# A
# Major Project Report

**On**

## "Real Time Emotion Recognition from Text Using Deep Learning and Feedback Analysis"

Submitted in partial fulfillment of the

Requirements for the award of the degree of

**Bachelor of Technology**

**In**

**Computer Science and Engineering – Artificial Intelligence and Machine Learning**

**By**


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**2024**

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## CERTIFICATE

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## DECLARATION

We hereby declare that the project entitled **"Real Time Emotion Recognition from text using Deep learning and Feedback Analysis"** is the work done during the period from **January 2024 to May 2024** and is submitted in partial fulfillment of the requirements for the award of degree of Bachelor of Technology in Computer Science and Engineering – Artificial Intelligence and Machine Learning from Jawaharlal Nehru Technology University, Hyderabad. The results embodied in this project have not been submitted to any other university or Institution for the award of any degree or diploma.

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## Department of Computer Science and Engineering - Artificial Intelligence and Machine Learning

## ABSTRACT

In the era of digital communication, understanding human emotions expressed through text has become increasingly vital, this increases the importance of accurate emotion recognition from text, which can be useful in various applications. This project delves into the realm of text-based emotion recognition precisely identifying and categorizing the emotions expressed in textual content by using a deep learning approach such as Bi-LSTM. Presently, a significant portion of ongoing research primarily centers on the classification of text based on sentiments, with a small fraction focusing towards emotion recognition, particularly within the context of business applications. The principal objective of our project is to bridge the gap between the business organizations and the customers by analyzing the customer reviews based on emotion classification. This helps furnish organizations with a systematic approach to comprehend customer emotions, providing a more precise evaluation of product performance.

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# APPENDIX-3
# ABBREVIATIONS

# ABBREVIATIONS

| | |
|---|---|
| Bi-LSTM | Bidirectional Long Short-Term Memory |
| NLP | Natural Language Processing |
| GloVe | Global Vectors for Word Representation |
| SMTP | Simple Mail Transfer Protocol |
| BERT | Bidirectional Encoder Representations from Transformers |
| NLTK | Natural Language Toolkit |
| ASR | Automated Speech Recognizer |
| ERNIE | Enhanced Representation through knowledge Integration |
| SVC | Support Vector Classifier |
| HTML | Hyper Text Markup Language |
| CSS | Cascading Style Sheets |
| API | Application Programming Interface |
| DB | Database |

# APPENDIX-4
# REFERENCES

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# CHAPTER 1

# INTRODUCTION

## 1.1 OVERVIEW

In today's digital age, understanding how emotions are expressed through text is becoming increasingly important. We have embarked on a project to create an innovative system which is capable of recognizing emotions from customer feedback in real time. Our goal is to help businesses connect with their customers by providing a better understanding of the emotions that shape their experiences.

Our solution is based on a sophisticated technique known as Bidirectional Long Short Term Memory (Bi-LSTM) model. This model excel at extracting contextual nuances and relationships from textual data. Using Bi-LSTM model, our system can accurately identify a wide range of emotions expressed in customer reviews and feedback, that include happiness, sadness, anger, and disgust. Our method is modular, with multiple connected parts that come together to provide a complete solution. A module that employs Bi-LSTM model to identify emotions, an automated system for providing customized responses based on the identified emotions, also an easy-to-use system for gathering customer information and product reviews, a portal for allocating customer support staff to help customers with negative feedback, and a dashboard that offers informative visualisations of emotion distributions. Businesses successfully deploy our innovative system will gain valuable insights into their customers' emotional landscape. This will allow them to better respond to customer concerns, prioritize critical issues, and make data-driven decisions, ultimately improving customer satisfaction and driving overall business performance.

## 1.2 PURPOSE OF THE PROJECT

The objective of our project is to use deep learning and data analysis methods to create a sophisticated, real-time text emotion recognition and feedback analysis system. The system attempts to overcome the weaknesses of conventional sentiment analysis techniques in capturing complex emotions, hence offering a more precise and accurate understanding of feedback from customers. Analysing customer feedback, automated response to save time of customer service and data visualisation for more in depth understanding of the consumer emotion towards the product are the main objectives of this project. A feedback collection system, an emotion detection module, response generation, a manager's portal, and a dashboard for data visualisation are all included in our solution. The project aims to assist companies in improving customer feedback analysis, reputation management, and increase in customer satisfaction. By giving companies a strong tool to better understand customer emotions they can provide better customer service, which helps to boost customer happiness and loyalty.

In conclusion, the goal of this project is to improve customer service through communication, and analysis of customer feedback by utilising the best approaches in deep learning and data analysis methodologies. The approach under consideration is intended to furnish enterprises with a more precise and perceptive comprehension of consumer feedback, hence facilitating the enhancement of customer service and reputation management.

## 1.3 MOTIVATION

In the current digital era, text-based channels like social media, online reviews, and messaging apps account for a large amount of communication. It is becoming more and more crucial to comprehend the feelings expressed in this textual content for a variety of applications, such as customer support, managing brand reputation, and tailored user experiences.

The complex range of human emotions is not adequately captured by conventional sentiment analysis methods, which divide text into binary classifications such as positive, negative, or neutral. Due to the complexity and diversity of emotions, a simple categorization may not offer sufficient understanding of the underlying sentiments conveyed in the text. By providing a deeper comprehension of the emotional context behind online chats, product reviews, and consumer feedback, accurate emotion recognition from text can help close this gap. Businesses can better understand consumer sentiments and respond to customers by detecting certain emotions like happiness, sorrow, anger, or disgust. This allows them to improve their products or services in response to client needs. Existing techniques for evaluating client feedback frequently oversimplify feelings or don't have elements for comprehensive data analysis and visualization. Combined with strong data analysis and visualisation capabilities, an integrated strategy that combines advanced emotion identification techniques is needed. Companies can now have a complete understanding of client feelings and preferences thanks to this integration. By addressing these challenges, companies can improve their understanding of the emotional dynamics of their customers, which will lead to better product innovation, more specialized marketing efforts, and eventually higher levels of customer happiness.

# CHAPTER 2

# LITERATURE SURVEY

A thorough review of the literature has been done by examining current methods for text-based emotion recognition. Before producing the survey, a sizable number of research papers, journals, and publications were also reviewed.

## 2.1 EXISTING SYSTEM

The existing system of text-based emotion recognition involves classifying the text into sentiments of positive, negative and neutral. There is no existing system which has the use case of text emotion recognition for business enterprises.

The responses to various research articles are documented below by the order of the number that have been used to specify them in the references in the end.

| **1** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9182441 | Yanrong Zhang<br>Jiayuan Sun<br>Lingyue Meng<br>Yan Liu | Sentiment analysis, tf-idf, sentiment dictionary, text similarity. |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| Proposed a sentiment analysis model for E-commerce Text Reviews by using sentiment dictionary. | Objective is to use sentiment dictionary-based method to mine e-commerce text reviews, and build a reverse sentiment dictionary for the problem that the same sentiment | 1. Extraction of Emotional Resources<br>2. Construction of emotion dictionary<br>3. Constructing reverse dictionary |

| | | |
|---|---|---|
| | word has different sentiment polarities. | 4. Emotion analysis |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| **1** | Pre-processing and part-of-speech tagging of the corpus. | Constructing a reverse emotion dictionary instead of just an emotion dictionary shows higher accuracy. | The results of part-of-speech tagging can be biased and need to be manually rectified. |
| **2** | TF-IDF algorithm is used to extract the keywords of the product.<br>-TF algorithm counts the number of times a word appears in a comment.<br>-The IDF algorithm counts how many comments a word exists in the corpus.<br>-TF-IDF are calculated for all nouns, and the top 50 values are taken. | The method proposed in the paper accurately extracts evaluation objects from text reviews. | The accuracy rate of sentiment classification in the phone field using the proposed sentiment dictionary is lower compared to the computer field. |
| **3** | Extraction of Evaluation Objects<br>-data is word-vectorized.<br>-Similarity between the feature words (words in the review) and the keywords (extracted) is calculated using cosine similarity and the most similar feature word is taken as the evaluation object. | The paper proposes the construction of a domain specific emotion dictionary for computer and phone products. | |
| **4** | Extracting emotional resources by using parts of speech filtering and some specific rules. | | |
| **5** | Construction of Benchmark Sentiment Dictionary<br>-SO-PMI (Sentiment Orientation Pointwise Mutual Information) algorithm to determine the polarity of the words and store them in the dictionary.<br>-It calculates the difference between the PMI between the word and the | | |

| | | | |
|---|---|---|---|
| | positive seed words and the PMI between the word and the negative seed words (seed word are frequent and have strong sentiment- positive or negative). | | |
| **6** | Constructing reverse emotion dictionary<br>-Maps sentiment words to their opposite sentiment.(Customer service-excellent-poor)<br>-eg: high price and fast electricity consumption means negative sentiment even though high and fast are positive sentiments. | | |
| **7** | Degree words are assigned with some weights. | | |
| **8** | Overall sentiment of the comment is analysed. | | |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Sentiment of the review | No. of negative words (N) | | |
| | Weight of the degree words (D) | | |
| | Emotional word (S=1 or -1) | | |

**Relationship Among The Above 4 Variables in This article**

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| **Input**: Text review of phone or computer<br>**Output**: Sentiment of the review | The solution builds its own sentiment dictionary for computers and phones, and the self-built sentiment | Got to know how to build a domain specific sentiment dictionary for sentiment analysis and about a new approach of reverse sentiment |

| | | |
|---|---|---|
| | dictionary shows better results than the public sentiment dictionary for sentiment classification. | dictionary for improved performance. |

| **Positive Impact of this Solution in This Project Domain** | **Negative Impact of this Solution in This Project Domain** |
|---|---|
| Reverse sentiment dictionaries are more robust to changes in language or domain than traditional sentiment dictionaries because they are not based on a fixed set of sentiment words. | It builds a domain specific emotion dictionary so it's not suitable to use for other domains. |

| **Analyse This Work By Critical Thinking** | **The Tools That Assessed this Work** | **What is the Structure of this Paper** |
|---|---|---|
| The paper provides an approach for sentiment analysis by building a domain specific sentiment dictionary, and to overcome the problem of the same sentiment word having different sentiment polarities for different evaluation objects, it builds a reverse sentiment dictionary which shows better accuracy mainly for e-commerce text reviews. | HowNet sentiment dictionary, Accuracy | I. Abstract<br>II. Introduction<br>III. Status at home and abroad<br>IV. Related work<br>V. Sentiment Analysis<br>VI. Experimental Results and Analysis<br>VII. Conclusion<br>VIII. Acknowledgment<br>IX. References |

| **Diagram/Flowchart** |
|---|

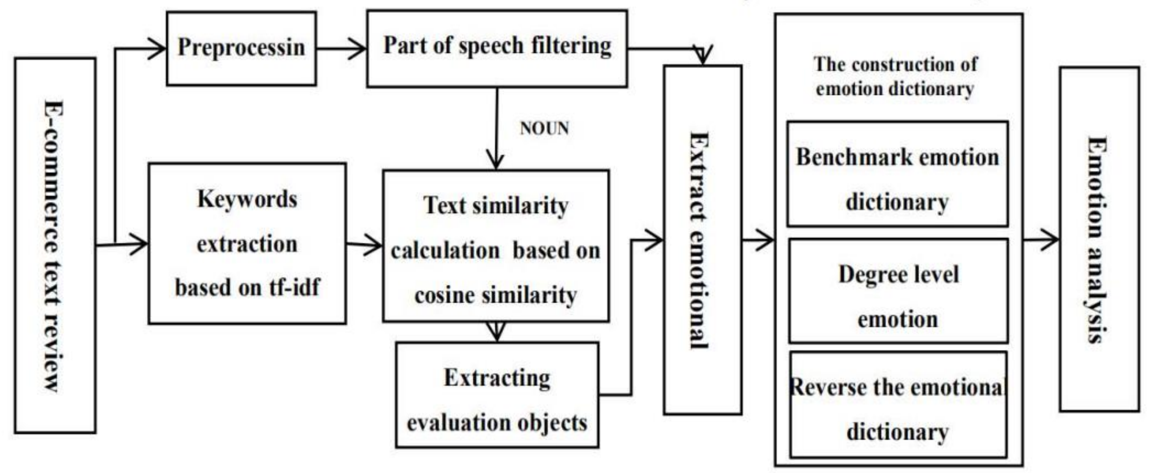



Fig. 1. E-commerce text review sentiment analysis roadmap

**---End of Paper 1--**

| 2 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/10212127 | Ghamya Kotapati, Suma Kamalesh Gandhimathi, Palthiya Anantha Rao, Ganesh Karthik Muppagowni, K Ragha Bindu, M Sharath Chandra Reddy | Deep Learning, Natural language processing, Emotion Recognition, BERT (Bidirectional Encoder Representations for Transformers). |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| A Natural Language Processing for Sentiment Analysis from Text using Deep Learning Algorithm | Main objective is to understand the context of the sentence and categorize the sentence into the correct emotion. | Components of BERT model-<br>CLS: added at the beginning of a text input, acts as a summary of the entire text.<br>SEP: added at the end of a text input, helps to understand |

| | | |
|---|---|---|
| | | the relationships between the different sequences.<br><br>Token embeddings: numerical representation of each token.<br><br>Segment Embeddings: used to determine to which sentence the token belongs to. Sentence 1- index 0, sentence 2- index 1<br><br>Position embeddings: shows where a word's position is in a sentence.<br><br>Hidden state: captures both the semantic and syntactic information of the token by considering all the embeddings.<br><br>Classification layer: outputs the probabilities of the emotion category. |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| **1** | Pre-processing the text data. | BERT models are excellent at identifying context and interpreting sentiment within the context of the entire input text. | It only classifies the emotion into three categories i.e. positive, negative and neutral. |
| **2** | Tokenization is done to divide the text into separate words. | Record delicate emotions or mixed feelings, in addition to more complex sentiments. | |
| **3** | Encode the input data. | | |
| **4** | Fine-tuning the BERT model. | | |

| | | | |
|---|---|---|---|
| 5 | Testing model. | | |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Accuracy | Fine tuning the model | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution in This Work |
|---|---|---|
| (see Input/Output table below) | The proposed model takes into account both the relationships between words and sentences and the overall context while determining the sentiment of the given input. It can also understand different degree of emotions. | Got to know how sentimental analysis can be used to monitor the movement of customer mood and feedback regarding a company's name, goods, and services. |

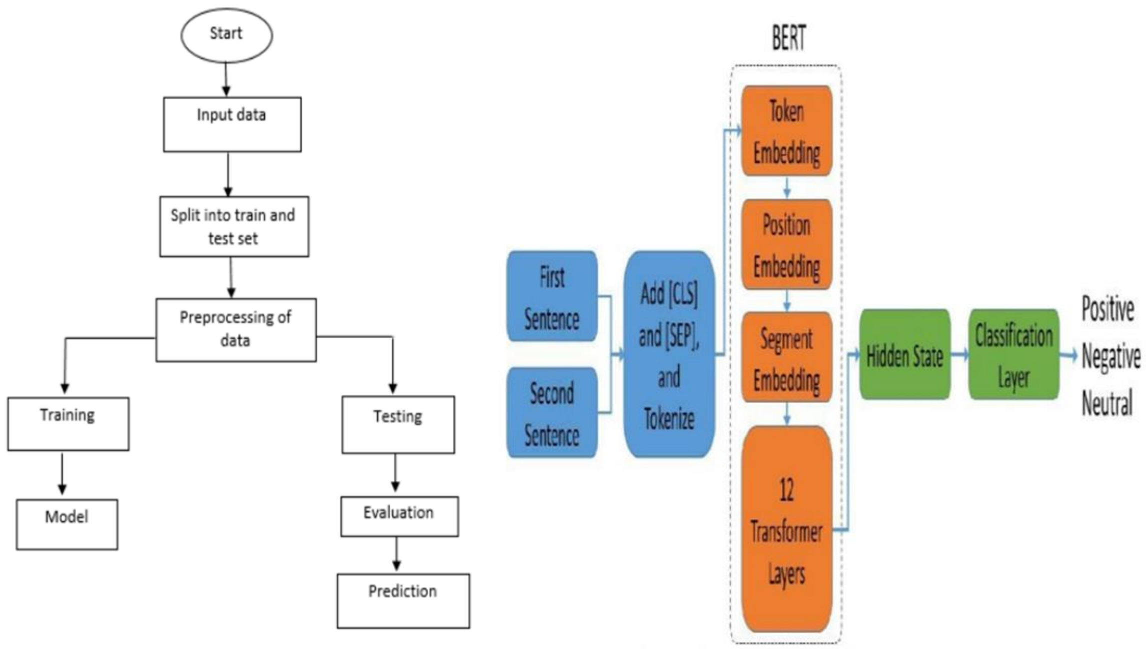
| Input | Output |
|---|---|
| Text from which sentiment needs to be recognized. | Analysed sentiment from the given text. |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| BERT has proven to be very successful at tasks requiring natural language processing, specially it performs accurately for sentiment analysis tasks. | BERT models are computationally expensive to train and use. This can make them inaccessible for people with limited resources. |

| Analyse This Work By Critical Thinking | The Tools That Assesse | What is the Structure of this Paper |
|---|---|---|
| | | |

| | **d this Work** | |
|---|---|---|
| BERT is trained on a huge text corpus, so the architecture or model is able to learn a variety of data patterns, comprehend language better, and effectively generalize and easily analyse the sentiment conveyed by the text. | Recall, precisio n and F1 score | Abstract<br>I. Introduction<br>II. Literature Survey<br>III. Methodology<br>IV. Results<br>V. Conclusion<br>VI. References |

**Diagram/Flowchart**




**--End of Paper 2--**

| **3** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/8769589 | Aljoharah Almjawel<br>Sahar Bayoumi<br>Dalal Alshehri<br>Soroor Alzahrani<br>Munirah Alotaibi | Text Visualization, Tableau, Rstudio, Amazon Reviews, Opinion Analysis, Sentiment Analysis. |

| The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc ) | The Goal (Objective) of this Solution & What is the problem that need to be solved | What are the components of it? |
|---|---|---|
| Sentiment Analysis and Visualization of Amazon Books' Reviews | The aim is to provide a practical way to visually analyze customer feedback sentiment using various visualization techniques. | 1. Sentiment analysis<br>2. Visualization of reviews using different visualization techniques |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | The used dataset formed from two separate datasets (details of product description + details of review) and has 4 attributes- overall, summary, title and time of reviews. | Helps the customers to make decisions by giving review analysis to the customer. | The proposed model relies on a lexicon-based approach for sentiment analysis, which may lead to incorrect classifications of reviews especially for slang, colloquial, and jargon words. |
| 2 | Sentiment or qdap packages in R can be used for sentiment analysis, sentiment package requires installation of tm and Rstem packages.<br>Tm-text preprocessing<br>Rstem- stemming algorithms | The model enables users to compare sentiment reviews of different books with an interactive user interface. | The lexicon-based approach used in the model may not cover all opinion words as it’s using a default sentiment dictionary, by creating a domain specific sentiment dictionary we can get more accurate results. |
| 3 | Several visualization techniques are used that helps users to visualize the information about different books. | | |
| 4 | Packed bubbles: represent the frequency of positive, negative and neutral reviews of a book.<br>Linear chart: represent the time when the reviews were written. | | |

| | | | |
|---|---|---|---|
| | Stacked bars: used to present the ratings of books and whether they are positive, neutral or negative.<br><br>Word-cloud: it shows the book that has most reviews, and shows the most frequently used word in the reviews of books. | | |

**Major Impact Factors in this Work**

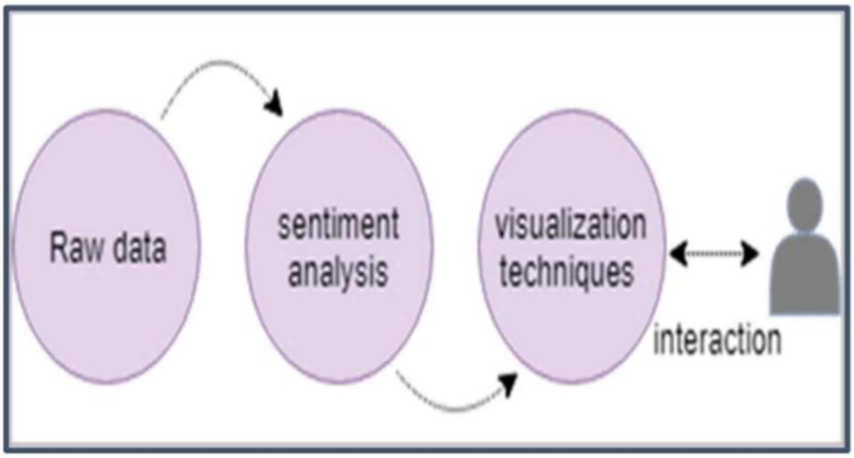
| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Review analysis | Rating | | |
| | Summary | | |
| | Title | | |
| | Time of reviews | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| <table><tr><th>Input</th><th>Output</th></tr><tr><td>Dataset of book reviews obtained from Amazon</td><td>Visual representation of the sentiment analysis results</td></tr></table> | Visualization of book reviews using 4 techniques allow users to-<br>1. Select a book and see if reviews are positive, neutral, or negative.<br>2. Get detailed information about a book of interest and compare the books. | The major contribution is the development of a visual approach for analyzing book reviews.<br><br>Users can select specific books and determining the sentiment and rating of reviews. |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| It gives better analytical powers to the customers while buying a product. It also can be used by the product development unit for analysing their product. | Low accuracy in determining the correct sentiment of the reviews. |

| Analyse This Work By Critical Thinking | The Tools That Assessed this Work | What is the Structure of this Paper |
|---|---|---|
| The proposed model has a dataset which includes 12 books reviews selected from Amazon, and contains 1000 records. This solution will help users to quickly and easily understand the overall sentiment of book reviews with visual analysis and find books of their interest. | Data Visualization- Tableau | Abstract<br>I. Introduction<br>II. Literature Review<br>III. System Design<br>IV. Results<br>V. Conclusion<br>VI. Future Work |

| Diagram/Flowchart |
|---|
|  |



**--End of Paper 3--**

| 4 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9792786 | Raghavendra Reddy<br>Ashwin Kumar U M | Sentiment Analysis, Opinion Mining, Convolutional Neural |

| | | |
|---|---|---|
| | | Network, Emoji and Social Network. |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| Proposed a multi-class sentiment analysis form text by using Enhanced Convolutional Neural Network (ECNN). | Objective is to find the emotion using text and emoji-based features. | 1. Preprocessing the input text<br>2. Feature extraction<br>3. Identifying the correct emotion using ECNN<br>4. Comparing the model with different classification models |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| **1** | The dataset we used for this study is Amazon product reviews dataset with 10,000 tweets. | Can recognize the emotion in the text containing emojis which improves the accuracy. | Different OS has different types of emojis, this can make it difficult for the model to predict the emotion of a text that contains emojis, as the model may not be familiar with all of the emojis that are used. |
| **2** | Preprocessing techniques such as tokenization, stop-word removal, stemming, and lemmatization to clean the text data. | | |
| **3** | The emotion of a sentence is analysed by dividing it into two parts. Emotion of the text is identified using an emotion dictionary and each emoji is replaced by its word meaning. | | |
| **4** | The DeepEMoji model is fine tuned with e-commerce emoji and then used to extract sentiment and emotion features | | |

| | | | |
|---|---|---|---|
| | from the text and emojis in a tweet. These features are represented as a vector of numbers. | | |
| **5** | The ECNN model then uses the features to classify the emotion of the text. | | |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Recognized emotion | Set of words | | |
| | Set of emojis | | |

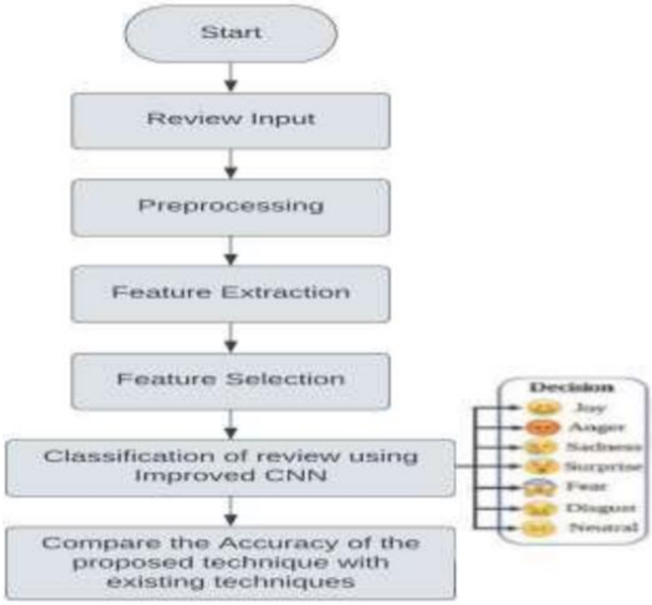
| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| (see Input/Output table below) | The model uses both text and emoji-based features to learn patterns in the data. This allows the model to recognize multiclass emotions. | Got to know how emojis can be used to classify the correct emotion of the given text. |

| Input | Output |
|---|---|
| Text from which emotion needs to be recognized. | Correct emotion of the given input text. |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| ECNN with DeepEMoji gives better results than traditional classifiers like CNN, SVM, DT and NB. | Heavily rely on emojis for accurate classification. |

| Analyse This Work By Critical Thinking | The Tools That Assessed this Work | What is the Structure of this Paper |
|---|---|---|
| The DeepEmoji model is fine tuned with features like emoji name, meaning, and review text using emoji-labeled texts from the E-commerce application for accurate classification of emotion from the reviews. | Accuracy, precision, recall and f-measure. | Abstract<br>I. Introduction<br>II. Related Work |

| | | |
|---|---|---|
| | | III. Methodology<br>IV. Experimental Results<br>V. Conclusion |
| **Diagram/Flowchart** | | |
| <br> | | |

