leading to inefficiencies in responding to grievances. With the rise of natural language processing (NLP) and machine learning, researchers have explored new avenues for automating sentiment analysis to streamline the process. Key advancements include the development of algorithms for accurately classifying sentiments in textual data, as well as systems designed to prioritize and resolve urgent grievances. This review examines the evolution of these technologies, highlighting the effectiveness of different machine learning models, the integration of sentiment analysis in various industries, and the potential for improving grievance redressal systems through data-driven insights. Let's see some literature reviews:

- In proposed work, a new algorithm called Sentiment Fuzzy Classification algorithm with parts of speech tags is used to improve the classification accuracy on the benchmark dataset of Movies reviews dataset. [1]
- In this paper, the authors 1) investigate the current sources and causes of online complaints; 2) seek effective ways of handling customer complaints by examining different product types; and 3) provide guidelines for successful e-CRM. One thousand customer complaints from three different publicized e-business customer service centers and five hundred complaints from online feedback systems were analyzed in this study. [2]
- In proposed framework for understanding natural language semantic knowledge provided by well-known knowledgebase WordNet is used. In prequery citizens inserts complaint to system and get immediate response to query with the help of knowledgebase and machine learning algorithm. In postquery system analyses the citizen sentiment to handle grievance level and accordingly prioritize the citizens by sentiment analysis. [3]
- Towards pre-processing the raw textual data, they employed techniques like document term matrix (DTM) driven by Term Frequency - Inverse Document Frequency (TF-IDF), embedding model likeWord2Vec and psycho-linguistic method like Linguistic Inquiry and Word Count (LIWC). For the purpose of classification, the raw textual data

of complaints is labeled as "moderate" or "extreme" by the three human annotators. Results indicate that the LIWC in combination with Random Forest and Naïve Bayes techniques performed the best in three banks datasets. The results were statistically corroborated with a t-test. [4]

- This paper aims to provide an interactive automatic system which predicts the sentiment of the review/tweets of the people posted in social media using hadoop, which can process the huge amount of data. [5]
- In this paper, they leveraged on Natural Language Processing (NLP), using sentiment analysis and text mining to analyze mobile network operators, in this case CellC followers' using the R platform. They used the polarity model of sentiment analysis to determine the level of potential detraction and promotion across South African Mobile Network Operator (MNO), based on public tweets. [6]
- In this paper, they recommended innovative sentiment analysis method based on common sense knowledge (Domain Specific Ontology). They created their own Oman tourism ontology based on ConceptNet. Entities were identified from the tweets using POS tagger and entities were compared with concepts in the domain specific ontology. Further the sentiment of the extracted entities were determined by the combined sentiment lexicon approach. Finally semantic orientations of domain specific features were combined with respect to the domain. They deliberate conceptual semantic as feature which can be combined with machine learning algorithm to enhance the performance of sentiment analysis of Oman tourism. [7]
- This paper proposes the creation of Myanmar sentiment lexicon for food and restaurant domain and analyses the Myanmar text reviews of customers using lexicon-based sentiment analysis for the recommendation. [8]
- In this paper a framework for sentiment analysis using R software which can analyze sentiment of users on Twitter data using Twitter API is proposed. Their methodology involves collection of data from twitter, its pre-processing and followed by a lexicon based approach to analyze user’s sentiment. [9]
- In this paper, sentiment compensation technique is used to automatically compensate the sentiment to a dimension where consumer’s review mentions the sentiment without a dimension. The results show that the proposed method outperform sentiment to dimension (S2D) and dimension to sentiment (D2S) methods with the overall accuracy 93.60%. [10]

- In this paper, they have compared between CNN, LSTM and LSTM-CNN architectures for sentiment classification on the IMDb movie reviews in order to find the best-suited architecture for the dataset. Experimental results have shown that CNN has achieved an F-Score of 91% which has outperformed LSTM, LSTM-CNN and other state-of-the-art approaches for sentiment classification on IMDb movie reviews. [11]
- This research aims to employ natural language processing (NLP), sentiment analysis and data mining technologies to build a public opinion analysis system to serve enterprises' need of online public opinion detection. [12]
- This work is centered around implementing a fresh approach to sentiment analysis. The sentiment analysis techniques have various phases which include pre-processing, feature extraction and classification. The various machine learning algorithms for sentiment analysis are reviewed in terms of certain parameters. [13]
- In this paper, the textual yelp reviews of businesses are analyzed to assign a probability for the review as having positive or negative sentiment. The data considered for the sentiment analysis are the reviews on restaurants about food, service, price and ambience. Machine learning algorithms in the nltk library of python proved to be very useful in any such research on Natural Language Processing and the library has been used extensively in this work. Each algorithm used has been analyzed and has been compared on the basis of their efficiency (confidence). [14]
- In this paper, they discussed various available lexicon resources and often used SA techniques in some Indian languages. Moreover, they presented the theoretical parametric evaluation of their studied techniques and also discussed challenges, which were identified during SA in Indian Languages. [15]
- In this paper, they construct the domain sentiment dictionary using external textual data. They propose a highly effective hybrid model combining different single models to overcome the weaknesses of single models. [16]
- This paper looks into the nascent area of Natural Language Processing (NLP) in the Sentiment Analysis of Chinese Text. The proposed Deep Learning method is the use of a sentence-based approach in the sentiment analysis of online reviews to gain more granularity and increased classification accuracy. Experimental results on a balanced (50:50), 2 class (positive, negative) test dataset of 1669 product reviews show an empirical accuracy of 87.66%, while results on an imbalanced (18:82) test dataset of