**--End of Paper 4—**

| **5** | | | |
|---|---|---|---|
| **Reference in APA format** | | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** | |
| https://ieeexplore.ieee.org/document/9756494 | Habib Izadkhah | Natural language processing (NLP), Deep learning, Convolutional neural network, Emotions. | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that** | **What are the components of it?** | |

| | need to be solved | |
|---|---|---|
| Detection of multiple emotions in texts using a new deep convolutional neural network X-module. | The purpose of this paper is to detect multiple emotions in texts. | 1. Creation of dataset<br>2. Creating customized X-module<br>3. Predicting multiple emotions from text |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

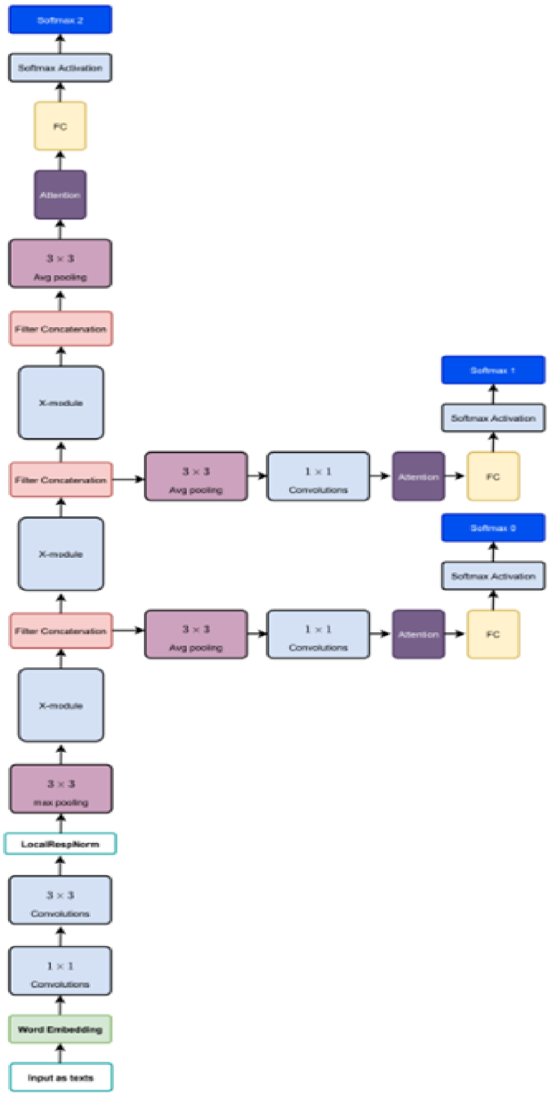
| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | Creation of multi-labeled dataset from CBET and semEval 18 datasets. | High accuracy in detecting multiple emotions from text. | It requires a large and balanced dataset of multi-labelled emotions, which may not be easily available or representative of real-world scenarios. |
| 2 | Preprocessing the raw data. | Created modified dataset for higher accuracy. | |
| 3 | Word embedding layer represent words as vectors of numbers using pre-trained word embedding models like FastText and GloVe. | | |
| 4 | The Attention mechanism focus on the most important parts of an input sequence to understand the meaning of the sentence by softmax function (0-1) | | |
| 5 | X-module is made up of R-blocks, X-modules are stacked upon each other and it performs emotion detection. | | |
| 6 | R-blocks are made up of two 1-D CNN, and the output of the R-blocks are concatenated using filter concatenation and it widens the network. | | |
| 7 | The fully connected layer gives the final output by using softmax activation function and produces probability of each emotion. | | |

| Major Impact Factors in this Work | | | |
|---|---|---|---|
| **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** |
| Multilabel Emotion | Text Data | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| **Input**: Text to detect emotion<br>**Output**: Vector of probabilities for each emotion class | 1. Existing systems tend to learn more single-emotion samples than multi-emotion samples in a dataset.<br>2. The number of texts from which only one emotion can be deduced is very small compared to texts from which more than one emotion can be deduced which reduces accuracy. But here a new dataset is created with multi | 1. Got to know that most of the datasets contain very less single emotion label which decreases their accuracy.<br>2. How 1-D CNN can be used for emotion detection. |

<table>
<tr><td colspan="2"></td><td colspan="2">label emotions.</td><td></td></tr>
<tr><td colspan="3">Positive Impact of this Solution in This Project Domain</td><td colspan="2">Negative Impact of this Solution in This Project Domain</td></tr>
<tr><td colspan="3">Employing a wider network instead of just a deeper one, the solution overcomes existing architecture limitations such as computing overhead and overfitting.</td><td colspan="2">Did not provide any possible solution to tackle the issue of single emotion label.</td></tr>
<tr><td>Analyse This Work By Critical Thinking</td><td colspan="3">The Tools That Assessed this Work</td><td>What is the Structure of this Paper</td></tr>
<tr><td>1. It proposes a new deep convolutional neural network architecture, called X-module, that considers both the depth(layers) and width(filters) of the network, and uses identity connections, filter concatenation, and intermediate classifiers to improve the learning and performance of the model.<br>2. It uses attention mechanism to focus on the most important words in each text that contribute to the emotions<br>3. Word embedding models (fast text and GloVe) convert into word vectors.<br>4. The intermediate classifiers are used in the X-module to prevent the "dying out" of the middle part of the network and to calculate the loss function, to improve the final loss function.<br>5. Identity Connection, connects the input to the output.</td><td colspan="3">Jaccard index, Hamming Loss, micro-average precision and recall, F1-score.</td><td>Abstract<br>I. Introduction<br>II. Related Work<br>III. Proposed Approach<br>IV. Experimental Results<br>V. Conclusion</td></tr>
<tr><td colspan="5">Diagram/Flowchart</td></tr>
</table>




**--End of Paper 5--**

| **6** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/8940267 | Qi Wang<br>Lei Sun<br>Zheng Chen | Sentiment analysis, Natural language processing, Deep learning, Neural Network |

| The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc ) | The Goal (Objective) of this Solution & What is the problem that need to be solved | What are the components of it? |
|---|---|---|
| Proposed a fusion model, made by combining the convolutional neural network and Bi-LSTM | The goal of this solution is to propose a deep learning model for sentiment analysis of movie reviews.The problem that needs to be solved is to find the best performing model for emotion recognition. | Preprocessing of text<br>Splitting of movie reviews<br>Using fusion model to get the results and accuracy<br>Comparing the accuracy of fusion model with other models |

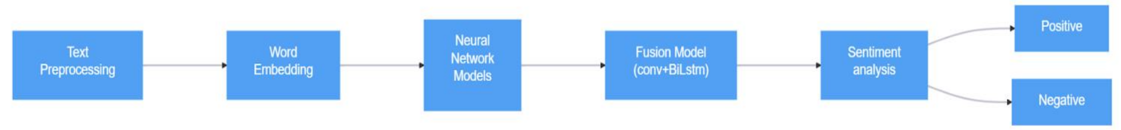
**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | We are using large Movie Review Dataset by Mass et al from its original Stanford AI Repository contains 25k movie reviews for training and 25k for testing | | . |
| 2 | The starting step of this solution is preprocessing of text by using Glove technique. | Helped in achieving better accuracy | Poor performance for rare words |
| 3 | Used many different algorithms to analyse the accuracies and performance | Understood different algorithms and their limitations for emotion recognition in text | Most of the algorithms are resource intensive |
| 4 | Found the better performing model in the combination of cnn and bi-lstm | | |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Sentiment polarity(Positive or negative) | The text given as input which are the movie reviews | | |

<table>
<tr><th colspan="4">Relationship Among The Above 4 Variables in This article</th></tr>
<tr><th colspan="2">Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>Textual reviews are given as an input</td><td>Emotion classification into positive or negative</td></tr></table></td><td>This solution is a combination of convolution neural network with Bi-directional LSTMwhich shows that fusion models can help in achieving better accuracies</td><td>It is a good thought of combining the two different models and opting a different vectorization method to get better accuracy</td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">Better accurate results is the positive impact of this solution in this project domain</td><td>Could have used different datasets and many other fusion models formed by different combination of existing models to get a better idea</td></tr>
<tr><th colspan="2">Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td colspan="2">The work done by authors gives a new way of approaching the problem. It do not focus only on the algorithm but focuses on each and every step to improve the overall accuracy</td><td>Accuracy</td><td>Abstract<br>I. Introduction<br>II. Text preprocessing<br>III. Neural networks models<br>IV. Experiment-based results<br>V. Conclusion</td></tr>
<tr><th colspan="4">Diagram/Flowchart</th></tr>
</table>




**--End of Paper 6—**

| 7 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/abstract/document/9913586 | Gourank Jain<br>Satyam Verma<br>Honey Gupta<br>Saloni Jindal<br>Mr. Mukesh Rawat,<br>Mr. Kapil Kumar | Text classification, emotion detection, BERT,NLP, Neural Network |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| Proposed a new way,BERT, which helps in emotion detection of text in social media platforms. | The goal is to get more accurate predictions of emotion in a text. The problem that needs to be solved is to create a better emotion prediction model. | Undersampling Technique<br>Splitting of dataset<br>Preprocessing<br>BERT<br>Regularization<br>Classification |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **1** | The first step of this process deals with making the dataset balanced by using undersampling technique followed by the splitting of dataset | This step prepares data for the BERT model and ensures that the data is consistent and representative which avoids the biased results | This step may lose some information or can remove the necessary words |
| **2** | The pre-trained BERT model is used to encode the input text into contextual embeddings.___The output is a pooled output that represents the whole input sequence as an embedding. | Helps in achieving the the best prediction of emotion in a given text | May require lots of computational resources and memory to run. |
| **3** | A dropout layer is applied to regularize the data | This step helps in avoiding overfitting problem | |
| **4** | The final step is to classify the emotion in text | | Classifies emotions into positive or negative |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Sentiments in the text (Positive or Negative) | Social media platforms text given as input | | |

**Relationship Among The Above 4 Variables in This article**

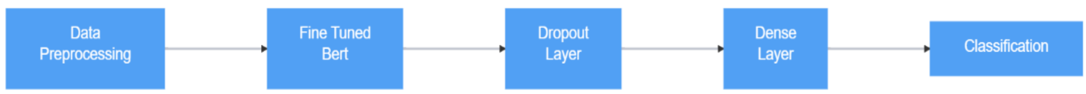
| Input and Output | Feature of This Solution | Contribution in This Work |
|---|---|---|
| (see Input/Output table below) | Unlike other approaches, this solution uses a balanced datase t their by avoiding the bias in result generation or emotion recognition | This work explains the necessity of having a balanced dataset for emotion recognition in text. Got to know about the technique to achieve a balanced dataset. |

| Input | Output |
|---|---|
| Textual data extracted from social media and many other sources is given as input. | The emotion of the text is expected as output,which is either positive or negative |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| | |

| | |
|---|---|
| Using BERT is one of the best choices for binary emotion classification. Accuracy can be improved by using different activation functions and mainly by using balanced dataset. | This solution is only for binary classification of emotions and trained only on movie review dataset. |

| **Analyse This Work By Critical Thinking** | **The Tools That Assessed this Work** | **What is the Structure of this Paper** |
|---|---|---|
| The author's work primarily focused on identifying the challenges faced by other researchers in this field, which mainly revolve around datasets. This helped in achieving better accuracy and best results | Precision<br><br>Accuracy<br><br>Support | Abstract<br>I. Introduction<br>II. Literature Review<br>III. Proposed Work<br>IV. Experiment & Result<br>V. Performance<br>VI. Conclusion |

| **Diagram/Flowchart** |
|---|
|  |

**--End of Paper 7--**

| **8** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9917655 | Asiya U A,<br>Mr Kiran V K | Audio Emotion Recognition, Text Emotion Recognition, AlexNet, BERT |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is** | **What are the components of it?** |

| | **the problem that need to be solved** | |
|---|---|---|
| The current solution is an unique attempt in achieving the better accuracy in recognising emotions from text | The goal of this solution is to get better accurate emotion prediction by changing the entire system's modality. The problem solved is improved classification of given input | Data Preprocessing<br>Feature Extraction<br>Audio Emotion Recognition<br>Text Emotion Recognition<br>Multimodal emotion recognition |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** |
|---|---|---|---|
| **1** | The first step is taking the dataset unnamed IEMOCAP and process it by selecting only the required attributes. | This helps us to reduces the data size and complexity | |
| **2** | Capturing the required features for emotion recognition which are spectrogram from audio signals and lexical features from text | | Requires the domain knowledge to perform this step |
| **3** | Using a CNN (named AlexNet) and transformers model (named BERT) to process the spectrogram of audio signal and lexical features of text | This step allows to learn contextual relationship between words and helps in reducing the problem of overfitting | Requires lot of computation power for training and testing along with huge amounts of data for training the models |
| **4** | Concatenating the audio and text embeddings to form a combined embedding for emotion recognition. | By performing this step we can achieve better emotion predictions | |

**Major Impact Factors in this Work**

| **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** |
|---|---|---|---|
| The emotion label predicted. | The text and audio signals which are given as input | | |

<table>
<tr><th colspan="4">Relationship Among The Above 4 Variables in This article</th></tr>
<tr><th colspan="2">Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>The speech signal is given as input which is the combination of text and audio</td><td>The emotion which is been classified is the output</td></tr></table></td><td>The proposed work explains the tremendous change in the accuracy by shifting our idea from uni modality to multi modality which is an important and useful feature of this solution</td><td>Demonstrates the effectiveness of a multimodal approach combining audio and text models for improved emotion recognition compared to unimodal models.</td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">The positive impact of this solution is that it iImproved emotion recognition accuracy to 98% from audio and text models. This can enable more effective applications.</td><td>The negative impact of this solution is that everytime we need to provide the speech signal to get better accurate results which is acceptable by few people. This also raises privacy concerns too.</td></tr>
<tr><th colspan="2">Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td colspan="2">All the papers till now read were able to improve the accuracy by just few percentage. On the other hand, this proposed system were able to improve the accuracy by large percentage</td><td>Precision<br>Accuracy<br>Recall</td><td>Abstract<br>I. Introduction<br>II. Related works<br>III. Proposed works<br>IV. Dataset<br>V. Result analysis<br>VI. Conclusions</td></tr>
</table>

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|---|---|---|
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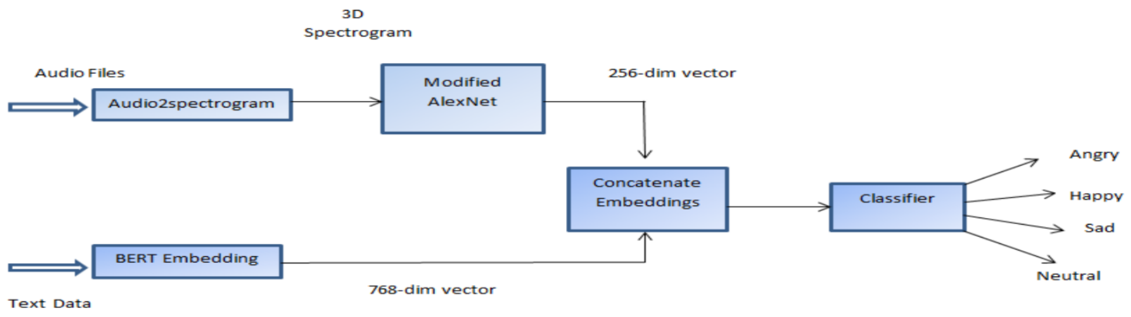
| **Diagram/Flowchart** |
|---|
|   |

**--End of Paper 8--**

| **9** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9058128 | Dr. Shailendra Narayan Singh<br><br>Twinkle Sarraf | Sentiment analysis, product reviews, random forest classifier, bag-of-words |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| The current proposed solution uses machine learning approach along with natural language processing techniques to help users/customers take the best decisions. The proposed solution is an user centric | The goal of this solution is to help users reduce the time of analysing a product. The problem of the user taking the decision to buy/not buy is solved. | Data Preparation<br><br>Review Analysis<br><br>Sentiment classification |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **1** | The initial step is data collection which is also a differentiator step from existing works | We can train our model from live and real data from popular sites. | The system depends on the availability and structure of the website,which are temporary |
| **2** | The system cleans and parses the data to extract the reviews and assigns an ID to each review. The system also removes irrelevant data such as the reviewer's name and date. | The system reduces the noise and redundancy in the data and makes it ready for analysis. | |
| **3** | The system uses natural language processing techniques and Vader sentiment analyzer to process the reviews and assign sentiment scores. The system also uses a bag-of-words model to represent the text as a document vector of word frequencies. | | Bag of model will ignore the word order which can be really important for a few cases. |
| **4** | The formed vector is sent to the model and random forest algorithm is used to classify the text as positive and negative review | This allows to hide the bias or incorrect result of one model by taking the result which is predicted by majority of the models | |
| **5** | The final step is classify the sentiments of each and every text or review then give a final score of number of positive and negative reviews | This step of providing the positive and negative scores helps the users to make best decisions. | |

**Major Impact Factors in this Work**

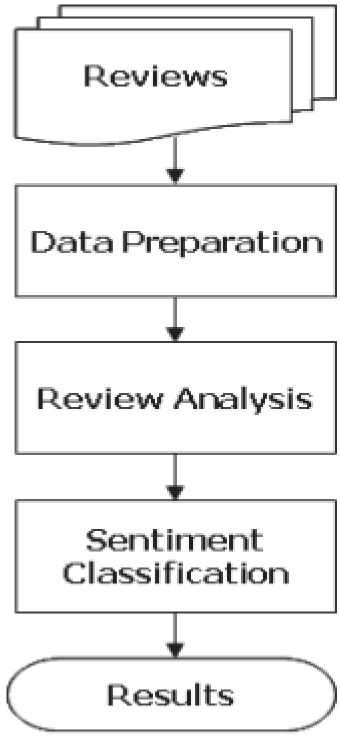
| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Sentiment scores of the product | Product name given as input | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| | The proposed work has a best feature of using live data extracted from | The proposed solution helped me to know the value of the real time data which can be |

| Input | Output |
|---|---|
| | |

<table>
<tr><td><table><tr><td>The product name is given as input</td><td>The number of positive and negative reviews of a product is given as output</td></tr></table></td><td colspan="3">website rather than using existing dataset for training</td><td>extracted from popular websites.</td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th colspan="2">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">The positive impact of this solution it helps to save the time of the user been spent on researching the reviews by directly giving the number of positive and negative reviews</td><td colspan="2">The negative impact of this solution is that it does not provide the detailed reasons of problems or negative reviews provided to the product which can affect the buyers satisfaction</td></tr>
<tr><th colspan="2">Analyse This Work By Critical Thinking</th><th colspan="2">The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td colspan="2">The proposed work is very effective in the view of the user. This work is not widely appreciable to use by the business owner as it does not provide any reason for negative reviews. But for users it saves a lot of time and helps to decide whether to buy a product or not.</td><td colspan="2"></td><td>Abstract<br>I. Introduction<br>II. Structural Design of Opinion Mining<br>III. Related Work<br>IV. Proposed Approach<br>V. Implementation and Result<br>VI. Conclusion<br>VII. Future Enhancements</td></tr>
<tr><th colspan="5">Diagram/Flowchart</th></tr>
</table>




**--End of Paper 9--**

| **10** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://aclanthology.org/S19-2039.pdf | Arik Pamnani<br>Rajat Goel<br>Jayesh Choudhari<br>Mayank Singh | SVM, Logistic Regression, Convolutional neural network, Long short term memory |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| The current solution is the comparison of all the available methods for emotion recognition | The goal of this solution is to compare the better | Data Preprocessing |

| | | |
|---|---|---|
| | emotion prediction model. | Machine Learning Model (SVM,Logistic Regression)<br>CNN<br>LSTM |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | The first step is to preprocess the dataset and handle the different cases like misspelled, elongated and emojis .We further divide the dataset into train,dev and test data | The emoji's and elongated words are a major challenges which have impact on the model.These are handled by this solution efficiently | |
| 2 | The next step is to use the machine learning models which are SVM and Logistic regression | Machine learning models are easy to implement and proved to be very fast | The emotion prediction accuracy has scope for improvements |
| 3 | For the next step we use the CNN to get our predictions | | The training of convolutional neural networks requires lot of hardware resources for training |
| 4 | Now we use the long short term memory neural networks,especially LSTM-1 to get our scores in test and dev data | Performs better than machine learning models,CNN and lstm-2. | |
| 5 | For the final step we are using the LSTM-2 neural network. | | Slightly performed worse than the lstm-1 |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Emotion Predictions by models | Textual Dialogues | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| <table><tr><th>Input</th><th>Output</th></tr><tr><td>The text is given as input</td><td>Emotion of the text is predicted as output</td></tr></table> | The feature of this solution is its data preprocessing and the way the solution handled the challenges of the textual emotion recognition like elongated words etc | The contribution of this work is it way to handle the challenges of the textual data set and their results which helped me to decide which is better for textual emotion recognition |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| The positive impact of this solution is that it helped me to solve few of the challenges related to preprocessing of the text like elongated words etc | The negative impact of this solution can be found by analysing the dataset statistics which tells that the it is not a well balanced dataset which can lead to biased prediction |

| Analyse This Work By Critical Thinking | The Tools That Assessed this Work | What is the Structure of this Paper |
|---|---|---|
| This proposed solution discussed all the possible ways of emotion recognition from the text. From all the way from machine learning models like SVM and logistic regression to deep learning models like CNN,LSTM along with the little variations, have been used and their accuracies have been compared. | F1 Score | Abstract<br>I. Introduction<br>II. Dataset<br>III. Experiment<br>IV. Results<br>V. Conclusion<br>VI. Future Work<br>VII. References |

| Diagram/Flowchart |
|---|
|  |



**--End of Paper 10--**

| 11 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9544554 | Priyanka Awatramani<br><br>Rucha Daware<br><br>Hrushabhsingh Chouhan<br><br>Anmol Vaswani<br><br>Sujata Khedkar | Sentiment Analysis, Data Preprocessing, Hinglish, Natural<br><br>Language Processing, Code-Mixed Text, TF-IDF features,<br><br>Logistic Regression, Random Forest, SVM, KNN, Machine<br><br>Learning, Lexicon Based Approach, Rule based approach |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| Lexicon based approach Rule based approach ML algorithms (SVM,Logistic Regression,KNN,Random Forest) | The aim of this paper is to solve the limitations and challenges by studying and analyzing the different approaches to tackle the Hinglish text. | Handling data with noise, Case folding, Punctuation Removal, Special character removal, Spelling Correction, Stop-Word Removal |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** |
|---|---|---|---|
| **1** | The datasets that have been considered here IIITH and SemEval, the first approach to the problem was to convert the Hindi Language to the English | Balanced dataset plays a crucial role. | |

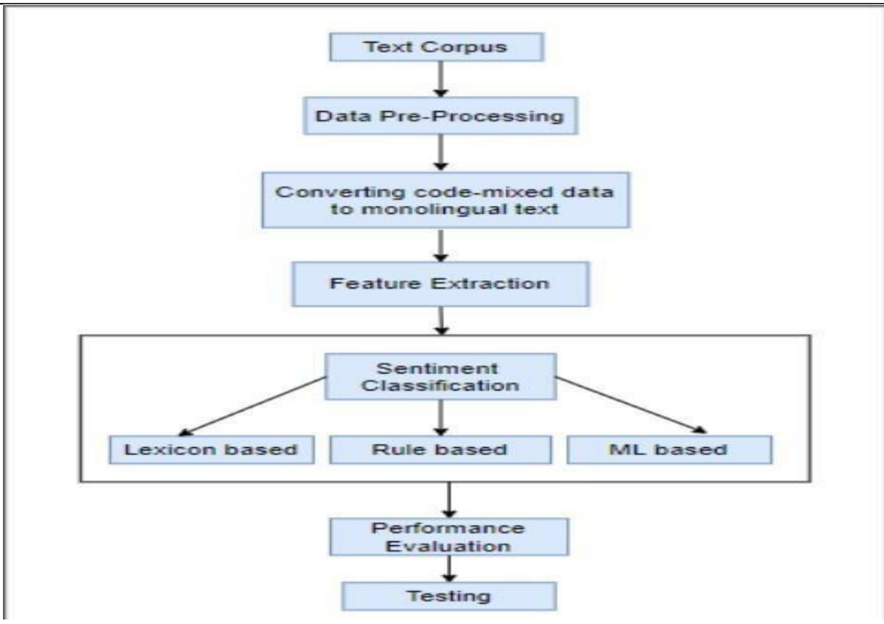
| | | | |
|---|---|---|---|
| | Language using Google Cloud Translate API | | |
| **2** | The API only detects the Hindi Language if the input given to it is written in Devanagari Script. For this purpose, there was a need to convert the romanized Hindi text to Devanagari Text using Indic-Transliteration API | The hindi language in the text is converted to english easily using the APIS | |
| **3** | Also Here the simple steps such as preprocessing has been done consisting of handling noisy data,case folding,punctuation removal,special character removal, etc. Also, in the data given the spellings of the words can also be wrong so spelling correction is also needed to be done | Sentiments can be properly be detected because here spelling correction is also done. | |
| **4** | Then after here the code mixed data is converted into monolingual data and on this text/data sentiment classification is carried out | | |
| **5** | The sentiment classifications that can be used here are: Lexicon based, Rule based, ML based Lexicon based:-AFINN Rule based:-TextBlob, Vader sentiment,ML based: SVM,KNN,Random Forest,Logistic Regression | Varied classification approaches helps in accurately classifying the sentiments | The NLP based approach much rely on the weightage of emotion related words which means that they are not beneficial for long term dependencies |
| **6** | Analyze the performance of chosen sentiment classification and the analysis of sentiment of hinglish text is done. | | Focused on classification of sentiments not on the emotions |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Sentiment(Positive,negative,neutral) | Set of Sentences, tweets | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

<table>
<tr><th>Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Hinglish text(Hindi+English)</td><td>Detecting sentiment present in the given text, either positive,negative or neutral</td></tr></table></td><td>1) The solution handles code-mixed text<br><br>2) A novel romanized Hindi dictionary is created using sentiment scores from HindiSentiWordNet. This helps overcome the lack of Hindi resources.</td><td>Good to have this knowledge from this paper, as we got better understanding about how to handle hinglish text and also gained insights about lexicon and rule based approach for sentiment analysis.</td></tr>
<tr><th>Positive Impact of this Solution in This Project Domain</th><th colspan="2">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td>Both NLP based approaches and ML approaches have been used in order to accurately determine sentiments. Also, the dictionary based approach used, i.e a dictionary of Romanized Words derived from Hindi SentiWordNet is helpful for properly translating hindi to english</td><td colspan="2">The research focuses only on Hindi-English code-mixing. It may not generalize well to other language pairs without further study.</td></tr>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>This work is good, as they tried to provide a good solution for sentiment analysis for hinglish text because on social media the text written is not always english it can be english in addition with the regional language (Hindi) so it is important to understand the sentiments in hinglish text.</td><td>Accuracy, Precision,Recall</td><td>Abstract<br><br>I. Introduction<br>II. Related Work<br>III. Problem Definition<br>IV. DataSet<br>V. Methodology<br>VI. Results<br>VII. Conclusion and Future work</td></tr>
<tr><th colspan="3">Diagram/Flowchart</th></tr>
</table>




**--End of Paper 11--**

| **12** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9633843 | Mahima M A,<br>Nidhi C Patel,<br>Srividhya Ravichandran,<br>Aishwarya N<br>Sumana Maradithaya | Text Mining, Multiple Emotion Detection, Natural Language Processing, Sentence embeddings, Cosine Similarity, Ekman's emotions |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| a new hybrid methodology for the detection of multiple emotions from the text using sentence embeddings along with rule based techniques. | The goal is to detect the multiple emotions present in the text and also if emoticons are used in text how can they be used in detecting the emotions. | Datasets<br>Preprocessing<br>Hybrid Model<br>Multiple Emotion Tagger |

| The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process | | | |
|---|---|---|---|
| | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** |
| **1** | The datasets used in this model include: ISEARs, MELD, EmoDB, GoEmotions, and their combinations. | Combining multiple datasets like conversations, social media and generic text makes the model more robust. | |
| **2** | Preprocessing of data is carried out, including Filtering, converting emoticons, and sentence tokenization | Conversion of emoticons helps in more precisely detecting/identifying the emotions | |
| **3** | next the Hybrid model consists mainly of the Rule-based methods, Sentiment Analyzer and the Context and Semantic based Disambiguation model. | | Rules and similarity matching have limitations for handling very complex language use cases. |
| **4** | The hybrid model has been developed by comparing two state-of-the art pre-trained models known as Sentence-BERT and InferSent. | Here the cosine similarity helps to find the closest matching sentences from the training set. | Need to train and ensemble multiple models (Sentence-BERT, InferSent) which increases complexity. |
| **5** | The Tagger gets the scores and assigns the respective emotions to each sentence and these emotions are combined to get the overall emotions present in the text | This allows capturing transitions in emotions within a text. | Restricted to only Ekman's basic emotions. Does not detect more complex or nuanced emotions. |

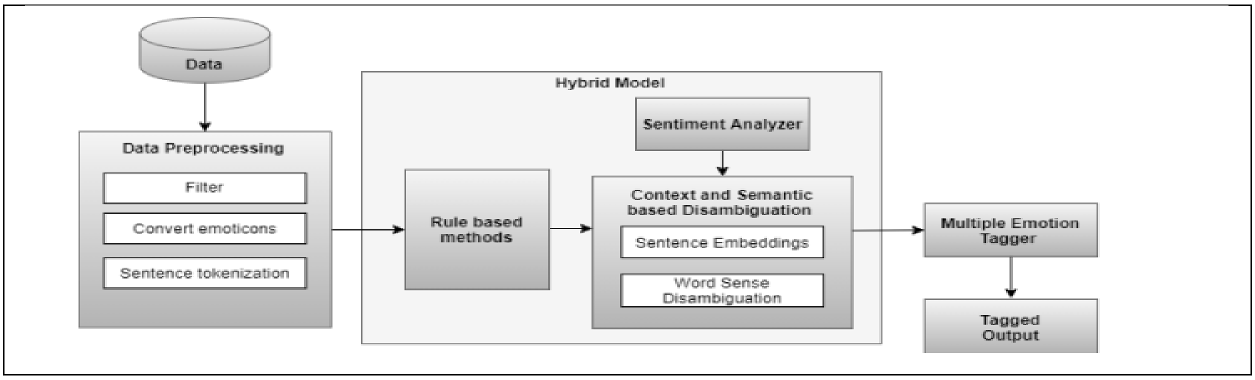
**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| | | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution in This Work |
|---|---|---|

<table>
<tr><td colspan="2">
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Given input as text</td><td>identifying the multiple emotions hidden in the text</td></tr>
</table>
</td><td>1. Able to detect multiple emotions present within a single text by splitting using rule-based techniques.<br><br>2.Employs similarity technique to find most similar sentences for emotion assignment</td><td>It was good to have this knowledge, as we got to know how to deal with the ambiguities in the words that can alter the recognition of emotion</td></tr>
<tr><td colspan="3">Positive Impact of this Solution in This Project Domain</td><td>Negative Impact of this Solution in This Project Domain</td></tr>
<tr><td colspan="3">Provides more contextual disambiguation of emotional language by combining semantic similarity and sentiment analysis</td><td>Requires large pretrained models like SentenceBERT and InferSent which are computationally expensive to run compared to simpler models.</td></tr>
<tr><td>Analyse This Work By Critical Thinking</td><td colspan="2">The Tools That Assessed this Work</td><td>What is the Structure of this Paper</td></tr>
<tr><td>As we know, the text does not contain a single emotion it has multiple emotions hidden in it, so here, the work mainly focuses on identifying multiple hidden emotions and also tries to detect the emotions without any ambiguity.</td><td colspan="2"></td><td>Abstract<br>I. 1.Introduction<br>II. Methodology<br>III. Related Works<br>IV. Experimentation and results<br>V. Conclusion and Future Work</td></tr>
<tr><td colspan="4">Diagram/Flowchart</td></tr>
<tr><td colspan="4"></td></tr>
</table>




**--End of Paper 12--**

| **13** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9230725 | Juyana Islam<br>Sadman Ahmed<br>M. A. H. Akhand<br>N. Siddique | Emotion Recognition, Emoticons, Deep Learning, Long Short-Term Memory. |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| Long Short-Term Memory | To improve emotion recognition from microblog keeping semantic relation among texts and emoticons | Dataset<br>Preprocessing<br>Emoticon Representation<br>Tokenization<br>Embedding Layer<br>LSTM Network |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **1** | The dataset considered is a collection of english tweets. Primarily here, tweepy is used, which is a very useful library to collect data from twitter. | | Smaller dataset is prefered, instead larger dataset can be used. |
| **2** | Then, after data preprocessing is carried out inorder to clean the data here, the cleaning involves case conversion, hashtag and username removal, punctuation removal | Preprocessing is an important step for removing inconsistencies. | |
| **3** | as here the text consists of emoticons here emoticons needed to be converted in to corresponding meanings using the function Emoticon meaning(). Here it uses lookup table for knowing the meaning | Emoticons are converted into text so that emotions can be predicted accurately. | |
| **4** | then after tokenization is carried where integer encoding of texts is performed. | | |
| **5** | Here LSTM is considered further, Finally the embedding step transforms integer value transforms in to a dense 2D vector | Word embeddings capture semantic meaning and relationships between words/emoticons. | Instead of LSTM other models such as BI-LSTM,BI-GRU can be considered. |
| **6** | A softmax output layer finally converts this context vector to probabilities over the emotion classes. | | |
| **7** | The highest probability class is taken as the predicted emotion for the microblog | | Only 4 emotions are considered love,happy,sad,angry |

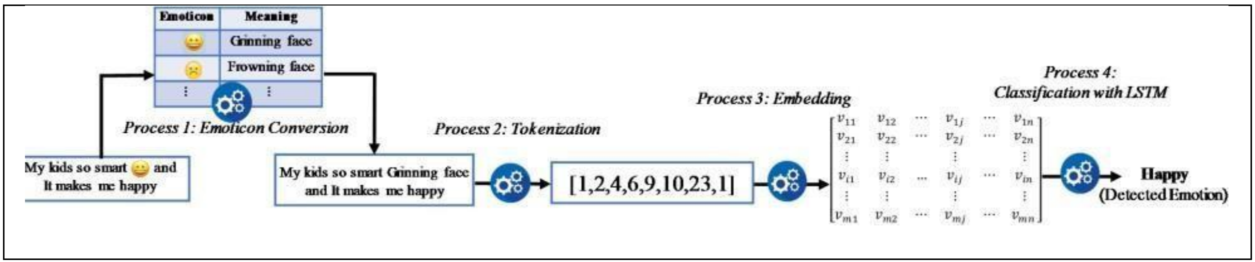
**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| | | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Text is given as input</td><td>Emotion intext</td></tr></table></td>
<td>1. The textual data is in the form of sequential manner so the model which is used (LSTM) is best suitable for text such that it can find the emotion hidden in it accurately.<br><br>2. Here, emoticons are fused into text embeddings.</td>
<td>It was good to have the knowledge, as we got to know the significance of considering emoticons as a valid data item in increasing the accuracy of model and also what kind of model to be chosen for sequential data</td>
</tr>
<tr>
<th>Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td>Better understanding of emotions expressed in microblogs by incorporating emoticons along with text.</td>
<td>Tested only on Twitter data. Effectiveness for other social media platforms or textual domains is unclear.</td>
<td></td>
</tr>
<tr>
<th>Analyse This Work By Critical Thinking</th>
<th>The Tools That Assessed this Work</th>
<th>Structure of this Paper</th>
</tr>
<tr>
<td>The work done is good because textual data is spread over microblogs/social media so identifying the emotions in the text plays an crucial role and always the text is not of words as now a days many are preferring the usage of emoticons, so identifying the emotions hidden in the text by considering the text as well as emoticons is crucial . So,here the solution suggested helps in finding the emotion in the text accurately.</td>
<td></td>
<td>Abstract<br>I. Introduction<br>II. Improved emotion recognition from microblog focusing on both emoticon and text<br>III. Experimental Studies<br>IV. Conclusion</td>
</tr>
<tr>
<th colspan="3">Diagram/Flowchart</th>
</tr>
</table>




**--End of Paper 13--**

| **14** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://www.ijsr.net/archive/v5i5/NOV163818.pdf | Ashish V C<br>Somashekar R<br>Dr. Sundeep Kumar | Digital systems, Human Behavior, Emotion, Intelligent Behavior, Human Express, plain text and Hybrid Based Approach |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| Keyword spotting method, Lexical Affinity Method, learning based method and hybrid methods | appropriately identifying the emotion in text and analyzing various approaches | Text document<br>preprocessing the data<br>Tokenization of data<br>Emotion keyword detection<br>Intensity analysis<br>Negation check<br>Emotion class |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **1** | Firstly, dataset needs to be considered and then after preprocessing, the data needs to be carried out. | | |
| **2** | And then after tokenization is carried out after that various approaches are considered those are:- keyword based, Lexical Affinity Method, learning based method and hybrid methods | | |
| **3** | The keyword based approach identifies the emotion related words and then analysis of the intensity of the emotion words is performed. The sentence is checked whether negation is presented in it or not then finally an emotion class will be found as the required output. | Simple and easy to implement | It is not a reliable method because it totally depends on the emotional related keywords as the meanings of keywords could be multiple and vague |
| **4** | The other approach is lexical affinity based approach, which is an extension of keyword based approach here it assigns probabilistic affinity for a particular emotion word | Uses probabilities for arbitrary words, not just keywords | Probabilities can be biased by corpus and doesn't recognize emotions |
| **5** | The other approach can be used is lexicon based approach here counting of number of emotion related words and then the emotion label of the text is determined | Identifies the class of emotion based on count such that if there are varied emotional words then that can be identfied properly as compared to keyword and lexical affinity based | |
| **6** | And, other approaches can be used are using SVM, and hybrid based approach | | |
| **7** | Here, the hybrid based approach is combination of the keyword based method and learning based method. | Hybrid based approach achieves good accuracy as compared to other approaches | |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| | | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

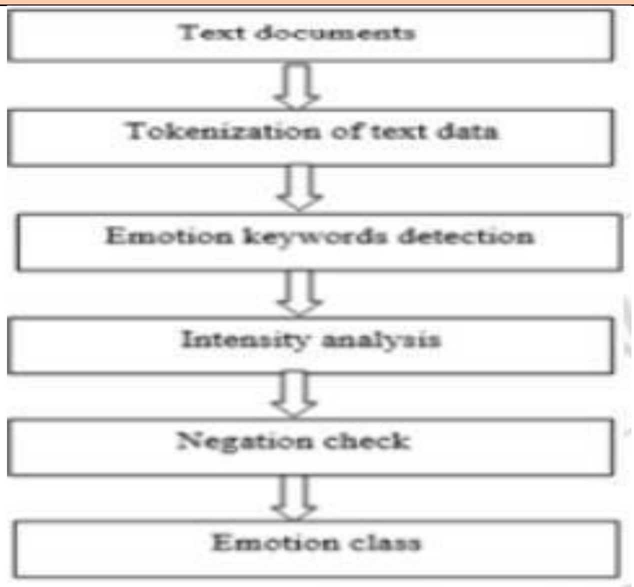
| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| **Input:** text document is taken as input<br>**Output:** output is generated as an emotion class | 1. Detects six different emotions.<br>2. Some covered techniques support multilingual emotion detection across languages. | It was good to have knowledge about various approaches for recognizing emotion from text where the simple and complex approaches help in recognizing emotion from simple text to moderate text. |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| Varied approaches have been discussed for emotion detection from text such that the methods can be used on the basis of type of text. | A firm solution/method has not been provided that can be helpful for detecting complex emotions or text. |

| Analyse This Work By Critical Thinking | The Tools That Assessed this Work | What is the Structure of this Paper |
|---|---|---|
| The work is good as they tried to provide varied solutions for detecting emotion from text because there are varied approaches for recognizing emotion ranging from simple to complex. However the performance of the emotion recognition from text can be enhanced by using the other approaches | | Abstract<br>I. Introduction<br>II. Text Based Emotion Recognition Methods<br>III. Limitations |

| | | |
|---|---|---|
| | | IV. Text Normalization Techniques For Resolving Short Messaging Language<br>V. Conclusion |

**Diagram/Flowchart**




**--End of Paper 14--**

| **15** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9392710 | Mahmud Hasan Munna<br>Md Rifatul Islam Rifat<br>A. S. M. Badrudduza | Sentiment Analysis, Online Product Review Classification, E-commerce, Bangla NLP, Deep Learning. |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem** | **What are the components of it?** |

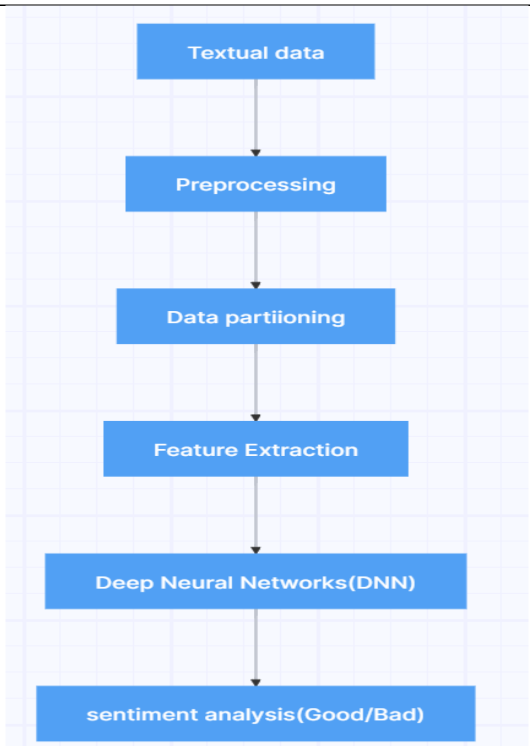
| | that need to be solved | |
|---|---|---|
| Deep Neural Network and Natural Language Processing | developed two Deep Neural Network (DNN) based models for review based classification and sentiment analysis. | Data Preprocessing<br>Removing Stop-words<br>Removing Punctuation<br>Removing Unnecessary Characters<br>Data Partitioning<br>Feature Extraction |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| **1** | Firstly, for dataset here, product reviews have been collected from various e-commerce sites such as Daraz, BDshop and Evally | Real-world ecommerce data | |
| **2** | Then, after data preprocessing is carried out involving stop words removal, punctuation removal, unnecessary character removal. | Cleaned and normalized data Improves model performance | Time-consuming process |
| **3** | Then after data partitioning is carried out where data is partitioned in to training,validation and test data | | |
| **4** | pre-trained FastText word embeddings to extract features | Helpful in capturing proper semantic meaning | |
| **5** | Then after Deep neural network model has been considered where one DNN model is for sentiment analysis and other DNN is for product reviews classification | | Computationally expensive |
| **6** | And the number of neurons in the input and out layers is decided based on the shape of training dataset where as number of neurons for output layer is decided up on number of classes | | |
| **7** | Then after number of hidden layers will be considered and followed by activation function | It defines the complexity and | |

| | | | |
|---|---|---|---|
| | | efficiency of DNN architecture | |
| **8** | The optimization is considered here to be Adam | It has relatively low memory requirements | |
| **9** | Finally the DNN is made ready and the performance will be evaluated using accuracy,precision,recall and F1 score | | |

| | | |
|---|---|---|
| | | **Negative Impact of this Solution in This Project Domain** |
| the solutions directly provide value in the e-commerce domain by harnessing NLP to extract insights from reviews. This is helpful for both customers and businesses. | | The model's mediocre accuracy can lead to misclassifications of reviews. |
| **Analyse This Work By Critical Thinking** | **The Tools That Assessed this Work** | **What is the Structure of this Paper** |
| The work done is good as they tries to provide a good solution for both sentiment analysis and product reviews classification by using the DNN models, they have not only focused on particular classes for product reviews they have focussed on various classes such as recommended,complain,wrong delivery, and appreciation these varied classifications can help the e-commerce platforms, customers and merchants  to better understand about their products and satisfaction level of customers. | | Abstract<br>I. Introduction<br>II. Related Work<br>III. Dataset Description<br>IV. DataPreprocessing<br>V. Methodology<br>VI. Result and Analysis<br>VII. Conclusion<br>VIII. References |
| **Diagram/Flowchart** | | |




**--End of Paper 15—**

| 16 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/abstract/document/8820254 | Vikas Goel<br>Amit Kr. Gupta<br>Narendra Kumar | Sentiment Analysis<br>NLP<br>Opinion mining<br>Deep learning<br>Naïve Bayes<br>RNN |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| The paper proposes the use of machine learning techniques, specifically Recurrent Neural Networks (RNN) and Naive Bayes algorithm, for sentiment analysis of multilingual Twitter data. | The goal of the proposed solution for sentiment analysis of multilingual Twitter data is to classify | Data Gathering |

| | | |
|---|---|---|
| | the sentiments expressed in the tweets. The solution aims to solve the problem of analyzing and understanding the feelings and opinions of users expressed in different languages on Twitter. | Data Preprocessing<br><br>Feature Extraction<br><br>Sentiment Classification<br><br>Evaluation and Comparison<br><br>Future Work |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | Data Gathering | It becomes possible to measure progress and success | Raw data typically includes errors, inconsistencies and other issues |
| 2 | Google translator | Allows translation of documents and entire websites, as well as words typed into the translation box | |
| 3 | Pre-processing of Tweets | It helps to reduce the amount of redundant data from the data set | |
| 4 | Feature Extraction | Improves model accuracy | |
| 5 | Apply Classification Algorithms | Classification algorithms are used in Machine Learning to predict the class label of a given data point | |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| sentiment (positive, negative, neutral) of the multilingual Twitter data | Features extracted from the tweets. | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

| Input and Output | Feature of This Solution | Contribution & The Value |
|---|---|---|

<table>
<tr><th></th><th></th><th>of<br>This Work</th></tr>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>machine learning techniques, such as Recurrent Neural Networks (RNN) and Naive Bayes algorithm. These techniques are used to analyze the feelings expressed in different ways, such as negative, positive, favorable, unfavorable, thumbs up, thumbs down, etc</td><td>The output discussed in the paper for sentiment analysis of multilingual Twitter data is the classification of the tweets into different sentiment categories such as positive, negative, favorable, unfavorable, etc.</td></tr>
</table>
</td>
<td>
<ul>
<li>Comparison of the accuracy of RNN and Naive Bayes algorithms.</li>
<li>Analysis of efficiency, demonstrating that the RNN algorithm performs better than the Naive Bayes algorithm.</li>
<li>Dataset classification results, showing that RNN is more effective than Naive Bayes in terms of data analysis.</li>
<li>Use of machine learning algorithms for sentiment analysis.</li>
<li>Preprocessing of tweets to remove noise and filter out irrelevant data.</li>
<li>Application of classification algorithms such as RNN and Naive Bayes.</li>
</ul>
</td>
<td>It addresses the problem of multilingual sentiment analysis, which is often overlooked in the field of natural language processing (NLP). The researchers highlight that most NLP models only support English language, making it impractical for analyzing sentiments in the thousands of other languages. This work proposes a solution by using Google Translator API to translate data into English and then applying classification algorithms like Naive Bayes (NB) and Recurrent Neural Network (RNN) for sentiment analysis.</td>
</tr>
</table>

<table>
<tr><td colspan="2"></td><td colspan="2"><ul><li>Use of Google Translator API for multilingual data analysis.</li><li>Feature extraction through stemming and lemmatization.</li><li>Use of Core NLP Library and DotNet framework for natural language processing.</li></ul></td><td></td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th colspan="2">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">The positive impact of this solution in the project domain is that it addresses the problem of multilingual sentiment analysis, which is rarely explored in research studies. By using the Google Translator API and the Core NLP Library, the solution allows for the analysis of sentiments in multiple languages. This is beneficial for organizations dealing with large amounts of data from different languages, as it enables them to extract useful information and gain insights from multilingual social media data.</td><td colspan="2">Language Limitations<br>Data Size and Complexity<br>Unstructured and Unorganized Data<br>Lack of Contextual Understanding<br>Bias and Inaccuracy<br>Need for Continuous Updates</td></tr>
<tr><th>Analyse This Work By Critical Thinking</th><th colspan="2">The Tools That Assessed this Work</th><th colspan="2">What is the Structure of this Paper</th></tr>
<tr><td><ul><li>The paper tackles an important real-world problem of analyzing sentiment from multilingual social media data. This has applications for marketing, public relations, politics etc.</li></ul></td><td colspan="2">Machine learning algorithms<br>Dataset</td><td colspan="2">Abstract<br>Introduction<br>Related Work</td></tr>
</table>

| | | |
|---|---|---|
| • The dataset size of 4000 labeled tweets is decent for training and testing the models.<br>• The authors use a sensible approach of translating non-English tweets to English using Google Translate before analysis. This allows handling diverse languages. | Evaluation metrics<br>Comparative analysis<br>Confusion matrices<br>Visual graphs | Problem Statement and Data Formation<br>Proposed Methodology<br>Implementation<br>Comparative Analysis<br>Conclusion |
| **Diagram/Flowchart** | | |