2519 product reviews show an accuracy of 87.9%, thus demonstrating the effectiveness and robustness of this proposed approach. [17]

- Work presented in this article adds to the growing debate on the institutional deployment of lecture recordings and their impact on students' engagement and learning. It also demonstrated how educational researchers could utilise social network and sentiment analysis to examine critical issues in education. [18]
- In this paper the Long Short-Term Memory (LSTM) classifier is used for analyzing sentiments of the IMDb movie reviews. It is based on the Recurrent Neural Network (RNN) algorithm. The data is effectively preprocessed and partitioned to enhance the post classification performance. The classification performance is studied in terms of accuracy. Results show a best classification accuracy of 89.9%. It confirms the potential of integrating the designed solution in modern text based sentiments analyzers. [19]
- In this paper, Recursive Deep model is used to identify sentiment orientation of review sentences. A review matrix is constructed to find the importance and polarity of each product feature. The experimental results show that the method proposed is effective and has achieved the desired objective. [20]
- In this paper, they adapt the first rank research at SemEval 2016 to improve the performance of aspect-based sentiment analysis for Indonesian restaurant reviews. They use six steps for aspect-based sentiment analysis i.e.: preprocess the reviews, aspect extraction, aspect categorization, sentiment classification, opinion structure generation, and rating calculation. [21]
- This project aimed to examine a number of tools regarding their suitability for healthcare data. Different approaches were followed for each tool to determine the polarity of each response (i.e. positive, negative or neutral). In addition, single-sentence responses were tested in isolation to determine the extent to which they more clearly express a single polarity. [22]
- In this study, naïve bayes and RF machine learning techniques were compared for measuring negative, positive and neutral reviews. [23]
- In this paper, firstly, subjective paragraphs were detected from the source materials by detecting subjective words. Secondly, the aspects of subjective paragraphs were defined by the frequency of words in each aspect. Finally, the sentiment of texts were classified by the machine learning for laptop data. [24]

- This study proposes a framework based on data mining method to find interesting patterns of sentiment and sales. The proposed model starts by defining sentiment topics with their corresponding terms and then follows by a fuzzy model to infer the sentiment scores for user opinions. Each transaction in the database is transformed to attach with public sentiment scores, influential users’ sentiment scores and volume of product sales. To better obtain the relationship among public sentiment, users’ sentiment and volume of product sales, a mining method of inter-transaction association rules is considered to extract the interesting patterns of sentiment and sales. [25]

PROPOSED WORK

Technology used:

- Front End- HTML, CSS, Java Script: HTML, CSS, and JavaScript work together to create web pages: HTML structures content, CSS styles it, and JavaScript adds interactivity and dynamic behavior to enhance user experience.
- Back End- Python (libraries: Open CV, sklearn): Python, along with its OpenCV library, provides a powerful platform for computer vision tasks, offering a wide range of functions and tools for image & video processing and analysis.
- Tools:
    - Github: GitHub is a web-based version control and collaboration platform that enables software developers to store, track changes, and collaborate on projects efficiently through features like repositories, branches, commits, and pull requests.
    - VSCode: Visual Studio Code is a lightweight yet powerful source code editor that supports various programming languages, offers intelligent code completion, debugging tools, and extensive customization options for efficient development workflows.