**--End of Paper 16--**

| **17** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/10007248 | Reema Goyal<br>Navneet Chaudhry<br>Mandeep Singh | PocketSphinx<br>Word2Vec<br>Automated Speech<br>Recognizer<br>ISEAR<br>Emotion detection |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| • PocketSphinx for automated speech recognition<br>• Word2Vec for text analysis<br>• K-means clustering<br>• TF-IDF vectorizer<br>• Training and testing on the ISEAR emotion dataset | The main goals are to create an emotion detection model that requires no labeled training data, works for low-resource languages, and can be | PocketSphinx for ASR<br><br>Word2Vec for text analysis |

| | | |
|---|---|---|
| | personalized for individual users in an unsupervised manner. This solves key limitations of existing supervised models relying on labeled data and lexical resources. | K-means clustering on word vectors<br><br>TF-IDF scoring<br><br>Weighted sentiment scoring<br><br>Emotion classification based on weighted sentiment and TF-IDF score |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | Import data and preprocess data | importing and preprocessing data in the proposed model contribute to better data quality, improved model performance, increased accuracy, and efficient data handling. | |
| 2 | Pocketsphinx ASR | the use of Pocketsphinx ASR in the proposed model ensures accurate and real-time speech recognition, along with noise suppression and integration with a knowledge base. | |
| 3 | Word2Vec model | its ability to recognize similar words | High computational cost: Training word2vec can be computationally expensive for large datasets. |
| 4 | K-means Clustering | Handling large datasets | Determining the number of clusters |
| 5 | Tfidf weighing and emotion detection | Captures word importance<br><br>Reduces the impact of common words | |

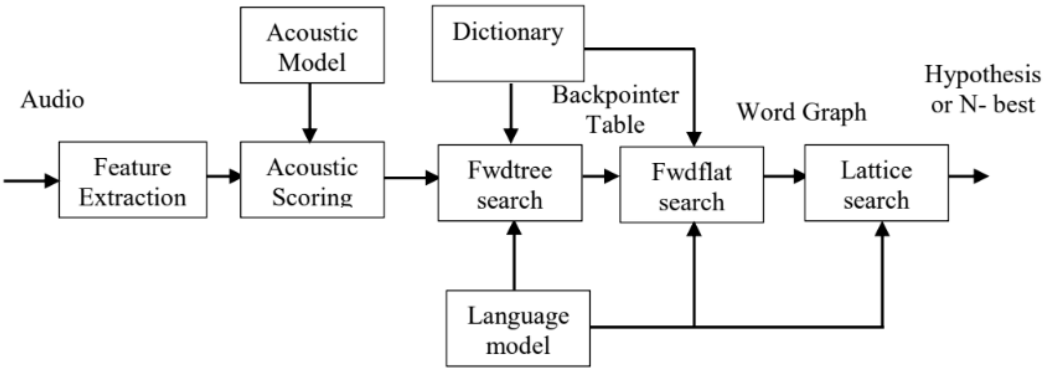
**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Emotion classification (positive, negative, neutral) predicted by the models | Features extracted from the text or speech input | | |

| Relationship Among The Above 4 Variables in This article | | |
|---|---|---|
| **Input and Output** | **Feature of This Solution** | **Contribution & The Value of This Work** |
| **Input**: The input of the proposed model described in the document can be either text or speech signals. If the input is in the form of speech signals, the model attempts to classify human emotions extracted from an Automated Speech Recognizer (ASR) along with text processing. If the input is text, it can be directly classified by the model<br><br>**Output**: The output of the proposed model is classification of emotions from text.<br>The goal is to extend the emotion classification to cover all users' emotions as the dataset becomes stronger | Emotion recognition using machine learning techniques<br>Use of natural language processing techniques for semantic analysis and keyword extraction<br><br>Utilization of the OCC model for connecting semantic analysis results to emotions<br>Implementation of PocketSphinx for Automatic Speech Recognition (ASR) | The contribution of this work is the development of a customized emotion detection approach that aims to make the recognition process more realistic. The proposed model can classify human emotions extracted from speech signals or text. The authors utilize natural language processing techniques, machine learning algorithms, and deep learning approaches to estimate and classify emotions |

| Positive Impact of this Solution in This Project Domain | Negative Impact of this Solution in This Project Domain |
|---|---|
| it offers a customized emotion detection approach that makes the recognition process more realistic. By using a combination of speech signals and text processing, the model can accurately classify human emotions. | To mitigate these concerns, emotion detection systems should be carefully designed with ethical principles in mind, obtain user consent, ensure transparency, test for biases, and safeguard data privacy and security. Overall |

| | | |
|---|---|---|
| | | societal impacts should be considered, not just individual benefits. Ongoing oversight is needed as use cases expand over time. |
| **Analyse This Work By Critical Thinking** | **The Tools That Assessed this Work** | **What is the Structure of this Paper** |
| Introduces a novel model for personalized emotion detection that cleverly combines NLP with speech processing. But further evaluation, ablation studies, comparative analysis, and discussion of limitations would significantly strengthen the paper and conclusions drawn. The critical analysis helps identify these areas for improvement while recognizing the innovative qualities demonstrated. | The tools used to assess this work include semantic analysis, case-based reasoning, natural language processing techniques, statistic-based parsing, dependency trees, emotion models, keyword-based techniques, supervised learning algorithms, unsupervised procedures, lexical resources, machine learning, deep learning algorithms, Pocket-sphinx (Automatic Speech Recognizer), Human Computer Interaction (HCI), linear support vector machine (Linear SVM), and ontologies such as Wordnet and Concept Net. | I. Introduction<br>II. Proposed Model and Methodology<br>III. Dataset<br>IV. Implementation<br>V. Results<br>VI. Conclusions and Future Work |
| **Diagram/Flowchart** | | |
| | | |




**--End of Paper 17--**

| 18 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/9776385 | Madhavi S. Darokar<br>Dr. Atul D. Raut<br>Dr. Vilas M. Thakre | Emotion Recognition, Social Network, Deep<br>learning, Facial Expression. |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| proposed a way to use the various AI and Machine learning tools that are available | The main goal is :<br>1. TO build a face detection model.<br>2. Extract features from face.<br>3. Built a layered Deep CNN and train it using face images and their features obtained from step 1 and Step 2. | Svm<br>Neural network<br>Deep cnn<br>Jaffe dataset<br>Face detection<br>Emotion recognition |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |
| | | |

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | The first step is Face detection and it is done by using various techniques. We use JAFFE dataset and C-means clustering algorithm | It gives better accurate outputs by analyzing the given data | System works well in front pose images only. |
| 2 | In the feature Extraction step we use techniques like Gabor Filter,Local Binary Pattern,SIFT. | Finds things at different sizes and angles<br>Works even in changing lights | Needs a lot computer power<br>Takes up lots of memory<br>Used to be expensive |
| 3 | Emotion Classification | It achieves higher level of accuracy than the input data | Classifying emotions based on context is very challenging |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Emotion classification predicted by the models | facial image features and encodings, as well as the labeled training datasets. | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

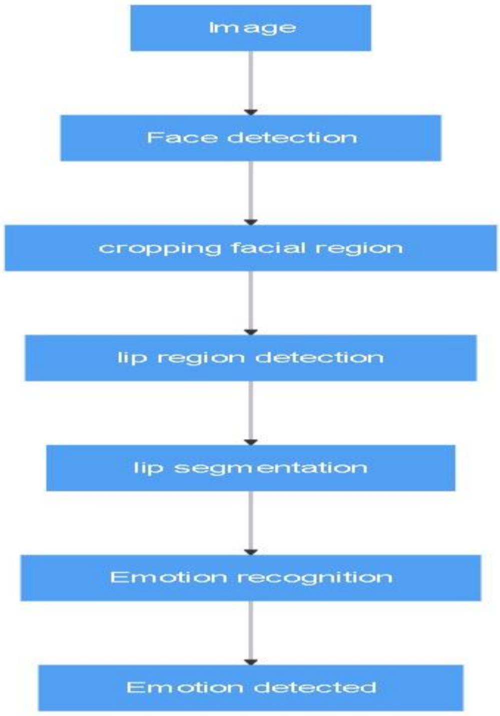
| Input and Output | Feature of This Solution | Contribution & The Value of This Work |
|---|---|---|
| (see Input/Output table below) | Able to detect multiple emotions present within a single image by splitting using rule-based techniques. | This work explains the necessity of having a balanced dataset for emotion recognition in text. Got to know about the technique to achieve a balanced dataset. |

| Input | Output |
|---|---|
| Pictorial or in the form of emoji's data, extracted from social media and many other sources is given as input. | The system is evaluated under the different parameters and is tested for the proper accuracy of output. It is also observed how the different objects in the image are classified and how accurately this classification is done. |

| **Positive Impact of this Solution in This Project Domain** | **Negative Impact of this Solution in This Project Domain** |
| --- | --- |
| Deep neural networks for emotion recognition in social media can enable impactful new applications in mental health, marketing, education and more by providing scalable, accurate, and less biased models compared to existing approaches. | Overall, facial emotion recognition from social media photos needs to be pursued cautiously. Steps to mitigate risks include transparent development processes, testing for biases, consent-based data collection, studying psychological impacts, and securing models against malicious uses. Thoughtful governance and ethics review processes are critical. |

| **Analyse This Work By Critical Thinking** | **The Tools That Assessed this Work** | **What is the Structure of this Paper** |
| --- | --- | --- |
| This paper provides a reasonable high-level overview of facial emotion recognition and proposes using deep learning. However, the technical details and evaluation are lacking to convincingly demonstrate the merits of their approach. More rigorous experiments, details, and critical discussion would strengthen the paper. The ideas show promise but require further development and validation. | Standard machine learning libraries like OpenCV, PyTorch, TensorFlow, Scikit-Learn etc. would likely provide the core tooling. | I. Introduction<br>II. Background<br>III. Previous Work Study<br>IV. Existing Methodologies<br>V. Analysis and Discussion<br>VI. Proposed Framework<br>VII. Outcomes and Results<br>VIII. Conclusion<br>IX.Future Scope |

| **Diagram/Flowchart** |
| --- |




**--End of Paper 18--**

| **19** | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/10194174 | Yuxin Huang<br>Shaidah Jusoh | Deep learning, Measurement, Sentiment analysis, social networking, text categorization, semantics, prototypes |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| The current solution is an emotion and sentiment analysis prototype that has been developed using the ERNIE Tiny pre-trained model. It allows users to analyze single texts or process texts in batches. The | The goal of this solution is to develop a prototype for emotion and | User Interface Layout |

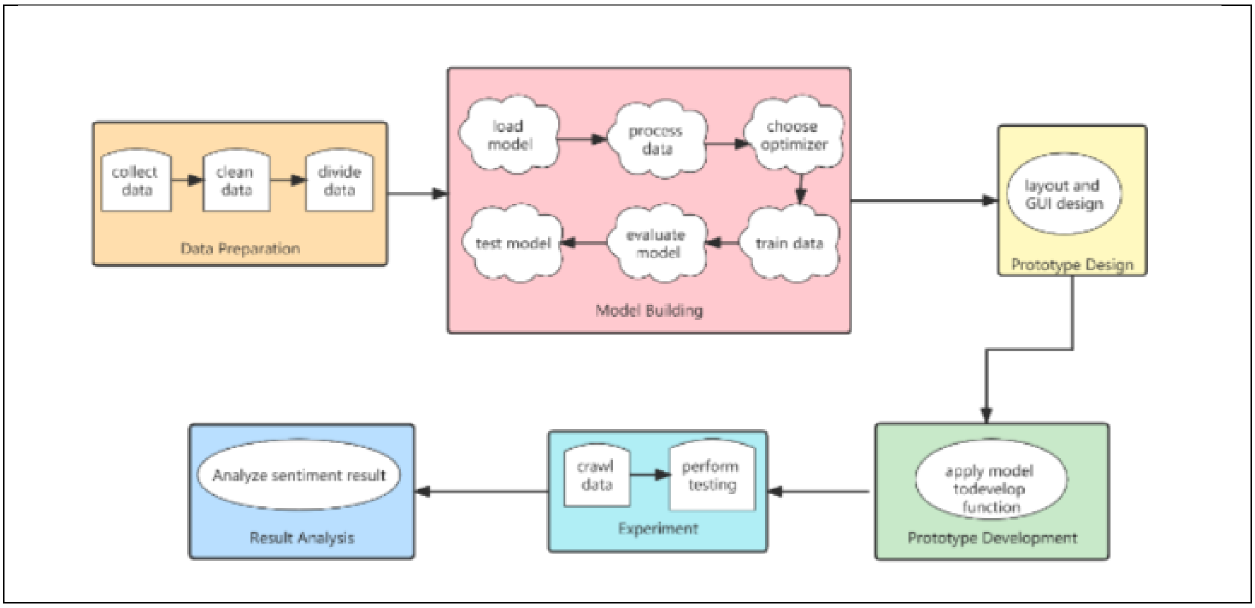
| | | |
|---|---|---|
| prototype can classify emotions such as sadness, happiness, disgust, anger, like, surprise, and fear, as well as sentiment polarity such as positive, negative, and none. | sentiment analysis of Chinese text. The prototype aims to assist individuals in analyzing and classifying emotions and sentiments in Chinese text, particularly in the context of social media and music platforms<br><br>The problem that needs to be solved is the accurate classification and analysis of emotions and sentiments in Chinese text. The solution aims to address the limitations of existing methods by using a deep learning model called ERNIE Tiny, which is trained on a dataset of Chinese social media comments | Single Text Function<br>Batch Text Function<br>Model Building<br>Optimization Strategy and Train<br>DataModel<br>Evaluation and Prediction<br>Testing Experiment |

**The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process**

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| **1** | Methodology | It provides a detailed plan that helps to keep researchers on track, making the process smooth, effective and manageable | |
| **2** | Model Building | The ability to create prototypes of products or structures before the final design is produced | The cost of a simulation model can be high |

| | | | |
|---|---|---|---|
| **3** | Optimization Strategy and Train Data | better results<br><br>optimized time management | |
| **4** | Model Evaluation and Prediction Testing | advantage to predictive maintenance, such as being able to warn users of potential problems before they happen. | Increased cost and time consuming work. |

<table>
<tr><th colspan="2"></th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="2">The developed solution using the ERNIE Tiny model has a positive impact on emotion and sentiment classification in the project domain. It provides accurate sentiment detection, demonstrates the feasibility of sentiment detection from emotion classification, and offers potential for future enhancements.</td><td>There are several limitations and potential negative impacts that should be considered in the project domain. These include the limited consideration of punctuation symbols, the lack of comparison with other machine learning methods, the simplicity and limited functionality of the prototype, the lack of attractiveness in the user interface, and the scope limited to</td></tr>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>adopts a sound methodology to address a novel problem combining emotion classification and sentiment analysis. More rigorous comparative evaluation and testing across diverse datasets would strengthen the conclusions and contributions. But within its scope, the work demonstrates promising initial results and capability of the proposed technique.</td><td>Critical thinking skills<br><br>Technical knowledge<br><br>Data analysis<br><br>Data Collection and Cleaning<br><br>Result Analysis</td><td>I. Introduction<br>II. Related Work<br>III. Methodology<br>IV. Prototype Implementation<br>V. Result Analysis<br>VI. Conclusion</td></tr>
<tr><th colspan="3">Diagram/Flowchart</th></tr>
</table>




**--End of Paper 19--**

| 20 | | |
|---|---|---|
| **Reference in APA format** | | |
| **URL of the Reference** | **Authors Names and Emails** | **Keywords in this Reference** |
| https://ieeexplore.ieee.org/document/10007248 | Amal Shameem<br>Ramesh babu<br>Vigneshwaran<br>Sundar<br>Mrs. K. Veena | Machine Learning<br>Emotion Detection<br>NLP<br>Learning |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | **What are the components of it?** |
| The main technique explored is using machine learning, specifically classifiers like Support Vector Machines and Random Forests, to automatically detect and categorize emotions expressed in textual data. The article evaluates this ML-based text emotion detection approach and finds it provides improved accuracy over previous methods. The use of machine learning for emotion detection in text seems to be the core technique under investigation in this paper. | The key problem is accurately detecting emotional content in textual data, like social media posts, customer reviews, forums etc. The goal is to develop an effective machine learning approach for classifying text by emotions, showing it improves over previous techniques. Solving this | Data Collection: The abstract notes using blog posts for variety in writing style. Data Pre-Processing: The abstract mentions techniques like |

| | | |
|---|---|---|
| | would have benefits for applications like sentiment analysis, chatbots, and social media monitoring. | removing noise, converting case etc. Feature Extraction: This converts the text into numeric feature vectors. Training and Test Sets: This provides data to train and evaluate the models. ML Models: Classification algorithms like Support Vector Machine, LinearSVC, and Random Forest Classifier are used to train emotion detection models on the data. Model Evaluation: This validates the machine learning approach.<br><br>Prediction: The best performing model is used to predict emotion categories for new text data. |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | |

| | Process Steps | Advantage | Disadvantage (Limitation) |
|---|---|---|---|
| 1 | Data preprocessing | It improves accuracy and reliability | Duplicate data. Integrating data from different sources may result in redundant columns and rows in the data set. |
| 2 | Feature extraction | It can help to reduce the number of features without losing too much information. | |
| 3 | Train/test split | This allows you to get a general sense of how well your model is performing, and also tells you whether or not your model is performing as expected | Eliminating data that could have been used for training a machine learning model (testing data isn't used for training). |
| 4 | Model training and evaluation | | Limited Scope |
| 5 | Model selection | The advantage of using a model is that it allows prediction and simplification of complex systems. | The disadvantage of a model is that they could be misleading and can be misinterpreted in a different way. |
| 6 | Prediction on new data | | If the data used to train the model is incomplete, inaccurate, or biased, the model's predictions will also be flawed. |
| 7 | Application to real-world tasks | The advantages of apps include convenience, easy communication with customers, and online usage. | The disadvantages of apps include difficulty to create, the cost to create them, the cost to make them available to people, and the need for updates and support. |

**Major Impact Factors in this Work**

| Dependent Variable | Independent Variable | Moderating variable | Mediating (Intervening ) variable |
|---|---|---|---|
| Emotion classification predicted by the machine learning models. | Testing data used to evaluate model performance | | |

| Relationship Among The Above 4 Variables in This article |
|---|
| |

<table>
<tr><th colspan="2">Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>The core input is the labeled text data used to train emotion detection models.</td><td>The output is the trained model that can categorize new text data into one of the predefined emotion classes.</td></tr></table></td><td>It uses machine learning algorithms such as logistic regression, K-NN classifier, and Adaboost classifier for text-based emotion detection. The proposed system investigates the effectiveness of Support Vector Classifier, LinearSVC, and RandomForestClassifier for identifying textual emotions. The system aims to improve the accuracy and effectiveness of emotion classification in text-based applications such as chatbots, customer support forums, and customer reviews</td><td>The key value is demonstrating a machine learning pipeline that provides state-of-the-art accuracy on a multiclass emotion detection task with real-world noisy text data. The comparative benchmarking and analysis is also a useful contribution. Overall, it helps advance the capability of systems to automatically understand emotional content in textual data.</td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">This work helps advance emotion AI particularly for textual data, enabling more nuanced analysis of human emotions at scale across many applications from sentiment analytics to empathetic chatbots and beyond. More work is needed to realize the potential societal benefits and mitigate risks.</td><td>key risks relate to privacy, misuse potential, algorithmic bias, lack of transparency, limited accuracy, and the possibility of exacerbating or misjudging mental health conditions if applied recklessly. Ongoing research into improving</td></tr>
</table>

| | | |
|---|---|---|
| | | robustness, avoiding bias, and enhancing transparency is important. |
| **Analyse This Work By Critical Thinking** | **The Tools That Assessed this Work** | **What is the Structure of this Paper** |
| This work provides a solid foundation demonstrating the potential of ML for text emotion detection. Analyzing limitations and setting ethical guidelines should be priorities for future work. Thorough, critical evaluation is key to developing reliable and socially responsible emotion AI systems. | Data Processing Tools<br>ML Tools<br>Model Evaluation<br>Coding Tools | Introduction<br>Literature review<br>Objective and problem statement<br>Existing statement<br>Proposed syatem<br>Conclusion |
| **Diagram/Flowchart** | | |


**--End of Paper 20--**

## 2.2 COMPARISION TABLE

| Authors | Year | Approach | Description |
|---|---|---|---|
| Yanrong Zhang | 2020 | Sentiment dictionary, Reverse sentiment dictionary | The proposed solution builds its own sentiment dictionary for computers and phones and shows better results. |
| Ghamya Kotapati, Suma Kamalesh Gandhimathi | 2023 | Bidirectional Encoder Representatios from Transformers | The proposed model considers relationships between the words and context of the sentences to determine sentiment of the given input. |

| | | | |
|---|---|---|---|
| Aljoharah Almjawel, Sahar Bayoumi | 2019 | Lexical based approach-sentiment analysis Tableau-Visualization | The solution gives the information about a book of interest and helps comparing the books by visual analysis. |
| Raghavendra Reddy, Ashwin Kumar U M | 2022 | ECNN - with text and emoji based emotion recognition | The model uses both text and emoji-based features to learn patterns in the data. This allows the model to recognize multiclass emotions. |
| Habib Izadkhah | 2022 | X-module using 1-D CNN | Generally the datasets contain very less multi labeled texts in comparison to single labeled texts due to which accuracy of the model decreases. But here a new dataset is created with multi label emotions for better accuracy. |
| Qi Wang, Lei Sun, Zheng chen | 2019 | Deep Learning Models (RNN,LSTM, GRU) | This solution combines both Convolution Neural Networks (CNN) with Bi-LSTM which shows that fusion models can help in achieving better accuracies. |
| Gourank Jain, Satyam Verma, Honey Gupta, Saloni Jindal, Mr. Mukesh Rawat, Mr. Kapil Kumar | 2022 | BERT | The paper is not only focussed on the usage of BERT algorithm but also focuses on importance of proper dataset. |
| Asiya U A, Mr Kiran V K | 2022 | MultiModality Approach | This paper’s aim is to explain the tremendous change in the accuracy by shifting our idea from uni modality to multi modality which is an important and useful feature of this solution. |
| Dr. Shailendra Narayan Singh, T. Sarraf | 2020 | Random Forests | The proposed work has the best feature of using live data extracted from websites rather than using existing dataset for training. |

| | | | |
|---|---|---|---|
| Arik Pamnani, Rajat Goel | 2019 | Logistic Regression, CNN, LSTM | The proposed approach mainly focuses on how to solve the problems during preprocessing of textual data. |
| Priyanka Awatramani, Rucha Daware,Hrushabhsingh Chouhan, Anmol Vaswani, Sujata Khedkar | 2021 | Lexicon based approach, Rule based approach, ML algorithms (SVM,Logistic Regression,KNN,Random Forest) | Discusses the different approaches to process the Hinglish text. |
| M. A. Mahima | 2020 | A new hybrid methodology for the detection of many emotions from text using sentence embeddings also with rule based techniques. | To detect the numerous emotions present in the text, also if emoticons are used in text how can they be used in detecting the emotions. |
| Juyana Islam, Sadman Ahmed, M. A. H. Akhand, N. Siddique | 2020 | Long Short-Term Memory | To improve emotion recognition of microblog by keeping semantic relation among texts and emoticons here, fused into text embeddings. |
| Ashish V C, Somashekar R , Dr. Sundeep Kumar | 2016 | Keyword spotting method, Lexical Affinity Method, learning based method and hybrid methods | Aims for appropriately identifying the emotion in text and analyzing various approaches to detect the six different emotions. |

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| Mahmud Hasan Munna, Md Rifatul Islam Rifat, A. S. M. Badrudduza | 2020 | Deep Neural Network and Natural Language Processing | To develop two Deep Neural Network (DNN) based models for review based classification and sentiment analysis. |
| Vikas Goel, Amit Kr. Gupta, Narendra Kumar | 2019 | Recurrent Neural Networks (RNN) and Naive Bayes algorithm | The solution aims in solving the problem of understanding feelings and opinions of users expressed in different languages on Twitter. |
| Reema Goyal, Navneet Chaudhry, Mandeep Singh | 2023 | PocketSphinx for automated speech recognition, Word2Vec for text analysis, K-means clustering | Utilizes the OCC model for connecting semantic analysis results to detect emotions. |
| Madhavi S. Darokar Dr. Atul D. Raut Dr. Vilas M. Thakre | 2022 | Deep CNN C-means clustering algorithm | Able to detect multiple emotions present within an image by using rule-based techniques. |
| Yuxin Huang Shaidah Jusoh | 2023 | ERNIE Tiny | This proposed approach focuses on relationship between emotion and sentiment analysis and presents a prototype for Chinese text emotion and sentiment analysis. |
| Amal Shameem Ramesh babu Vigneshwaran Sundar Mrs. K. Veena | 2023 | K-NN classifier, and Adaboost classifier | The system aims to improve the accuracy and effectiveness of emotion classification which can be used in text-based applications such as chatbots |

## 2.3 WORK EVALUATION TABLE

| | Work Goal | System's Components | System's Mechanism | Features /Characteristics | Performance | Advantages | Limitations /Disadvantages | Platform | Results |
|---|---|---|---|---|---|---|---|---|---|
| **Yanrong Zhang, Jiayuan Sun, Lingyue Meng, Yan Liu 2020** | sentiment dictionary-based method to mine e-commerce text reviews, and build a reverse sentiment dictionary for sentiment analysis. | Extraction of Emotional Resources. Construction of emotion dictionary. Constructing reverse dictionary. Emotion analysis. | Sentiment dictionary Reverse sentiment dictionary. | Builds its own sentiment dictionary for computers and phones and shows better results. | The self-built sentiment dictionary performs better than public HowNet sentiment dictionary. | Constructing a reverse emotion dictionary instead of just an emotion dictionary shows higher accuracy. Domain specific sentiment dictionary. | The results of part-of-speech tagging can be biased and need to be manually rectified. Lower accuracy for mobile reviews. | Python | Computer sentiment - 89.2 % Phone- 84.3 |
| **Ghamya Kotapati, Suma Kamalesh Gandhimathi, Palthiya Anantha Rao, Ganesh** | Main objective is to understand the context of the sentence and categorize the senten | CLS SEP Token embeddings Segment Embeddings Position | BERT | The proposed model takes into account both the relationships between words and sentences and the | BoW, Naive Bayes, Support Vector Machines (SVM), or Random Forests has | BERT models are excellent at identifying context and interpreting sentiment. | It only classifies the emotion into three categories i.e. positive, negative and neutral. | Python | Accuracy- 95% |

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|---|---|---|---|---|---|---|---|---|---|
| **Karthik Muppagowni, K Ragha Bindu, M Sharath Chandra Reddy 2023** | ce into the correct emotion. | Embeddings Hidden State Classification layer | | overall context while determining the sentiment of the given input. | limited contextual understanding and BERT outperforms them. | Different degree of emotions. | Computationally expensive. | | |
| **Aljoharah Almjawel, Sahar Bayoumi, Dalal Alsheheri, Soroor Alzahrani, Munirah Alotaibi 2019** | The aim is to provide a practical way to visually analyze customer feedback sentiment using various visualization techniques. | Sentiment analysis Visualization | Lexical based approach- sentiment analysis Tableau- visualization | Get detailed information about a book of interest and compare the books. | Performs better for visual analysis of customer sentiment. | Helps the customers to make decisions. Interactive interface | lexicon-based approach for sentiment analysis is not efficient. | R, Tableau | Review analysis of a book |
| **Raghavendra Reddy, Ashwin Kumar U M 2022** | Objective is to find the emotion using text and emoji- | Preprocessing the input text Feature extraction | ECNN - with text and emoji based emotion | The model uses both text and emoji-based features to learn patterns | The proposed ECNN model performs better than CNN, | Can recognize the emotion in the text containing emojis | Different OS has different types of emojis, this can make it difficult for the model to | Anaconda, python | accuracy- 90% precision- 83.5 |

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|---|---|---|---|---|---|---|---|---|---|
| | based features. | Identifying the correct emotion using ECNN<br>Comparing the model with different classification models | recognition | in the data. This allows the model to recognize multiclass emotions. | SVM, DT and NB classifiers. | which improves the accuracy. | predict the emotion. | | recall - 95%<br>f-measure- 92% |
| **Habib Izadkhah**<br>**2022** | The purpose of this paper is to detect multiple emotions in texts using X-module | Creation of dataset<br>Creating customized X-module<br>Predicting multiple emotions from text | X-module using 1-D CNN | The number of texts from which only one emotion can be deduced is very small compared to texts from which more than one emotion can be deduced which reduces accuracy. But here a new dataset is created with multi label | CNN + GLOVE performs better | High accuracy in detecting multiple emotions from text.<br>Created modified dataset for higher accuracy. | It requires a large and balanced dataset of multi-labelled emotions, which may not be easily available. | Python | Accuracy- 0.64663<br>Hamming Loss- 0.12864<br>micro F1-<br>0.72739<br>macro F1- 0.56238 |

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|---|---|---|---|---|---|---|---|---|---|
| | | | | emotions. | | | | | |

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| **Qi Wang, Lei Sun, Zhengchen**<br>**2019** | The goal of this solution is to propose a deep learning model for sentiment analysis of movie reviews. | Preprocessing of text<br>Splitting of movie reviews<br>Using fusion model to get the results and accuracy<br>Comparing the accuracy of fusion model with other models | RNN<br>LSTM<br>GRU | This solution is a combination of convolution neural network with Bi-directional LSTMwhich shows that fusion models can help in achieving better accuracies | The fusion model Glove+CNN/Conv+Bi-lstm gave best results compared with other models | It helps in understanding different algorithms and their limitations for emotion recognition in textDomain specific sentiment dictionary. | Most of the algorithms are resource intensive | Python | GloVe + Conv + BiGRU gave accuracy 0.88<br>Glove+CNN/Conv+Bi-lstm gave accuracy of 0.89 |
| **Gourank Jain,**<br>**Satyam Verma,**<br>**Honey Gupta,**<br>**Saloni Jindal,**<br>**Mr. Mukes** | The goal is to get more accurate predictions of emotion in a text. | Undersampling Technique<br>Splitting of dataset<br>Preprocessing<br>BERT | BERT | Unlike other approaches, this solution uses a balanced dataset their by avoiding the bias in result generation or | BERT is performing better than many other existing models | Prepares data for the BERT model and ensures that the data is consistent and | May require lots of computational resources and memory to run. | Python | BERT succeeded in getting an accuracy of 75% |

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|---|---|---|---|---|---|---|---|---|---|
| **h Rawat, Mr. Kapil Kumar 2022** | | Regularization<br>Classification | | emotion recognition | | representative which avoids the biased results<br>Helps in avoiding overfitting | | | |
| **Asiya U A, Mr Kiran V K 2022** | The goal of this solution is to get better accurate emotion prediction by changing the entire system's modality | Data Preprocessing<br>Feature Extraction<br>Audio Emotion Recognition<br>Text Emotion Recognition<br>Multimodal emotion recognition | Alex Net<br>BERT | The proposed work explains the tremendous change in the accuracy by shifting our idea from uni modality to multi modality which is an important and useful feature of this solution | Multimodal helped in getting the accurate results or prediction | Allows to learn contextual relationship between words and helps in reducing the problem of overfitting | Requires lot of computation power for training and testing along with huge amounts of data for training the models | Python | Alex Net gave 55% accuracy,BERT gave 69% where as combination has given 98% accuracy |
| **Dr. Shailendra Narayan Singh Twinkle Sarraf** | The goal of this solution is to help users reduce the | Data Preparation<br>Review Analysis<br>Sentiment | Random Forests | The proposed work has a best feature of using live data extracted from website | This is a use case of sentiment analysis therefore not compared with | This allows to hide the bias or incorrect result of one | The system depends on the availability and structure of the website, which | Python | The result is that we get a final score of number of negati |

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|---|---|---|---|---|---|---|---|---|---|
| **2020** | time of analyzing a product. The problem of the user taking the decision to buy/not buy is solved. | classification | | rather than using existing dataset for training | any other existing models | model by taking the result which is predicted by majority of the models | are temporary | | ve and positive reviews for a product |
| **Arik Pamnani**<br>**Rajat Goel**<br>**Jayesh Choudhari**<br>**Mayank Singh**<br>**2019** | The goal of this solution is to compare the better emotion prediction model. | Data Preprocessing<br>Machine Learning Model (SVM, Logistic Regression)<br>CNN<br>LSTM | Logistic Regression<br>CNN<br>LSTM | The feature of this solution is its data preprocessing and the way the solution handled the challenges of the textual emotion recognition like elongated words etc | SVM,Logistic Regression has given a score of 0.46, 0.48 while LSTM, CNN has given a score of 0.68,0.63 | The emoji's and elongated words are a major challenges which have impact on the model .These are handled by this solution efficiently | The training requires lot of hardware resources and computing power | Python | Among any other model available for comparison LSTM has given the best score |

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|---|---|---|---|---|---|---|---|---|---|
| **Priyanka Awatramani Rucha Daware Hrushabhsingh Chouhan Anmol Vaswani Sujata Khedkar 2021** | The goal of this paper is to solve the limitations and challenges by studying and analyzing the different approaches to tackle the Hinglish text. | Handling data with noise, Case folding, Punctuation Removal, Special character removal, Spelling Correction, Stop-Word Removal | Lexicon based approach Rule based approach ML algorithms (SVM ,Logistic Regression, KNN, Random Forest ) | The solution handles code-mixed text A novel romanized Hindi dictionary is created using sentiment scores from HindiSentiWordNe t. This helps overcome the lack of Hindi resources . | Out of all the approaches the SVM(Support Vector Machine) and Logistic Regression have performed well | The hindi language in the text is converted to english easily using the APIS Sentiments can be properly be detected because here spelling correction is also done. | Focu sed on class ificat ion of senti ment s not on the emot ions | Python | Varied appro ache s have been discussed and evaluated through accuracy, precision and the accuracy obtained is 86% |
| **Mahima M A, Nidhi C Patel, Srividhya Ravichandran , Aishwarya N Sumana** | The goal is to detect the multiple emotions present in the text and also if emoti | Datasets Preprocessing Hybrid Model Multiple Emotion Tagger | A new hybrid methodology for the detection of multiple emotions from the text | Able to detect multiple emotions present within a single text by splitting using rule-based techniques. Employs similarit | Traditional approaches ignore the presence of disambiguitie s but, here using rules, sentiments and | Conversion of emoticons helps in more precisely detecting/identifying the | Rules and similarity matching have limitations for handling very complex language use cases. | Python | It can be observed that using EmoDBG Oemotion s datasets With vsm produces |

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|---|---|---|---|---|---|---|---|---|---|
| **Maradithaya 2021** | cons are used in text how can they be used in detecting the emotions. | | using sentence embeddings along with rule based techniques | y technique to find most similar sentences for emotion assignment | context the model looks to have good performance as compared t traditional approaches | emotions allows capturing transitions in emotions within a text. | | | highest classification with 57.447% |
| **Juyana Islam Sadman Ahmed M. A. H. Akhand N. Siddique 2020** | To improve emotion recognition from microblog keeping semantic relation among texts and emoticons. | Dataset Preprocessing Emoticon Representation Tokenization Embedding Layer LSTM Network | Long Short-Term Memory | The textual data is in the form of sequential manner so the model which is used (LSTM) is best suitable for text such that it can find the emotion hidden in it accurately. Here, emoticons are fused into text embeddings. | - | Comparing the text where the emoticons are eliminated it has been observed that the performance is not good as compared with the text where emoticons are considered. | Word embeddin gs capture semantic meaning and relations hi ps between words/e m oticons. | Python | The accuracy obtained is 82.1% |

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|---|---|---|---|---|---|---|---|---|---|
| **Ashish V C Somas hekar R**<br>**Dr. Sundee p Kumar**<br>**2016** | The goal of this paper is to appro priatel y identif ying the emoti on in text and analyz ing variou s appro aches | Text docume nt, preproc e ssing the data, Tokeni zation of data, Emotio n keywor d detectio n, Intensit y analysis , Negatio n check,E motion class | Keyw ord spotti ng metho d, Lexic al Affini ty Metho d, learni ng based metho d and hybrid metho ds | Detects six different emotions . Some covered techniqu es support multiling ual emotion detection across language s. | Hybrid based approac h achieve s good accurac y as compar ed to other approac hes | Simpl e and easy to imple ment<br><br>Identi fies the class of emoti on based on count such that if there are varied emoti onal words then that can be identfi ed proper ly as comp ared to keyw ord and lexica l affinit y based | It is not a reliable method because it totally depends on the emotion al related keyword s as the meaning s of keyword s could be multiple and vague | Pyth on | Under sto od the limitat ion s of existi ng appro ache s and as an result it can be under stoo d that the hybrid appro ache s perfor m better. |
| **Mahm ud Hasan Munna**<br>**Md Rifatul** | Devel oped two Deep Neura l Netw | Data Preproc essing Removi ng Stop-words | Deep Neura l Netw ork and Natur | Uses deep neural network architect ure for text | The Perfor m ance of the model is good | Helpf ul in captur ing proper seman tic | Com putati onall y expe nsive | Pyth on | The senti men t analys is obtain ed an |

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|---|---|---|---|---|---|---|---|---|---|
| **Islam Rifat A. S. M. Badrudduza 2020** | ork (DNN) based models for review based classification and sentiment analysis. | Removing Punctuation Removing Unnecessary Characters Data Partitioning Feature Extraction | al Language Processing | classification tasks. Can capture semantic information better than traditional ML models. | for sentiment analysis as compared with product review classific ation | meaning Activation functions define the complexity and efficiency of DNN architecture | | | accuracy of 84% and product review classifica tion obtained an accuracy of 69% |

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|---|---|---|---|---|---|---|---|---|---|
| **Vikas Goel Amit Kr. Gupta Narendra umar 2019** | Classify sentiments expressed in tweets into positive, negative, or neutral categories using machine learning techniques. | Data Gathering, Data Preprocessing, Feature Extraction, Sentiment Classification, Evaluation and Comparison | Data Gathering<br><br>Google Translator<br><br>Preprocessing of Tweets<br><br>Feature Extraction<br><br>Apply Classification Algorithms | Sentiment analysis of multilingual Twitter data, Used RNN and Naive Bayes algorithms, Google Translator API for multilingual data, NLP Library and .NET framework | RNN performs better than Naive Bayes in terms of data analysis and accuracy. | Addresses multilingual sentiment analysis, Use of machine learning algorithms, Preprocessing of tweets | Language limitations, Data size and complexity, Lack of contextual understanding, Bias and inaccuracy, Need for continuous updates | Python | Comparison of RNN and Naive Bayes algorithms, Dataset classification results |
| **Reema Goyal, Navneet Chaudhry, Mandeep Singh 2023** | Create an emotion detection model that requires no labeled training | PocketSphinx for ASR, Word2Vec for text analysis, K-means clustering | Import and preprocess data<br><br>PocketSphinx ASR | Emotion recognition using machine learning, Natural language processing for semantic | The paper proposes an unsupervised emotion detection approach combinin | Customized emotion detection approach, Handles speech signals | Privacy and security concerns, Potential biases, Need for oversight and ethical | python | The key result is a customized emotion detection approach that |

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| | data, works for low-resource languages, and can be personalized for individual users in an unsupervised manner. | , TF-IDF vectorizer | Word2Vec model<br><br>K-means clustering<br><br>TF-IDF weighting and emotion detection | analysis, OCC model for mapping semantics to emotions, PocketSphinx for Automatic Speech Recognition | g PocketSphinx for speech recognition, Word2Vec for text analysis, K-means clustering, and TF-IDF weighting. | and text, Unsupervised and personalized | considerations | | works in an unsupervised manner, handles speech and text input, and can be personalized for users.. |
| **Madhavi S. Darokar, Dr. Atul D. Raut, Dr. Vilas M. Thakre**<br><br>**2022** | Build a face detection model<br><br>Extract features from faces<br><br>Build and train a layered Deep CNN using face images and features | SVM, Neural Network, Deep CNN, JAFFE dataset, Face detection, Emotion recognition | Face detection using JAFFE dataset and C-means clustering<br><br>Feature extraction using Gabor Filter, Local Binary Pattern, SIFT<br><br>Emotion classification | Facial emotion recognition from social media, Use of deep learning and neural networks, Ability to detect multiple emotions in an image | Higher accuracy than input data | Detects multiple emotions in an image, Explains need for balanced dataset | Works well only for front pose images, High computational requirements, Challenging to classify emotions based on context | Python | Evaluates system parameters and classification accuracy |
| **Yuxin Huang, Shaidah Jusoh**<br><br>**2023** | Develop a prototype for emotion and sentiment analysis of | User Interface Layout, Single Text Function, Batch Text Function, Model | Methodology<br><br>Model Building<br><br>Optimization Strategy | Emotion and sentiment classification for Chinese text, Use of ERNIE Tiny pre-trained | The paper develops a prototype system using the ERNIE Tiny pre-trained | Addresses limitations of existing methods, Explores deep learning | : Limited consideration of punctuation, Lack of comparison with other ML methods, Simple and | Python | Prototype development, Model evaluation, Experiment and |

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|---|---|---|---|---|---|---|---|---|---|
| | Chinese text to assist in classifying emotions and sentiments, particularly in social media and music platforms | Building, Optimization Strategy and Train Data, Model Evaluation and Prediction Testing, Experiment | and Train Data<br><br>Model Evaluation and Prediction Testing | model, Classifies emotions like sadness, happiness, anger, etc., Classifies sentiment polarity like positive, negative, none | model for emotion and sentiment analysis of Chinese text. The prototype can classify emotions and sentiment polarity, suggesting it is capable of performing the intended tasks to some degree. | approaches, Develops a working prototype | limited prototype functionality, Unattractive user interface, Limited scope to Chinese text | | result analysis |
| **Amal Shameem, Ramesh babu, Vigneshwaran, Sundar, Mrs. K. Veena**<br><br>**2023** | Develop an effective machine learning approach for classifying text by emotions, showing improvement over previous techniques | Data Collection, Data Preprocessing, Feature Extraction, Training and Test Sets, ML Models (SVM, LinearSVC, Random Forest), Model Evaluation, Prediction | Data preprocessing<br><br>Feature extraction<br><br>Train/test split Model training and evaluation<br><br>Model selection<br><br>Prediction on new data | Machine learning for text-based emotion detection, Use of algorithms like SVM, LinearSVC, Random Forest, Evaluation on noisy real-world text data | Improved accuracy compared to previous techniques | Effective for multiclass emotion detection, Comparative benchmarking and analysis, Advances capability for understanding emotions in text | Limited scope, Potential for bias and inaccuracy, Lack of transparency, Privacy concerns, Risks of misuse and misdiagnosis | Python | Benchmarks accuracy of different models on emotion detection task |

## 2.4 DISADVANTAGES OF EXISTING SYSTEM

a. Concisely summarizing the disadvantages of the above implementations:
b. Disparity between theoretical developments and practical applications in customer feedback analysis and emotion recognition.
c. Falls short in capturing complex emotions.
d. Inadequate data visualization and unreliable data analysis of the gathered customer feedback.
e. Lack of prompt response to customer complaints leading to dissatisfaction.
f. Ineffective utilisation of customer service manpower reading and responding to each customer review.
g. Existing feedback analyzers have a flaw that they rely too heavily on oversimplified emotional classifications such as positive, negative, or neutral.

# CHAPTER 3

# PROPOSED SYSTEM

## 3.1 PROPOSED SYSTEM

The proposed solution presents an integrated architecture for analyzing customer reviews through deep learning models, with a focus on emotion recognition and feedback processing. The system encompasses a user-friendly frontend interface, a backend for emotion analysis and data storage, and additional components for customer care alerting, automated responses, and finally geographical, age-group and gender-based analytics. The proposed model can be an innovative solution that can be helpful for responding to the sentiments of the customers.

## 3.2 OBJECTIVES OF PROPOSED SYSTEM

a. Creating a hassle-free user experience front end.
b. Storing the customer information in the database for data analysis purpose.
c. Using Deep Learning model known as Bi-LSTM to find the emotion of the review.
d. Creating an alerting module for the customer care to look into the customer dissatisfaction
e. Automated reply to the customer.
f. Data Analysis based on product, location, age group and gender.

## 3.3 ADVANTAGES OF PROPOSED SYSTEM

The proposed system has the following advantages:

a. Accurate emotion analysis enables deeper insights into customer preferences, concerns, and sentiments.
b. Real-time emotion recognition allows for personalized and targeted responses to customer feedback, enhancing satisfaction and loyalty.
c. Automated emotion recognition optimizes customer care allocation for prompt issue resolution.
d. Organizations can identify trends, patterns, and areas for improvement, leading to enhancements in products and services.
e. Customer care monitoring system for effective resolution of issues by the executives.

f. Data visualization of customer emotion trends, facilitates easier interpretation and decision-making for stakeholders.

## 3.4 SYSTEM REQUIREMENTS

The system requirements for the development and deployment of the project as an application are specified in this section. These requirements are not to be confused with the end-user system requirements. There are no specific, end-user requirements as the intended application is web based feedback form and is supposed to work on devices of all configurations.

### 3.4.1 SOFTWARE REQUIREMENTS

Below are the software requirements for application development:

a. Editor for HTML, CSS, Python, Streamlit, Flask - VS Code
b. Google Chrome, Firefox, Microsoft Edge or Brave Browser for feedback form, business owner dashboard and managers portal.
c. Google collab and kaggle notebooks for training.

### 3.4.2 HARDWARE REQUIREMENTS

Hardware requirements for application development are as follows:

a. CPU - intel i3 or higher
b. RAM - 4 GB or higher
c. GPU - RTX 3050 or higher
d. VRAM - 4GB or higher

### 3.4.3 IMPLEMENTATION TECHNOLOGIES

**Deep Learning:**

The implemented system utilizes a deep learning approach, specifically the Bi-directional Long Short-Term Memory (Bi-LSTM) neural network architecture, for emotion recognition from text. Bi-LSTM is a sophisticated technique that can understand word context and extract nuances from text by looking at it from both directions, enhancing the accuracy of emotion detection. The Bi-LSTM helps in accurate emotion classification of textual customer feedback.

**Natural Language Processing (NLP):**

The system employs various Natural Language Processing (NLP) techniques such as text preprocessing (tokenization, spelling correction), and word embeddings like GloVe for encoding text. These techniques are crucial for preparing the textual data and converting it into a suitable format for the deep learning model to analyze and extract emotional insights effectively.

**Web Technologies:**

The solution is implemented as a web application using the Flask web framework based on Python. It integrates the frontend which is created with HTML/CSS with the backend for seamless user interaction. Additionally, a MySQL database is utilized for securely storing customer data collected through the feedback system. This helps in providing a hassle free user interface for collecting feedback and serves as the backend for processing and storing data.

**Data Visualization:**

The streamlit Python library is used for creating interactive data visualisations, such as bar charts, to analyze the distribution of emotions across various categories, including products, locations, age groups, and genders. This visual representation of data aids in understanding customers emotion and identifying trends. This allows us to understand insights from customers' emotions which can also help in improving product performance by understanding interactive visualisations.

**Email Integration:**

The system integrates automated email responses that are generated based on the detected emotions from customer feedback. These responses are sent to customers via SMTP email server, providing personalized communication and reducing the workload on customer support staff. By sending automated email responses tailored to the detected emotions in customer feedback the customer care man power can be effectively utilized.

The deep learning approach (Bi-LSTM) and NLP techniques are used for accurate emotion recognition from customer feedback text. The web application, built with Flask and MySQL, serves as the frontend and backend for data collection and processing. Data visualization with streamlit provides insights into customer emotions and product performance. Email integration enables automated, personalized responses based on detected emotions.

## CHAPTER 4

## SYSTEM DESIGN

### 4.1 PROPOSED SYSTEM ARCHITECTURE

The proposed system uses deep learning models to analyze customer feedbacks, the integrated architecture provides a holistic solution that prioritizes feedback processing and emotion recognition. It has an easy-to-use front end, an emotion analysis and data storage back end, alerting system for customer support, automated response generation, and data analytics. By efficiently responding to customer reviews, this methodology seeks to improve customer engagement and service effectiveness. The below figure 1 represents the architecture of the proposed system.

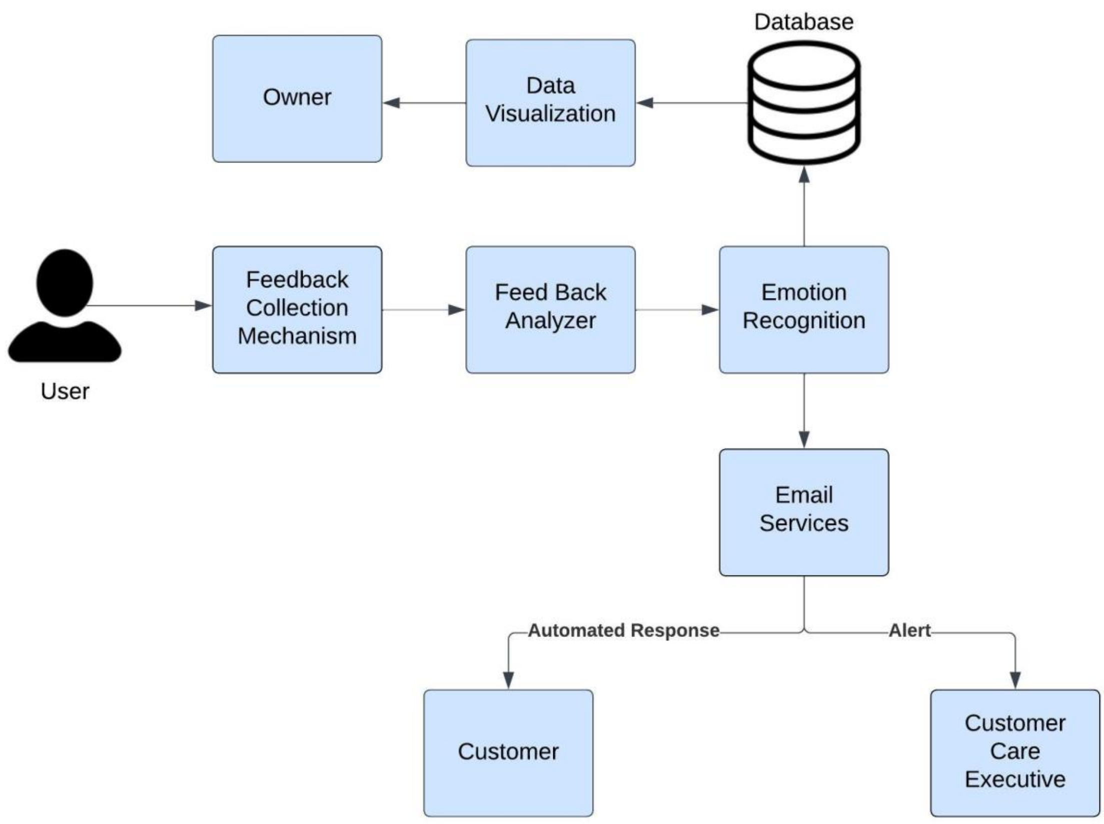



Figure 1: Architecture of Proposed solution

## 4.2 APPLICATION MODULES

The following modules are involved in the proposed implementation:

a. Feedback System
b. Emotion Recognition
c. Response Generation
d. Manager’s Portal for customer support
e. Data Visualization Dashboard

### 4.2.1 Feedback System:

Our approach starts by taking essential customer information such as name, email, age, gender, location, product name, order ID, and feedback about the product. The Feedback System features an easy-to-use interface that is straight forward and aimed to promote smooth customer interactions. A reliable database system safely stores the gathered input. This method establishes the framework for additional analysis and processing while guaranteeing the privacy and accuracy of consumer input.