PROPOSED WORK

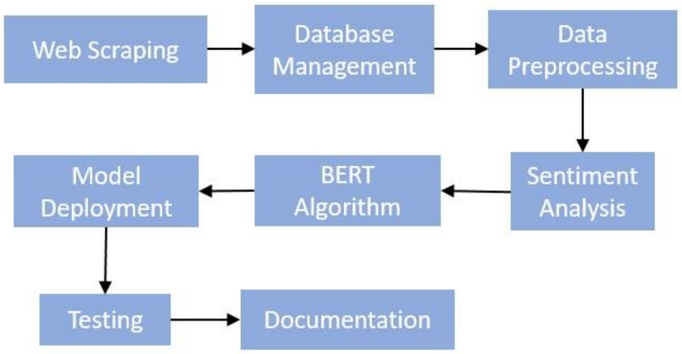

Fig. Workflow Diagram

Technology used:

- Programming Language – Python
- Frameworks – Tensorflow, Hugging Face
- Data Sources – APIs, Databases
- Deployment – Flask/Django, Docker
- Tools:
  1. Github: GitHub is a web-based version control and collaboration platform that enables software developers to store, track changes, and collaborate on projects efficiently through features like repositories, branches, commits, and pull requests.
  2. VSCode: Visual Studio Code is a lightweight yet powerful source code editor that supports various programming languages, offers intelligent code completion, debugging tools, and extensive customization options for efficient development workflows.

PROPOSED METHODOLOGY

In this section, let’s see the way to solve the given problem:

- **Web Scraping**
  - **Define Data Sources:** Identify and list websites, forums, social media platforms, or other sources relevant to grievance tracking.
  - **Choose Scraping Tools:** Select appropriate tools or libraries for scraping (e.g., BeautifulSoup, Scrapy, Selenium).
  - **Implement Scraping Scripts:** Write and test scripts to extract relevant text data from identified sources.
  - **Handle Data Extraction Challenges:** Manage issues such as dynamic content, CAPTCHA, and anti-scraping mechanisms.
  - **Store Raw Data:** Save the scraped data in a structured format (e.g., CSV, JSON).

- **Database Management**
  - **Database Design:** Define schema for storing scraped data, including tables for raw data, processed data, and metadata.
  - **Setup Database:** Choose a database system (e.g., SQL, NoSQL) and set up the database environment.
  - **Data Insertion:** Import raw data into the database from the storage format used in web scraping.
  - **Database Optimization:** Implement indexing and query optimization for efficient data retrieval.

- **Data Preprocessing**
  - **Data Cleaning:** Remove duplicates, correct errors, and handle missing values in the dataset.
  - **Text Normalization:** Convert text to lowercase, remove punctuation, and correct typos.
  - **Tokenization:** Break text into individual tokens or words.

- **Stop Words Removal:** Eliminate common words that do not contribute to sentiment (e.g., "and", "the").
- **Lemmatization/Stemming:** Reduce words to their base or root form.

➢ Model Deployment

- **Environment Setup:** Configure the computational environment for model deployment (e.g., server setup, cloud services).
- **Integrate Model:** Deploy the sentiment analysis model into the chosen environment.
- **API Development:** Develop APIs for interacting with the model (if applicable).

➢ BERT Algorithm Implementation

- **Model Selection:** Choose an appropriate BERT variant (e.g., BERT-base, BERT-large).
- **Fine-Tuning:** Fine-tune BERT on a relevant dataset for sentiment analysis tasks.
- **Tokenization with BERT:** Use BERT's tokenizer to preprocess text data for the model.
- **Model Training:** Train the model on labeled sentiment data (if available).
- **Evaluation:** Evaluate model performance using metrics like accuracy, F1-score, precision, and recall.

➢ Sentiment Analysis

- **Apply Model:** Use the fine-tuned BERT model to predict sentiments from the preprocessed data.
- **Classify Sentiments:** Categorize sentiments into classes (e.g., positive, negative, neutral).
- **Aggregate Results:** Summarize the sentiment results to identify trends or patterns.

Testing

- **Unit Testing:** Test individual components (e.g., scraping scripts, preprocessing functions).
- **Integration Testing:** Test the entire workflow from data scraping to sentiment analysis.
- **Performance Testing:** Evaluate the system’s performance in terms of speed, accuracy, and reliability.
- **User Testing:** Conduct tests with potential end-users to ensure the system meets their needs.

Documentation

- **Project Overview:** Document the goals, scope, and objectives of the project.
- **Methodology:** Provide detailed descriptions of each step and its implementation.
- **Code Documentation:** Include comments and explanations within the codebase for maintainability.
- **User Guides:** Create user manuals or guides for interacting with the system.
- **Maintenance Plans:** Outline procedures for updating and maintaining the system.

CONCLUSION

In conclusion, this sentiment analysis project for grievance tracking is poised to make a significant impact by applying advanced natural language processing techniques to real-world challenges. By following a structured methodology that will encompass web scraping, database management, and the deployment of the BERT algorithm, the project aims to create a robust system capable of accurately analyzing sentiments expressed in grievances. The planned approach will ensure a comprehensive data preprocessing pipeline, which is expected to enhance data quality and model accuracy. Utilizing BERT, a leading language model, will allow the project to achieve high levels of precision in sentiment classification. Rigorous testing will be conducted to validate the system's effectiveness and reliability, confirming its potential to provide valuable insights into customer feedback and grievances.

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