### 4.2.2 Emotion Recognition:

A novel method called Bidirectional Long Short-Term Memory – BiLSTM is used by the emotion recognition module. The system can recognize and understand emotion indicated in textual responses. Because of this method being bidirectional, it can be used to comprehend contextual dependencies in the given text in a more sophisticated way. By integrating consumer emotion into the whole feedback processing method, a seamless understanding of consumer preference can be noted.

### 4.2.3 Response Generation:

The main problem identified is, over utilization of customer care manpower, which involves responding to every customer feedback. This can be solved by implementing our proposed approach, by creating a response tailored to the emotion of the feedback. The emotion will be recognized by emotion recognition module, and based on it an automated pre-composed response will be sent to the customer via email.

### 4.2.4 Manager's Portal for customer support:

The problem of over utilization of customer care manpower will be solved by the previous module combined with this module. The above module sends a response to the customer which is then followed by sending an email to customer care executives to assist only those customers whose feedback depicts the need for some help.

### 4.2.5 Data Visualisation Dashboard:

The Data Visualization Dashboard is a powerful tool that helps you analyse information from the database in an easy way. It gives you a complete view of the business by showing clear pictures of what customers think and how well products are doing. Using this dashboard, a business owner can make better decisions. They can understand trends, recognize patterns, and come up with smart strategies for better sales of their products.

## 4.3 UML DIAGRAMS

### 4.3.1 Use Case Diagram

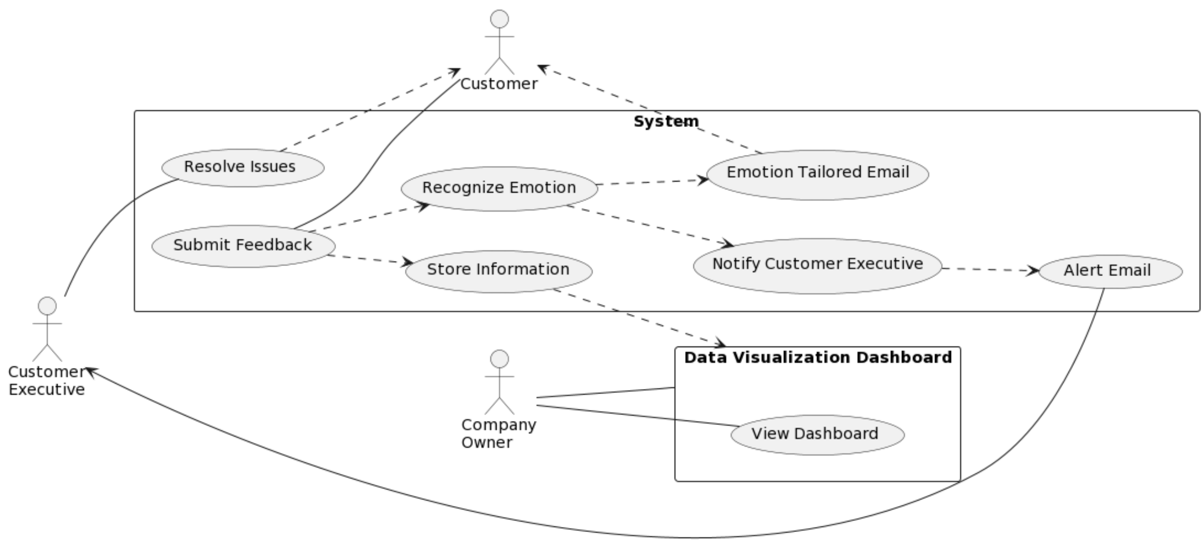



Figure 2: Use case diagram of the proposed system

A use case diagram is a behavioral diagram in the Unified Modeling Language (UML) that depicts the interactions between the system and its actors (users or external systems). It helps to visualize the system's functionalities from the user's perspective.

The use case diagram shown in the figure 2 illustrates the various interactions between the actors (Customer, Customer Executive, and Company Owner) and the system's functionalities related to customer feedback management and emotion recognition.

a. The interaction starts with the customer actor. The customer can submit feedback to the system, which then stores customer information and recognizes emotion from the feedback. Based on the detected emotion, the system sends an emotion tailored response via email to the customer. Additionally, the system notifies the customer executive by sending an alert email.
b. Then the interactions involve the Customer Executive and Company Owner actors. The customer executive receives the alert email from the system when a customer's feedback requires prompt attention. The company owner, on the other hand, can view visualisations of the data through the data visualisation dashboard, which provides insights and visualisations based on the collected customer feedback data.

### 4.3.2 Sequence Diagram

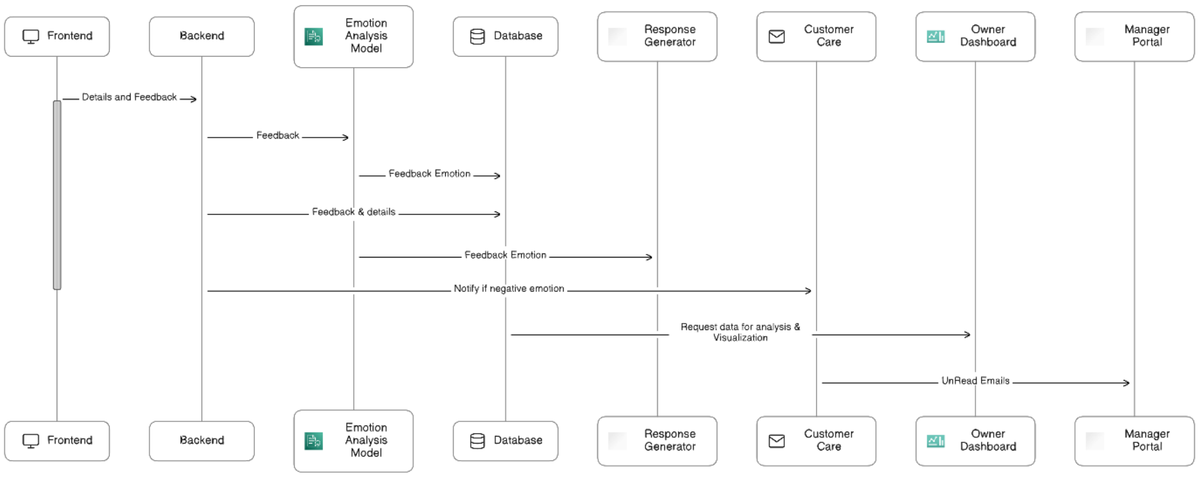



Figure 3: Sequence diagram of the proposed system

The figure 3 represents a sequence diagram that illustrates the flow of interactions and data exchange between different components of the proposed system. The sequence diagram provides a visual representation of the system's behaviour over time, depicting the chronological order of events and the communication between the components.

a. The process begins with the frontend component, where the customer enters their details and feedback. This information is sent to the backend component. The backend then forwards the feedback data to the emotion analysis model, which analyses the textual feedback to detect the underlying emotion, such as happy, sad, angry, or disgusted. The detected emotion is sent back to the backend and stored in the database component.

b. If the detected emotion is negative (e.g., sad, angry, or disgusted), the backend notifies the customer care component i.e to the customer care executive. The database is accessed by the data analysis and visualisation component, for retrieving the necessary data from the Database and provides visualisations in the owner's dashboard.

c. Based on the detected emotion, the response generator component generates an appropriate emotion-tailored response and delivers the personalised response to the customer via email. Additionally, if the detected emotion requires further attention, the customer care component sends an email to the customer care executive.

d. The owner dashboard component allows the company owner to view the visualisations of the data to get the insights, enabling them to monitor customer emotion, product performance, and make informed decisions.

### 4.3.3 Activity Diagram

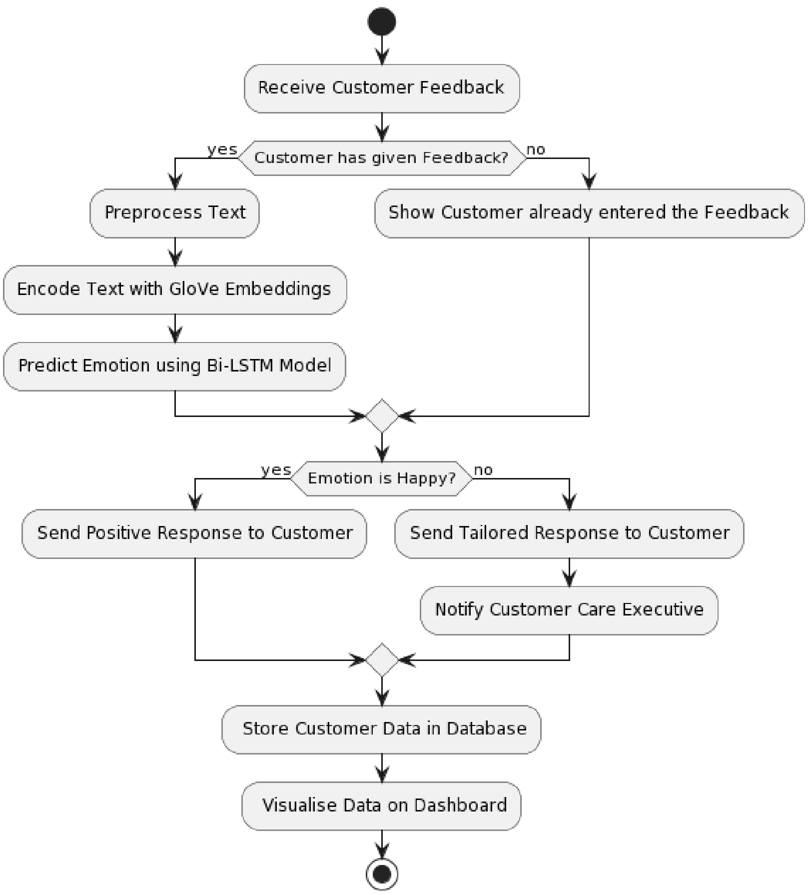



Figure 4: Activity diagram of the proposed system

Activity diagram is a graphical representation used to illustrate the flow of activities or actions within a system, process, or workflow. It depicts the sequence of tasks, decisions, and actions involved in completing a specific process. They provide a clear visualization of the workflow, making it easier to understand, analyze, and communicate complex processes within a system.

The figure 4 shows an activity diagram of proposed solution which covers the following key steps:

a. Receiving customer feedback
b. Check if customer has already given feedback
c. Preprocessing and encoding the text
d. Predicting the emotion using the Bi-LSTM model
e. Generating an automated response based on the emotion (positive for happy, or assigning a customer executive for other emotions)
f. Storing the emotion data in the database
g. Visualizing the data on the dashboard

### 4.3.4 Class Diagram

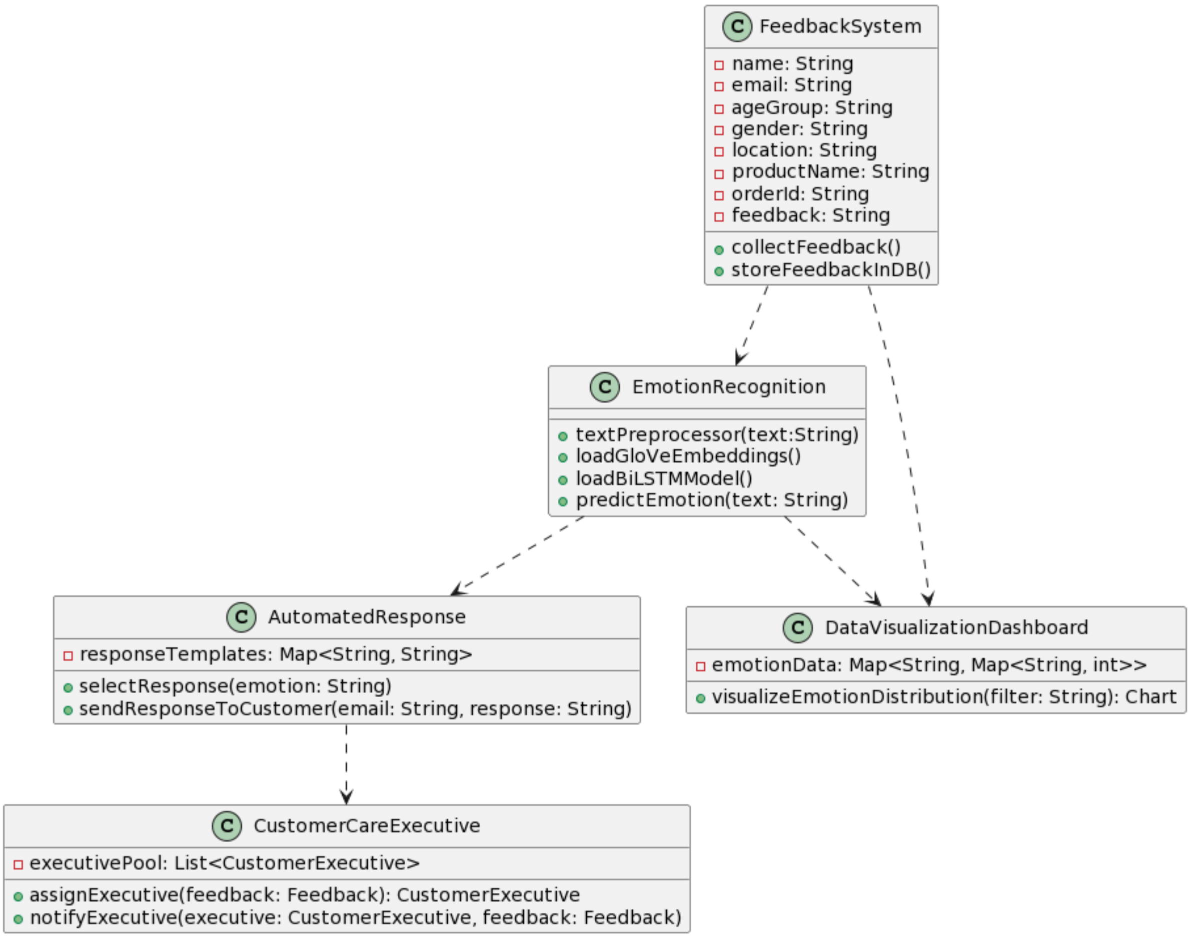



Figure 5: Class diagram of the proposed system

A class diagram is a fundamental component of object-oriented modeling used to visualize the structure of a system. It provides a high-level overview of the classes within the system, their attributes, methods, and relationships with other classes. Each class in a class diagram represents a blueprint for creating objects, encapsulating both data (attributes) and behavior (methods) relevant to the system's functionality. Attributes represent the properties or characteristics of a class, such as name, age, or size, and are depicted as variables within the class. Methods, on the other hand, represent the operations or actions that a class can perform, such as calculating, updating, or querying data, and are depicted as functions within the class.

The figure 5 represents class diagram that depicts the architecture of a feedback system designed to handle customer feedback efficiently. The FeedbackSystem class, responsible for collecting various aspects of customer feedback such as name, email, age group, gender, location, product name, order ID, and the actual feedback text. It exposes methods like collectFeedback() to gather feedback from users and storeFeedbackInDB() to store this feedback in a database for further processing.

The EmotionRecognition class plays a crucial role in analyzing the emotional content of the feedback. It employs methods such as textPreprocessor() to preprocess text, loadGloVeEmbeddings() to load pre-trained word embeddings, loadBiLSTMModel() to load a Bidirectional Long Short-Term Memory (BiLSTM) model, and predictEmotion() to predict the emotional tone of the feedback text. This emotional analysis then triggers the AutomatedResponse class, which selects appropriate response templates based on the detected emotions and sends personalized responses to customers via methods like selectResponse() and sendResponseToCustomer().

The CustomerCareExecutive class manages a pool of customer care executives and assigns them to resolve the customer issues. Finally, the DataVisualizationDashboard class offers visualization capabilities, allowing stakeholders to view emotion distributions and gain insights into customer sentiment trends over time or across different parameters.

# CHAPTER 5

# IMPLEMENTATION

## 5.1 IMPLEMENTATION WITH DIFFERENT SCENARIOS

This subsection explains the behaviour of the application in various situations.

### 5.1.1 Successful Feedback Submission

a. The customer visits the feedback page to enter their details and feedback.
b. The customer enters their personal details (name, email, age, gender, location), order ID, product name, and feedback.
c. The application checks if the provided order ID exists in the database.
d. If the order ID is valid, the application proceeds for further processing.
e. The application corrects the spellings in the feedback using the autocorrect library.
f. The application passes the corrected feedback to the emotion recognition model for emotion prediction.
g. The application stores the customer's information, corrected feedback, and predicted emotion in the MySQL database.
h. Based on the predicted emotion (happy, sad, angry, or disgusted), the application generates and sends an automated email response to the customer.
i. If the predicted emotion is sad, angry, or disgusted, the application also sends an email to a randomly selected customer service executive, notifying them about the customer who needs assistance.
j. The customer receives a thank-you message on the website, acknowledging the successful submission of their feedback.

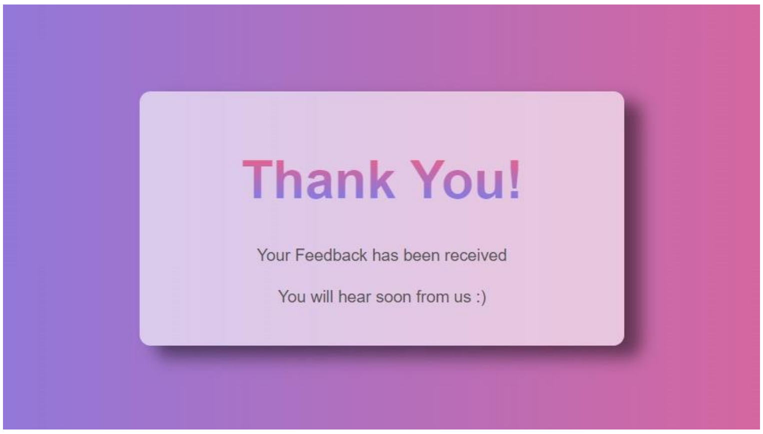



Figure 6: Thankyou Response

### 5.1.2 Customer submits feedback for an order ID that doesn't exist

a. The customer enters their personal details, order ID, product name, and feedback.
b. The application checks if the provided order ID exists in the database.
c. If the order ID is invalid, the application does not proceed with the feedback processing.
d. The application displays an error message to the customer, indicating that the provided order ID does not exist.
e. The customer is prompted to contact customer support if the issue persists.

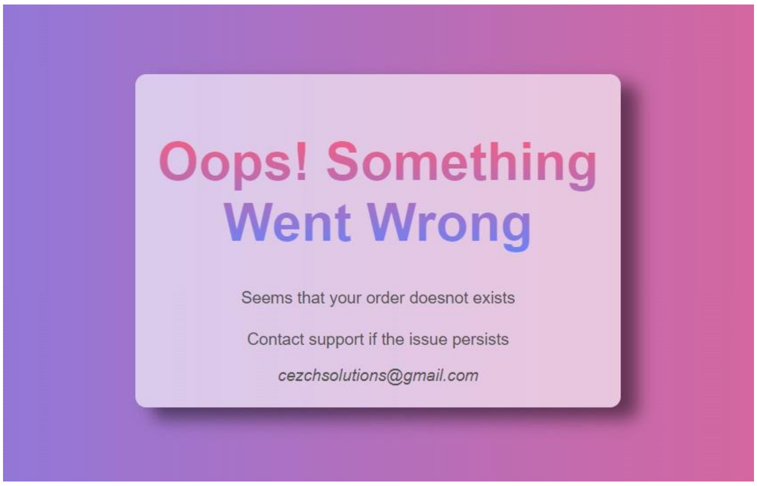



Figure 7: Order does not exist's

### 5.1.3 Prevention of duplicate feedback

a. The customer enters their personal details, an order ID for which they have already submitted feedback.
b. The application checks if the provided order ID exists in the database.
c. Since the order ID already has feedback associated with it, the application does not proceed with the feedback processing.
d. The application displays an error message to the customer, indicating that their feedback for the given order ID has already been received and is being processed.

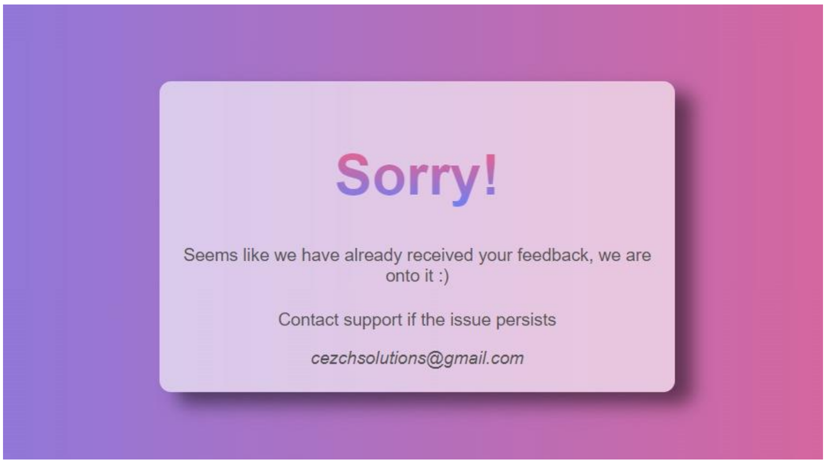



Figure 8: Feedback already given

## 5.2 SOURCE CODE

### index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>User Feedback Form</title>
    <link href="https://fonts.googleapis.com/css2?family=Patua+One&display=swap"
rel="stylesheet">
    <!-- <link rel="stylesheet" href="styles.css"> -->
    <link rel="stylesheet" href="{{ url_for('static', filename='styles.css') }}">
</head>
<body>
    <div class="main">
        <form id="feedbackForm" action="{{ url_for('submit')}}" method="POST">
            <h2 class="form-heading">Czech Unified Solutions
                <br>
                Feedback Form
            </h2>
            <label for="name">Name</label>
            <input type="text" id="name" name="name" placeholder="Enter Name" required>

            <label for="email">Email</label>
            <input type="email" id="email" name="email" placeholder="Enter email id" required>

            <label for="age">Age</label>
            <select id="age" name="age" required>
                <option disabled selected value="">Select Age Group</option>
                <option value="under18">Under 18</option>
                <option value="18-24">18-24</option>
                <option value="25-34">25-34</option>
                <option value="35-44">35-44</option>
                <option value="45-54">45-54</option>
                <option value="55-64">55-64</option>
                <option value="65+">65 and over</option>
            </select>

            <label for="gender">Gender</label>
            <select id="gender" name="gender" required>
                <option disabled selected value="">Select Gender</option>
```

```
                <option value="male">Male</option>
                <option value="female">Female</option>
            </select>

            <label for="location">Location</label>
            <!-- <input list="city" id="location" name="location"> -->
            <input list="city" id="location" name="location"
pattern="Telangana|Maharashtra|Delhi|Karnataka|Punjab|Gujarat|Odisha|Tamil Nadu|Andhra
Pradesh|Uttar Pradesh" required>
            <datalist id="city">
                <option value="Telangana"></option>
                <option value="Maharashtra"></option>
                <option value="Delhi"></option>
                <option value="Karnataka"></option>
                <option value="Punjab"></option>
                <option value="Gujarat"></option>
                <option value="Odisha"></option>
                <option value="Tamil Nadu"></option>
                <option value="Andhra Pradesh"></option>
                <option value="Uttar Pradesh"></option>
            </datalist>

            <label for="orderId">Order Id</label>
            <input type="text" id="orderId" name="orderId" placeholder="Enter Order Id"
required>

            <label for="product">Product Name</label>
            <select id="product" name="product" required>
                <option disabled selected value="">Select product</option>
                <option value="mobile">Mobile</option>
                <option value="laptop">Laptop</option>
                <option value="tablet">Tablet</option>
                <option value="ear_dopes">Ear Dopes</option>
                <option value="smart_watch">Smart Watch</option>
            </select>

            <label for="feedback">Feedback</label>
            <textarea id="feedback" style="resize:none" name="feedback" rows="4"
spellcheck="true" placeholder="Give your Feedback" required></textarea>

            <div class="button-container">
                <button type="submit" value="submit">Submit</button>
                <button type="reset">Clear</button>
            </div>
        </form>
    </div>
</body>
</html>
```

## styles.css

```
body{
  background: #FC5C7D;  /* fallback for old browsers */
  background: -webkit-linear-gradient(to right, #6A82FB, #FC5C7D);  /* Chrome 10-25, Safari
5.1-6 */
  background: linear-gradient(to right, #6A82FB, #FC5C7D); /* W3C, IE 10+/ Edge, Firefox 16+,
Chrome 26+, Opera 12+, Safari 7+ */
}
.main {
  font-family: Arial, sans-serif;
  margin: 0;
  padding: 0;
  display: flex;
  justify-content: center;
  align-items: center;
```

```
}
.form-heading {
  text-align: center;
  transition: all 0.5s ease-out;
}

.form-heading:hover{
  background-color: #fff;
  color: #FC5C7D;
  border-radius: 10px;
}

form {
  font-size: 16px;
  font-family: 'Patua One', serif;
  color:rgba(2, 9, 13, 0.793);
  background-color: rgba(248, 247, 247, 0.375);
  padding: 20px;
  margin: 15px 20px;
  border-radius: 27px;
  border: 2px solid #ccc;
  box-shadow: 12px 10px 15px rgba(0, 0, 0, 0.5);
  width: 300px;
  text-align: center;
  transition: transform 0.3s ease-in-out;
}

label {
  display: block;
  margin: 10px 0 5px;
}

input,
select,
textarea {
  width: 100%;
  padding: 8px;
  margin-bottom: 10px;
  box-sizing: border-box;
  border: 1px solid #ccc;
  border-radius: 4px;
  transition: border-color 0.3s ease-in-out;
}

input:focus,
select:focus,
textarea:focus {
  /* border: none; */
  outline: none;
  border-color: #FC5C7D;
  box-shadow: 0 0 15px #FC5C7D;
}

button {
  background-color: #4caf50;
  color: #fff;
  padding: 10px;
  border: none;
  border-radius: 4px;
  cursor: pointer;
  transition: background-color 0.3s ease-in-out;
}

button:hover {
  background-color: #45a049;
```

```
}

.button-container {
  display: flex;
  justify-content: space-between;
}

@media (min-width: 600px) {
  form {
    width: 400px;
  }
}
```

## response.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Thank You!</title>
    <style>
        .linear-text-gradient {
                background: linear-gradient(to top, #6A82FB, #FC5C7D);
                -webkit-background-clip: text;
                background-clip: text;
                color: transparent;
            }
        body {
            background: #FC5C7D;  /* fallback for old browsers */
            background: -webkit-linear-gradient(to right, #6A82FB, #FC5C7D);  /* Chrome 10-25,
Safari 5.1-6 */
            background: linear-gradient(to right, #6A82FB, #FC5C7D); /* W3C, IE 10+/ Edge,
Firefox 16+, Chrome 26+, Opera 12+, Safari 7+ */
            margin: 0;
            font-family: 'Arial', sans-serif;
            display: flex;
            align-items: center;
            justify-content: center;
            height: 100vh;
            color: #555353;
        }

        .container {
            text-align: center;
            background-color: rgba(255, 255, 255, 0.615); /* White background with
transparency */
            height: auto;
            width: 400px;
            padding: 20px;
            border-radius: 10px;
            margin: 15px 20px;
            box-shadow: 15px 10px 15px rgba(0, 0, 0, 0.5); /* Box shadow for a subtle effect
*/
        }

        h1{
            font-size: 3rem;
            font-weight: bolder;
        }
        p {
            font-size: 15px;
        }

        .footer {
```

```
            margin-top: 20px;
            font-size: 15px;
            /* color: #333; */
        }
    </style>
</head>
<body>
    <div class="container">
        <h1 class="linear-text-gradient">Thank You!</h1>
        <p font="Black">Your Feedback has been received</p>
        <div class="footer">
            <p>You will hear soon from us :)</p>
        </div>
    </div>
</body>
</html>
```

## failure.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Oops! Something Went Wrong</title>
    <style>
        .linear-text-gradient {
            background: linear-gradient(to top, #6A82FB, #FC5C7D);
            -webkit-background-clip: text;
            background-clip: text;
            color: transparent;
        }

        body {
            background: #FC5C7D;  /* fallback for old browsers */
            background: -webkit-linear-gradient(to right, #6A82FB, #FC5C7D);  /* Chrome 10-25,
Safari 5.1-6 */
            background: linear-gradient(to right, #6A82FB, #FC5C7D); /* W3C, IE 10+/ Edge,
Firefox 16+, Chrome 26+, Opera 12+, Safari 7+ */
            margin: 0;
            font-family: 'Arial', sans-serif;
            display: flex;
            align-items: center;
            justify-content: center;
            height: 100vh;
            color: #555353;
        }

        .container {
            text-align: center;
            background-color: rgba(255, 255, 255, 0.615); /* White background with
transparency */
            height: auto;
            width: 400px;
            padding: 20px;
            border-radius: 10px;
            margin: 15px 20px;
            box-shadow: 15px 10px 15px rgba(0, 0, 0, 0.5); /* Box shadow for a subtle effect
*/
        }

        h1 {
            font-size: 3rem;
            font-weight: bolder;
            color: #FF0000; /* Red color for failure message */
```

```
        }

        p {
            font-size: 15px;
        }

        .footer {
            margin-top: 20px;
            font-size: 15px;
        }
    </style>
</head>
<body>
    <div class="container">
        <h1 class="linear-text-gradient">Oops! Something Went Wrong</h1>
        <p>Seems that your order doesnot exists</p>
        <div class="footer">
            <p>Contact support if the issue persists</p>
            <i>cezchsolutions@gmail.com</i>
        </div>
    </div>
</body>
</html>
```

## duplicate.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Oops! Something Went Wrong</title>
    <style>
        .linear-text-gradient {
            background: linear-gradient(to top, #6A82FB, #FC5C7D);
            -webkit-background-clip: text;
            background-clip: text;
            color: transparent;
        }

        body {
            background: #FC5C7D;  /* fallback for old browsers */
            background: -webkit-linear-gradient(to right, #6A82FB, #FC5C7D);  /* Chrome 10-25, 
Safari 5.1-6 */
            background: linear-gradient(to right, #6A82FB, #FC5C7D); /* W3C, IE 10+/ Edge, 
Firefox 16+, Chrome 26+, Opera 12+, Safari 7+ */
            margin: 0;
            font-family: 'Arial', sans-serif;
            display: flex;
            align-items: center;
            justify-content: center;
            height: 100vh;
            color: #555353;
        }

        .container {
            text-align: center;
            background-color: rgba(255, 255, 255, 0.615); /* White background with 
transparency */
            height: auto;
            width: 400px;
            padding: 20px;
            border-radius: 10px;
            margin: 15px 20px;
```

```
            box-shadow: 15px 10px 15px rgba(0, 0, 0, 0.5); /* Box shadow for a subtle effect
*/
        }

        h1 {
            font-size: 3rem;
            font-weight: bolder;
            color: #FF0000; /* Red color for failure message */
        }

        p {
            font-size: 15px;
        }

        .footer {
            margin-top: 20px;
            font-size: 15px;
        }
    </style>
</head>
<body>
    <div class="container">
        <h1 class="linear-text-gradient">Sorry!</h1>
        <p>Seems like we have already received your feedback, we are onto it :)</p>
        <div class="footer">
            <p>Contact support if the issue persists</p>
            <i>cezchsolutions@gmail.com</i>
        </div>
    </div>
</body>
</html>
```

## App.py

```
from flask import Flask,render_template,request,redirect,url_for
# Importing the required libraries
import re
import numpy as np
import tensorflow as tf
from sklearn.preprocessing import OneHotEncoder
from keras.layers import *
from keras.models import load_model
from autocorrect import Speller
from tensorflow.keras.preprocessing.sequence import pad_sequences

# for sending mail
# we are importing the send_email() function from the emailTesting.py file which is in
Emailmodule folder
# Emailmodule folder --> emailTesting.py --> send_email() function is called
from Emailmodule.emailTesting import send_email

#----------- MySQL-----------------
from flask_mysqldb import MySQL
app=Flask(_name_,template_folder="Template")
app.config['MYSQL_HOST']="localhost"
app.config['MYSQL_USER']="root"
app.config['MYSQL_PASSWORD']=""
app.config['MYSQL_DB']="customer"
mysql=MySQL(app)
# ----------MySQL inports-----------

@app.route('/')
def home():
    return render_template("index.html")
```

```
# info dictionary to store customer information
info={"name":"","email":"","age":"","gender":"","location":"","orderId":"","product":"","feedb
ack":"","emotion":""}

@app.route('/response')
def response():
    return render_template("response.html")

@app.route("/failure")
def failure():
    return render_template("failure.html")

@app.route('/submit',methods=['GET','POST'])
def submit():
    if request.method=='POST':
        name=request.form['name']
        email=request.form['email']
        age=request.form['age']
        gender=request.form['gender']
        location=request.form['location']
        orderId=request.form['orderId']
        product_name=request.form['product']
        feedback=request.form['feedback']

        # Create a cursor to interact with the database
        cur = mysql.connection.cursor()

        # Check if the orderId exists in the orders_table
        cur.execute("SELECT * FROM orders_table WHERE order_id = %s", (orderId,))
        existing_orderid = cur.fetchone()

        if existing_orderid==None:
            print(f"Order ID {orderId} does not exist in the orders_table.")
            cur.close()
            return redirect(url_for('failure'))

        spell = Speller(lang="en") #autocorrect library
        correct_feedback=spell(feedback)

        emotion=EmoDet(name,email,age,gender,location,orderId,product_name,correct_feedback)
        try:
            cur.execute("INSERT INTO customer_info 
VALUES(%s,%s,%s,%s,%s,%s,%s,%s,%s)",(name,email,age,gender,location,orderId,product_name,corre
ct_feedback,emotion))
            mysql.connection.commit()
            cur.close()

            # sending mail to customer
            send_email(name, email, emotion)

            #thankyou page--load after submitting the form
            return redirect(url_for('response'))
        except Exception as e:
            print("duplicate order EXCEPTION")
            return render_template("duplicate.html")  #if the user again tries to give 
feedback, then render the duplicate feedback template

# Load the saved model
mo = load_model("(balanced)20epochs_Own_Amazon.h5")

glove ='glove.6B.50d.txt'

def load_glove_embeddings(path):
    embeddings_index = {}
    with open(path, 'r', encoding='utf8') as f:
```

```
        for line in f:
            values = line.split()
            word = values[0]
            coefs = np.asarray(values[1:], dtype='float32')
            embeddings_index[word] = coefs
    return embeddings_index

Glove = load_glove_embeddings(glove)

Sentiments = ['Angry', 'Sad', 'Happy', 'Disgusted']

# Perform one-hot encoding on df[0] i.e emotion
def encoding(sentences, Glove):
    Encoded_vec = []
    for sentence in sentences:
        sent_vec = []
        for token in sentence:
            token = token.numpy().decode('utf-8')
            if token in Glove:
                sent_vec.append(Glove[token])
            else:
                sent_vec.append(np.zeros(50))
        Encoded_vec.append(sent_vec)
    return Encoded_vec

enc = OneHotEncoder(handle_unknown='ignore')
Y = enc.fit_transform(np.array(Sentiments).reshape(-1, 1)).toarray()


def preprocess(Sentences):
    # Extract a substring of up to 300 characters
    sentences = tf.strings.substr(Sentences, 0, 300)

    # Replace HTML line breaks with spaces
    sentences = tf.strings.regex_replace(sentences, b"<br\\s*/?>", b" ")

    # Replace characters that are not letters or apostrophes with spaces
    sentences = tf.strings.regex_replace(sentences, b"[^a-zA-Z']", b" ")

    # Initialize the Speller class
    spell = Speller(lang="en")

    # Convert the TensorFlow tensor to a Python list of strings
    python_strings = [sentence.decode('utf-8') for sentence in sentences.numpy()]

    # Apply spelling correction on each string
    corrected_sentences = [spell(sentence) for sentence in python_strings]

    # Split the sentences into words
    sentences = tf.strings.split(corrected_sentences)

    # Convert to lowercase
    sentences = tf.strings.lower(sentences)

    # Convert the result to a tensor with padding
    sentences = sentences.to_tensor(default_value=b"<pad>")

    return sentences

def pad_or_truncate(sentences, max_length, glove_embedding):
    # Preprocess and encode sentences
    processed_sentences = preprocess(sentences)
    encoded_sentences = encoding(processed_sentences, glove_embedding)

    # Pad or truncate to the specified max_length
```

```
    padded_or_truncated = pad_sequences(encoded_sentences, maxlen=max_length, padding='post',
truncating='post', dtype='float32')

    return padded_or_truncated

# function to predict emotion
def get_emotion(i):
    # Input sentences
    twt = [i]

    # Specify max_length based on your model's requirements
    max_length = 72

    # Preprocess and pad/truncate
    Twt = pad_or_truncate(twt, max_length, Glove)

    # Predict the sentiment by passing the sentence to the model
    sentiment = mo.predict(Twt)[0]
    label = np.argmax(sentiment)
    emotion = enc.categories_[0][label]
    return emotion

# function to detect emotion and printing..
def EmoDet(name,email,age,gender,location,orderid,product,feedback):
    emotion=get_emotion(feedback)
    print(emotion)
    info["name"]=name
    info["email"]=email
    info["age"]=age
    info["gender"]=gender
    info["location"]=location
    info["orderId"]=orderid
    info["product"]=product
    info["feedback"]=feedback
    info["emotion"]=emotion
    print(info)
    return emotion

if _name=="main_":
    app.run(debug=True, port=5000)
```

## EmailModule

## emailTesting.py

```
from jinja2 import Template
import os
import random
# We will need smtplib to connect to our smtp email server
import smtplib
from email.mime.text import MIMEText
from email.mime.multipart import MIMEMultipart

# contains emails of the customer executives along with their working logs
executive_details=["teja.czechsolutions@gmail.com","anand.czechsolutions@gmail.com","walter.cz
echsolutions@gmail.com"]

def send_email(name, receiver_email, emotion):

    # Get the absolute path to the directory of this script
    script_directory = os.path.dirname(os.path.realpath(_file_))

    if emotion=="Happy":
        # Construct the path to the Happy email template within the Emailmodule folder
```

```
        template_path = os.path.join(script_directory, "email_templates", "joy_template.html")
        subject="Acknowledging Your Satisfaction and Elevating Your Positive Experience"

    elif emotion=='Sad' or emotion=='Angry' or emotion=='Disgusted':
        cust_care_email=random.choice(executive_details)
        # Construct the path to the unhappy email template within the Emailmodule folder
        template_path = os.path.join(script_directory, "email_templates",
"unhappy_template.html")
        template_path_care = os.path.join(script_directory, "email_templates",
"customercare_template.html")
        subject="Your Feedback Respected-Aiming for Swift Resolution" # subject for CUSTOMER
        subject_care=f"Emergency!! {name} need assistance" # subject for CUSTOMER CARE

        # Read the Jinja2 email template for CUSTOMER CARE
        with open(template_path_care, "r") as file:
            template_str_care = file.read()
        jinja_template_care = Template(template_str_care)

    # Read the Jinja2 email template for CUSTOMER
    with open(template_path, "r") as file:
        template_str = file.read()
    jinja_template = Template(template_str)

    # Define email server and credentials
    smtp_server = "smtp.gmail.com" #change smtp.server.com to smtp.gmail.com

    smtp_port = 587
    sender_email = "cezchsolutions@gmail.com"

    # generate the password by going to 2-step verification and create a new password for
different apps as google has removed the access for third party websites like SMTP server
    sender_password = "fiot nkgv ummv fgco"

    # Set up email server
    server = smtplib.SMTP(smtp_server, smtp_port)
    server.starttls()
    server.login(sender_email, sender_password)

    # Create email content using Jinja2 template
    if emotion=='Sad' or emotion=='Angry' or emotion=='Disgusted':
        # ----------------------------------------SENDING MAIL TO CUSTOMER--------------------
        email_data = {
            "greeting": f"Hello {name}!",
            "sender_name": "Czech Unified Solutions"
        }

        email_content = jinja_template.render(email_data) # render CUSTOMER UNHAPPY TEMPLATE

        # Create the email message
        msg = MIMEMultipart()
        msg["From"] = sender_email
        msg["To"] = receiver_email  #customer mail
        msg["Subject"] = subject

        # Attach the HTML content to the email
        msg.attach(MIMEText(email_content, "html"))

        # Print and send the email to customer
        print(f"Sent email to CUSTOMER {receiver_email}")
        server.sendmail(sender_email, receiver_email, msg.as_string())

        # Close the server connection for customer
        # server.quit()

        # ---------------------------------SENDING MAIL TO CUSTOMER CARE----------------------
```

```
        email_data = {
            "greeting": f"Hello Assistance Ace!",
            "sender_name": "Czech Unified Solutions",
            "customer_name": name,
            "customer_email": receiver_email #this is the CUSTOMER MAIL that the customer
executive needs to contact
        }
        email_content = jinja_template_care.render(email_data) # render CUSTOMER CARE TEMPLATE

        # Create the email message
        msg = MIMEMultipart()
        msg["From"] = sender_email
        msg["To"] = cust_care_email  #customer care mail
        msg["Subject"] = subject_care

        # Attach the HTML content to the email
        msg.attach(MIMEText(email_content, "html"))

        # Print and send the email to customer care
        print(f"Sent email to CUSTOMER EXECUTIVE {cust_care_email}")
        server.sendmail(sender_email, cust_care_email, msg.as_string())

        # Close the server connection
        server.quit()

    else:
        # SENDING MAIL TO CUSTOMER ONLY
        email_data = {
            "greeting": f"Hello {name}!",
            "sender_name": "Czech Unified Solutions"
        }

        email_content = jinja_template.render(email_data)
        # Create the email message
        msg = MIMEMultipart()
        msg["From"] = sender_email
        msg["To"] = receiver_email
        msg["Subject"] = subject

        # Attach the HTML content to the email
        msg.attach(MIMEText(email_content, "html"))

        # Print and send the email
        print(f"Sent email to {receiver_email}")
        server.sendmail(sender_email, receiver_email, msg.as_string())

        # Close the server connection
        server.quit()

if _name=="main_":
    # sample
    name='Atul Kumar Nayak'
    receiver_email="atulnayak7869@gmail.com"
    emotion="Sad"
    send_email(name,receiver_email,emotion)
```

## EmailModule \ email_templates

## customercare_template.html

```
<!DOCTYPE html>
<html lang="en">
  <head>
    <meta charset="UTF-8" />
```

```
    <meta name="viewport" content="width=device-width, initial-scale=1.0" />
    <title>Document</title>
    <style>
      .container {
        color: black;
        padding-bottom: 10px;
        padding-left: 5px;
      }

    </style>
  </head>
  <body>
    <div class="container">
      <header>
        <h1>Attention : Customer need assistance!!</h1>
      </header>

      <main>
        <p>{{ greeting }}</p>
        <p>It has come to my notice that one of our valued customers, {{customer_name}}, has
expressed dissatisfaction with their recent experience with our products.
          <br />
          I kindly request your immediate attention to this matter. Please reach out to
{{customer_name}} at {{customer_email}} and listen to their concerns. If there are specific
issues or challenges they have encountered, please make every effort to address and resolve
them promptly.
          <br />
          Thank you for your prompt attention to this matter. I am confident that, with your
assistance, we can turn this situation around and ensure that {{customer_name}} remains a
satisfied and loyal customer.
        </p>
        <p>Best regards, <br />{{ sender_name }}</p>
      </main>

      <footer>
        <i>This email was sent from Czech Unified Solutions...</i>.
      </footer>
    </div>
  </body>
</html>
```

## joy_template.html

```
<!DOCTYPE html>
<html lang="en">
  <head>
    <meta charset="UTF-8" />
    <meta name="viewport" content="width=device-width, initial-scale=1.0" />
    <title>Document</title>
    <style>
      .container {
        background: rgb(238,174,202);
        background: radial-gradient(circle, rgba(238,174,202,1) 0%, rgba(148,187,233,1) 100%);
        color: black;
        padding-bottom: 10px;
        padding-left: 5px;
      }

    </style>
  </head>
  <body>
    <div class="container">
      <header>
        <h1>Acknowledging Your Satisfaction and Elevating Your Positive Experience</h1>
      </header>
```

```
      <main>
        <p>{{ greeting }}</p>
        <p>We trust this email finds you well and enjoying the benefits of our product. Your
satisfaction is our utmost priority, and we are delighted to hear that you are pleased with
your experience.
          <br />
          Your positive feedback energizes our team, and we sincerely appreciate you taking
the time to share your satisfaction. It's customers like you that motivate us to continue
delivering exceptional products and services.
          <br />
          Once again, thank you for choosing {{ sender_name }}. We look forward to serving you
in the future and exceeding your expectations.</p>
        <p>Best regards, <br />{{ sender_name }}</p>
      </main>

      <footer>
        <i>This email was sent from Czech Unified Solutions...</i>.
      </footer>
    </div>
  </body>
</html>
```

**unhappy_template.html**

```
<!DOCTYPE html>
<html lang="en">
  <head>
    <meta charset="UTF-8" />
    <meta name="viewport" content="width=device-width, initial-scale=1.0" />
    <title>Document</title>
    <style>
      .container {
        background: rgb(238,174,202);
        background: radial-gradient(circle, rgba(238,174,202,1) 0%, rgba(148,187,233,1) 100%);
        color: black;
        padding-bottom: 10px;
        padding-left: 5px;
      }

    </style>
  </head>
  <body>
    <div class="container">
      <header>
        <h1>Your Feedback Respected-Aiming for Swift Resolution</h1>
      </header>

      <main>
        <p>{{ greeting }}</p>
        <p>I hope this message finds you well. We've recently learned that you may not be
completely satisfied with our product, and we genuinely apologize for any inconvenience this
may have caused.
            <br />
            Your satisfaction is our top priority, and we're eager to address your concerns.
Our dedicated customer care team will reach out to you shortly to discuss the issue and work
towards a resolution.
            <br />
            Thank you for bringing this to our attention, and we appreciate your patience as
we strive to make things right.</p>
        <p>Best regards, <br />{{ sender_name }}</p>
      </main>

      <footer>
```

```
        <i>This email was sent from Czech Unified Solutions...</i>
      </footer>
    </div>
  </body>
</html>
```

## EmailDashboard

## inbox_template.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta http-equiv="X-UA-Compatible" content="IE=edge">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Email Dashboard</title>
    <style>
        body {
            font-family: Arial, sans-serif;
            background-color: #176B87;
            margin: 20px;
            box-sizing: border-box;
        }
        .container{
            display: flex;
            flex-direction: row;
            flex-wrap: wrap;
            gap: 50px;
        }
        .account-container {
            background: rgba(29, 29, 29, 0.271);
            backdrop-filter: blur(10px);
            width: 400px;
            height: 200px;
            border-radius: 8px;
            padding: 15px;
            margin-bottom: 20px;
            overflow-y: scroll;
            transition: box-shadow 0.3s ease-in-out;
        }
        .account-container:hover {
            box-shadow: 0 0 25px #28282B;
        }
        .email-card {
            background: rgb(238,174,202);
            background: radial-gradient(circle, rgba(238,174,202,1) 0%, rgba(148,187,233,1)
100%);
            border-radius: 8px;
            padding: 15px;
            margin-bottom: 15px;
            transition: box-shadow 0.3s ease-in-out;
        }
        .email-card:hover {
            box-shadow: 0 0 7px #8dc6ff;
        }
        h1{
            text-align: center;
            color: #DCF2F1;
        }
        h2 {
            color: #8dc6ff;
        }
    </style>
```

```
</head>
<body>
    <h1>Czech Unified Solutions : Manager's Portal</h1>
    <div class="container">
        <div class="account-container">
            <h2>Teja Kishore</h2>
            {% for email in emails1|reverse if email.unread %}
                <div class="email-card">
                    <strong>Subject:</strong> {{ email.subject }}<br>
                    <strong>Date:</strong> {{ email.date }}
                </div>
            {% endfor %}
        </div>

        <div class="account-container">
            <h2>Anand Mehera</h2>
            {% for email in emails2|reverse if email.unread %}
                <div class="email-card">
                    <strong>Subject:</strong> {{ email.subject }}<br>
                    <strong>Date:</strong> {{ email.date }}
                </div>
            {% endfor %}
        </div>

        <div class="account-container">
            <h2>Walter Ken</h2>
            {% for email in emails3|reverse if email.unread %}
                <div class="email-card">
                    <strong>Subject:</strong> {{ email.subject }}<br>
                    <strong>Date:</strong> {{ email.date }}
                </div>
            {% endfor %}
        </div>

        <!-- <div class="account-container">
            <h2>Anil Kumar</h2>
            {% for email in emails3|reverse if email.unread %}
                <div class="email-card">
                    <strong>Subject:</strong> {{ email.subject }}<br>
                    <strong>Date:</strong> {{ email.date }}
                </div>
            {% endfor %}
        </div> -->
    </div>
</body>
</html>
```

## email_dashboard.py

```
from flask import Flask, render_template
import imaplib
from email.parser import BytesParser
from email.policy import default

app = Flask(_name_)

# Function to fetch emails from an inbox
def fetch_emails(username, password, server, port, unread_only=True):
    emails = []
    connection = None

    try:
        connection = imaplib.IMAP4_SSL(server, port)
        connection.login(username, password)
        connection.select("inbox")
```

```
        criteria = "UNSEEN" if unread_only else "ALL"
        result, data = connection.search(None, criteria)

        if result == "OK":
            for num in data[0].split():
                result, message_data = connection.fetch(num, "(BODY.PEEK[HEADER.FIELDS (FROM
SUBJECT DATE FLAGS)])")
                if result == "OK":
                    msg = BytesParser(policy=default).parsebytes(message_data[0][1])
                    flags = msg.get("flags", [])
                    unread = b"\\Seen" not in flags
                    emails.append({
                        "subject": msg.get("subject", ""),
                        "date": msg.get("date", ""),
                        "unread": unread,
                    })

    except Exception as e:
        print(f"An error occurred: {e}")

    finally:
        if connection:
            connection.logout()

    return emails


# Route for the dashboard
@app.route('/')
def dashboard():
    # Example usage for 4 email accounts
    email_account1 = {
        "username": "teja.czechsolutions@gmail.com",
        "password": "twlc alix xtnl knso opew",
        "server": "imap.gmail.com",
        "port": 993,
    }

    email_account2 = {
        "username": "anand.czechsolutions@gmail.com",
        "password": "pzqk ckgj fpnc jzrh opwe",
        "server": "imap.gmail.com",
        "port": 993,
    }

    email_account3 = {
        "username": "walter.czechsolutions@gmail.com",
        "password": "zzqd eclz taru yile opew",
        "server": "imap.gmail.com",
        "port": 993,
    }


    # Fetch emails for the first account
    emails1 = fetch_emails(**email_account1)

    # Fetch emails for the second account
    emails2 = fetch_emails(**email_account2)

    # Fetch emails for the third account
    emails3 = fetch_emails(**email_account3)

    return render_template('inbox_template.html', emails1=emails1, emails2=emails2,
emails3=emails3)
```

```
if _name_ == '_main_':
    app.run(debug=True, port=3000)
```

## Dashboard

## dashboard.py

```
import streamlit as st
import pandas as pd
import plotly.express as px
import mysql.connector
from streamlit_option_menu import option_menu

# Function to connect to MySQL and fetch data
def fetch_data():
    # Replace these with your MySQL database credentials
    db_config = {
        'host': 'localhost',
        'user': 'root',
        'password': '',
        'database': 'customer'
    }

    # Connect to MySQL
    conn = mysql.connector.connect(**db_config)

    # Fetch data from MySQL into a DataFrame
    query = "SELECT * FROM customer_info;"
    data = pd.read_sql(query, conn)

    # Close the connection
    conn.close()

    return data

# Load data from MySQL
data = fetch_data()

# Streamlit app favicon and title
st.set_page_config(page_title="Emotional analysis",
                   page_icon=":bar_chart:",
                   layout="wide")

selected = option_menu(None, ["Home", "Location", "Age Group", "Gender"],
                        icons=['house', 'bi-geo-alt-fill', "bi-diagram-2-fill", 'bi-gender-
ambiguous'], key='menu_5', orientation="horizontal")

if selected=='Home':
    # st.write("home")

    # Streamlit App
    st.title('Emotion Analysis Dashboard')

    # Sidebar for selecting emotion
    st.sidebar.title('Filter Options')
    selected_emotion = st.sidebar.selectbox('Select Emotion', ["Select emotion"] +
list(data['emotion'].unique()))

    if st.sidebar.button('Visualize'):
        # Filter data based on selected emotion
        if selected_emotion=="Select emotion":
            st.warning('Please select a valid emotion and click the button to start
visualizing.')
```

```
        else:
            filtered_data = data[data['emotion'] == selected_emotion]

            # Display filtered data
            st.subheader(f'Emotions Distribution for {selected_emotion} across Products')
            st.write(filtered_data)

            # Create a Plotly chart (bar chart for emotions distribution across products)
            # st.subheader(f'Emotions Distribution Across Products for {selected_emotion}')
            products_chart = px.bar(filtered_data, x='product_name', title=f'Emotions
Distribution Across Products for {selected_emotion}')
            st.plotly_chart(products_chart)
    else:
        st.info('Click the button to start visualizing.')

elif selected=='Location':
    # st.write("Loc")

    # App
    st.title('Emotion Analysis Dashboard')

    # Sidebar for selecting emotion and product
    st.sidebar.title('Filter Options')
    selected_emotion = st.sidebar.selectbox('Select Emotion', ["Select emotion"] +
list(data['emotion'].unique()))
    selected_product = st.sidebar.selectbox('Select Product', ["Select product"] +
list(data['product_name'].unique()))

    if st.sidebar.button('Visualize'):
        if selected_emotion=="Select emotion" or selected_product=="Select product":
            st.warning('Please select a valid emotion and product then click the button to
start visualizing.')
        else:
            # Filter data based on selected emotion and product
            filtered_data = data[(data['emotion'] == selected_emotion) & (data['product_name']
== selected_product)]

            # Display filtered data
            st.subheader(f'Emotions for {selected_product} with {selected_emotion} emotion')
            st.write(filtered_data)

            # Create a Plotly chart (bar chart for emotions distribution across locations)
            # st.subheader(f'Emotions Distribution Across Locations for {selected_product}')
            emotions_chart = px.bar(filtered_data, x='location', color='emotion',
title=f'Emotions Distribution Across Locations for {selected_product}')
            st.plotly_chart(emotions_chart)
    else:
        st.info("Click the button to start visualizing.")

elif selected=="Age Group":
    # st.write("age")

    # App
    st.title('Emotion Analysis Dashboard')

    # Sidebar for selecting emotion and product
    st.sidebar.title('Filter Options')
    selected_emotion = st.sidebar.selectbox('Select Emotion', ["Select emotion"] +
list(data['emotion'].unique()))
    selected_product = st.sidebar.selectbox('Select Product', ["Select product"] +
list(data['product_name'].unique()))

    if st.sidebar.button('Visualize'):
        if selected_emotion=="Select emotion" or selected_product=="Select product":
```

```
            st.warning('Please select a valid emotion and product then click the button to
start visualizing.')
        else:
            # Filter data based on selected emotion and product
            filtered_data = data[(data['emotion'] == selected_emotion) & (data['product_name']
== selected_product)]

            # Display filtered data
            st.subheader(f'Emotions for {selected_product} with {selected_emotion} emotion')
            st.write(filtered_data)

            # Create a Plotly chart (bar chart for emotions distribution across locations)
            # st.subheader(f'Emotions Distribution Across age-group for {selected_product}')
            emotions_chart = px.bar(filtered_data, x='age', color='emotion', title=f'Emotions
Distribution Across Age Groups for {selected_product}')
            st.plotly_chart(emotions_chart)
    else:
        st.info("Click the button to start visualizing.")

elif selected=="Gender":
    # st.write("gender")

    # App
    st.title('Emotion Analysis Dashboard')

    # Sidebar for selecting emotion and product
    st.sidebar.title('Filter Options')
    selected_emotion = st.sidebar.selectbox('Select Emotion', ["Select emotion"] +
list(data['emotion'].unique()))
    selected_product = st.sidebar.selectbox('Select Product', ["Select product"] +
list(data['product_name'].unique()))

    if st.sidebar.button('Visualize'):
        if selected_emotion=="Select emotion" or selected_product=="Select product":
            st.warning('Please select a valid emotion and product then click the button to
start visualizing.')
        else:
            # Filter data based on selected emotion and product
            filtered_data = data[(data['emotion'] == selected_emotion) & (data['product_name']
== selected_product)]

            # Display filtered data
            st.subheader(f'Emotions for {selected_product} with {selected_emotion} emotion')
            st.write(filtered_data)

            # Create a Plotly chart (bar chart for emotions distribution across locations)
            # st.subheader(f'Emotions Distribution Across Genders for {selected_product}')
            emotions_chart = px.bar(filtered_data, x='gender', color='emotion',
title=f'Emotions Distribution Across genders for {selected_product}')
            st.plotly_chart(emotions_chart)
    else:
        st.info("Click the button to start visualizing.")
```

## emotion_recognition_training.ipynb

```
import re
import nltk
import numpy as np
import pandas as pd
from keras.layers import *
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
from keras.utils import to_categorical
from nltk.tokenize import word_tokenize
from keras.models import Sequential,Model
```

```
from keras.callbacks import ModelCheckpoint
from keras.layers import Dense,Bidirectional
from keras.preprocessing.text import Tokenizer
from keras.models import Sequential, load_model
from sklearn.preprocessing import OneHotEncoder
from nltk.stem.lancaster import LancasterStemmer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras.layers import Dense, GRU, LSTM, Bidirectional, Embedding, Dropout

df=pd.read_excel('/content/Own_Amazon_AddedRows(Final).xlsx')
df.head()
anger_count = len(df[df['emotion'] == 'Angry'])
disgusted_count = len(df[df['emotion'] == 'Disgusted'])
happy_count = len(df[df['emotion'] == 'Happy'])
sadness_count = len(df[df['emotion'] == 'Sad'])

print("Number of rows with sentiment 'Angry':", anger_count)

print("Number of rows with sentiment 'Disgusted':", disgusted_count)

print("Number of rows with sentiment 'Happy':", happy_count)

print("Number of rows with sentiment 'Sad':", sadness_count)

Sentences = df['review'].astype(str)
Sentiments = df['emotion'].astype(str)

glove ='glove.6B.50d.txt'

def load_glove_embeddings(path):
    embeddings_index = {}
    with open(path, 'r', encoding='utf8') as f:
        for line in f:
            values = line.split()
            word = values[0]
            coefs = np.asarray(values[1:], dtype='float32')
            embeddings_index[word] = coefs
    return embeddings_index

Glove = load_glove_embeddings(glove)

def cosine_similarity(a, b):
    """
    Computes the cosine similarity between two vectors a and b.
    """
    return np.dot(a, b) / (np.linalg.norm(a) * np.linalg.norm(b))

import tensorflow as tf

def preprocess(Sentences):
    sentences = tf.strings.substr(Sentences, 0, 300)
    sentences = tf.strings.regex_replace(sentences, b"<br\\s*/?>", b" ")
    sentences = tf.strings.regex_replace(sentences, b"[^a-zA-Z']", b" ")
    sentences = tf.strings.split(sentences)
    sentences = tf.strings.lower(sentences)
    sentences = sentences.to_tensor(default_value=b"<pad>")
    return sentences


sentences = preprocess(Sentences)
sentences.shape


def encoding(sentences, Glove):
    Encoded_vec = []
```

```
    for sentence in sentences:
        sent_vec = []
        for token in sentence:
            token = token.numpy().decode('utf-8')
            if token in Glove:
                sent_vec.append(Glove[token])
            else:
                sent_vec.append(np.zeros(50))
        Encoded_vec.append(sent_vec)
    return Encoded_vec


Encoded_vec = encoding(sentences, Glove)
X = np.array(Encoded_vec)
print(X.shape)

enc = OneHotEncoder(handle_unknown='ignore')
Y = enc.fit_transform(np.array(Sentiments).reshape(-1,1)).toarray()
print(Y.shape)

from keras.layers import Embedding
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=23)

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Bidirectional, LSTM, Dropout, Dense

# Defining the BiLSTM Model
class BiLSTMModel:
    def _init_(self):
        self.model = Sequential()
        self.model.add(Bidirectional(LSTM(150, input_shape=(100, 50))))  # Increase units in
LSTM
        self.model.add(Dropout(0.5))  # Increase dropout
        self.model.add(Dense(4, activation='softmax'))
        self.model.compile(optimizer='Adam', loss='categorical_crossentropy',
metrics=['accuracy'])

    def fit(self, X_train, Y_train, X_val, Y_val, epochs, batch_size):
        history = self.model.fit(X_train, Y_train, epochs=epochs, batch_size=batch_size,
validation_data=(X_val, Y_val))
        return history  # Return the training history for later visualization

    def evaluate(self, X, Y, batch_size):
        return self.model.evaluate(X, Y, batch_size=batch_size)

    def predict(self, X):
        return self.model.predict(X)

# create an instance of the BiLSTMModel class
model = BiLSTMModel()

hist = model.fit(X_train, Y_train, X_test, Y_test,
                 epochs=20,
                 batch_size=64)
# Saved model for Decreased emotions count.
model.model.save('(balanced)20epochs_Own_Amazon.h5')

Loss, acc = model.evaluate(X_test, Y_test, batch_size=64)
print("Loss: %.2f" % (Loss))
print("Accuracy: %.2f" % (acc))

model.model.summary()

import matplotlib.pyplot as plt
```

```
history=hist

# Assuming history contains the training history
# Plot training and validation loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Plot training and validation accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Now you can also generate a confusion matrix using the test data
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Get predictions on the test data
Y_pred = model.predict(X_test)

# Convert predictions and true labels back from one-hot encoding
Y_pred_labels = np.argmax(Y_pred, axis=1)
Y_true_labels = np.argmax(Y_test, axis=1)

# Create confusion matrix
conf_matrix = confusion_matrix(Y_true_labels, Y_pred_labels)

# Visualize the confusion matrix using seaborn
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=enc.categories_[0],
yticklabels=enc.categories_[0])
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()


from tensorflow.keras.utils import plot_model
plot_model(model.model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)

while True:
  i=input("Enter : ")
  twt = [i]
  #Next, tokenize it.
  Twt = preprocess(twt)

  # Encoding
  Twt = encoding(Twt, Glove)
  Twt = np.array(Twt)
  print(Twt.shape)
  #Predict the sentiment by passing the sentence to the model we built.
  sentiment = model.predict(Twt)[0]
  label = np.argmax(sentiment)
  print(enc.categories_[0][label])
```

# CHAPTER 6

# RESULTS

This section provides a concise overview of the outcomes and findings obtained from the implementation and evaluation of the system. It presents key insights, and observations derived from the analysis of data, user feedback, and system behavior.

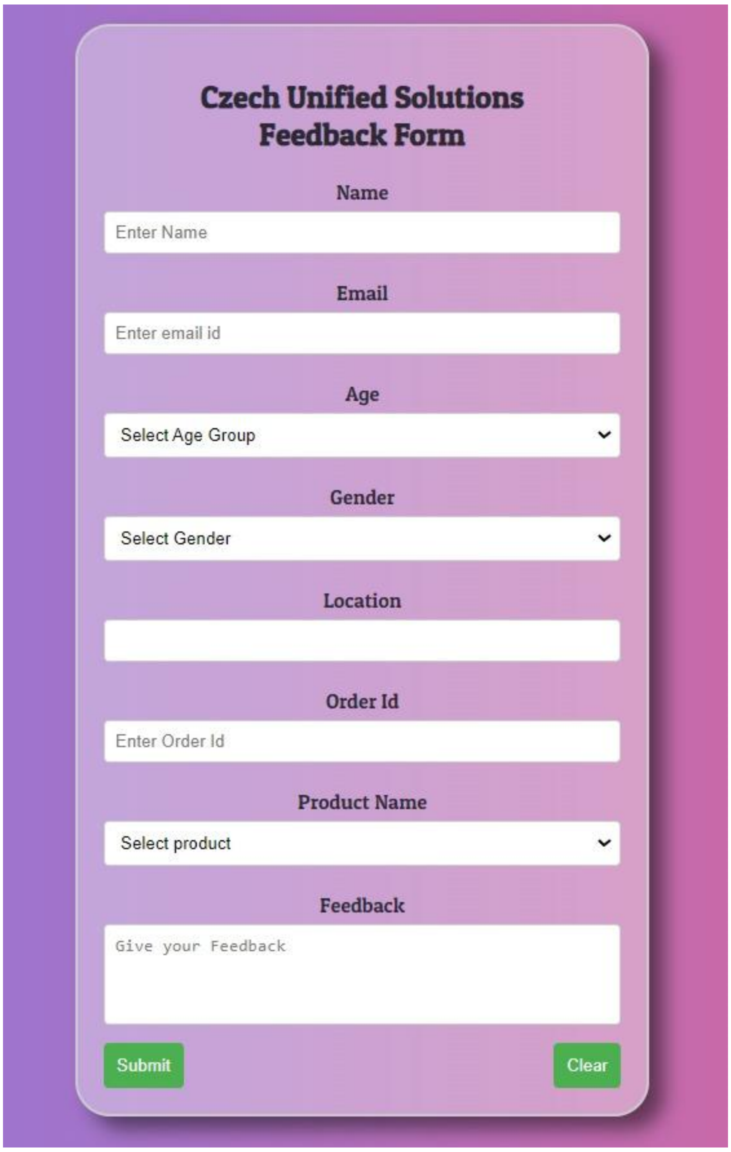



Figure 9: Feedback Form

Figure 9 represents the feedback form where customers are required to provide their personal details along with feedback regarding the product they have purchased.

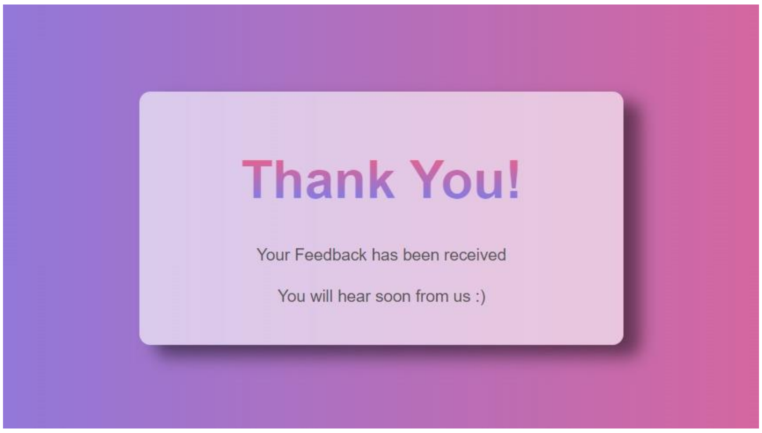



Figure 10: Thankyou Response Page

Figure 10 displays the thank you page that is shown to the user after successfully submitting their feedback and details.

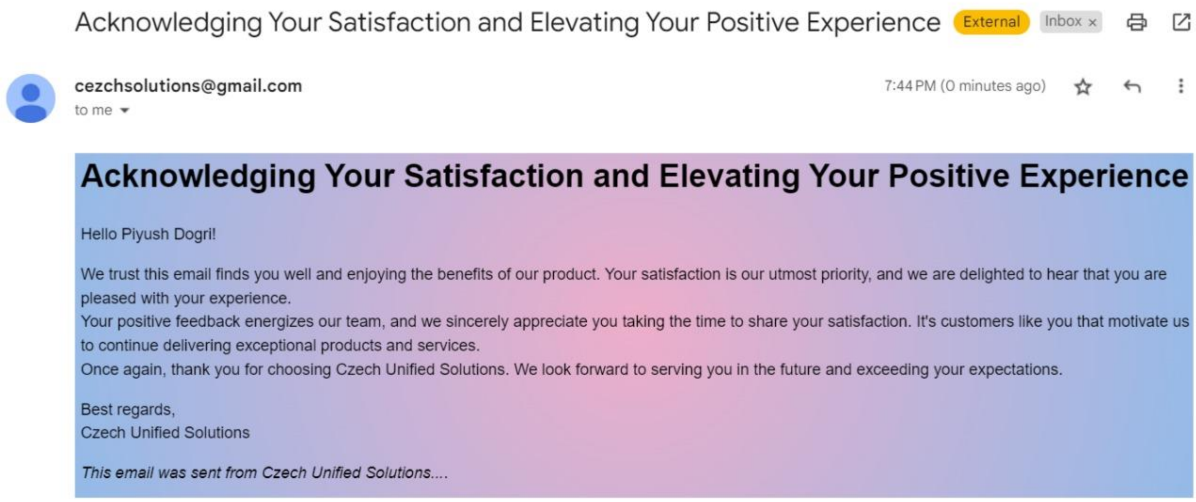
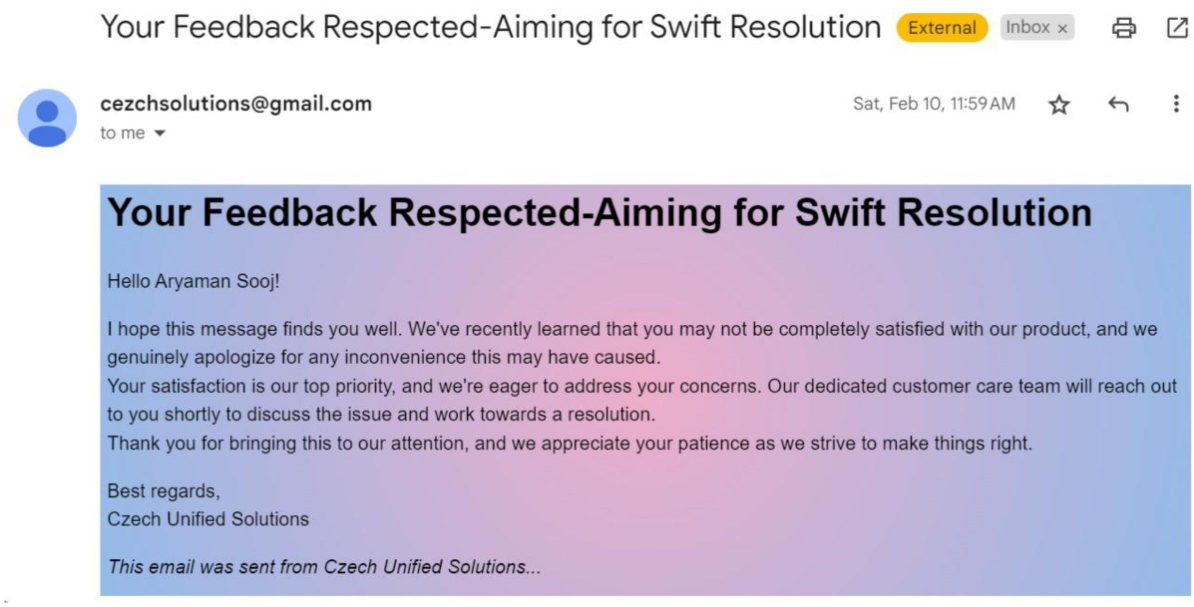



Figure 11: Email to Customer for Positive Feedback

The figure 11 shows the email sent to the customer when the detected emotion in the feedback given by the customer is happy.

Figure 12 illustrates the email sent to the customer when the detected emotion in their feedback is sad, disgusted, or angry.



Your Feedback Respected-Aiming for Swift Resolution External Inbox ×

cezchsolutions@gmail.com
to me

Sat, Feb 10, 11:59 AM

**Your Feedback Respected-Aiming for Swift Resolution**

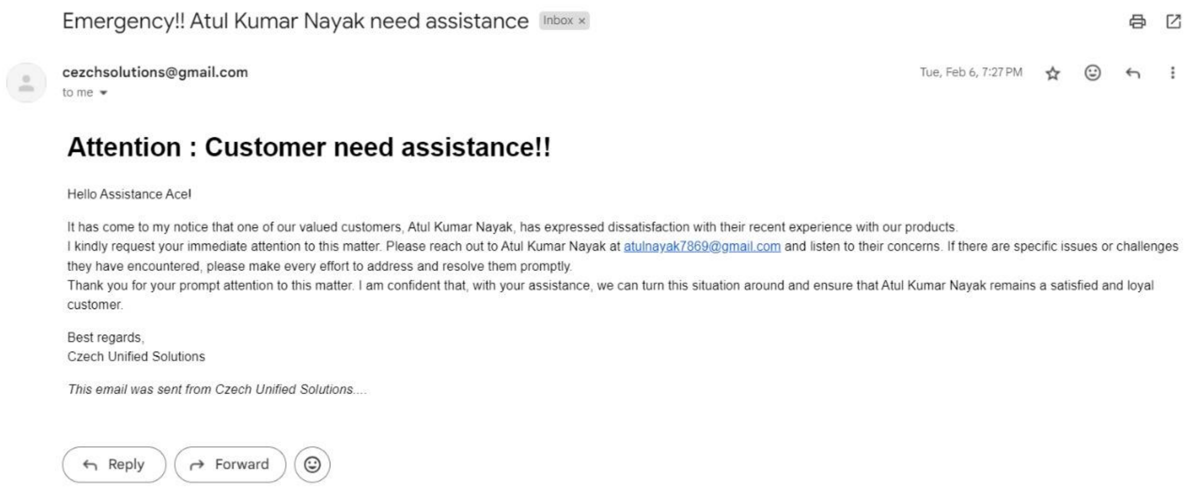
Hello Aryaman Sooj!

I hope this message finds you well. We've recently learned that you may not be completely satisfied with our product, and we genuinely apologize for any inconvenience this may have caused.
Your satisfaction is our top priority, and we're eager to address your concerns. Our dedicated customer care team will reach out to you shortly to discuss the issue and work towards a resolution.
Thank you for bringing this to our attention, and we appreciate your patience as we strive to make things right.

Best regards,
Czech Unified Solutions

*This email was sent from Czech Unified Solutions...*

Figure 12: Email to Customer for Negative Feedback



Emergency!! Atul Kumar Nayak need assistance Inbox ×

cezchsolutions@gmail.com
to me

Tue, Feb 6, 7:27 PM

**Attention : Customer need assistance!!**

Hello Assistance Ace!

It has come to my notice that one of our valued customers, Atul Kumar Nayak, has expressed dissatisfaction with their recent experience with our products.
I kindly request your immediate attention to this matter. Please reach out to Atul Kumar Nayak at atulnayak7869@gmail.com and listen to their concerns. If there are specific issues or challenges they have encountered, please make every effort to address and resolve them promptly.
Thank you for your prompt attention to this matter. I am confident that, with your assistance, we can turn this situation around and ensure that Atul Kumar Nayak remains a satisfied and loyal customer.

Best regards,
Czech Unified Solutions

*This email was sent from Czech Unified Solutions....*

Reply Forward

Figure 13: Email to Customer Executive

Figure 13 shows the email sent to a customer care executive if the detected emotion in the feedback is sad, disgusted, or angry. This ensures that customer care executives receive prompt notifications about unhappy customers or customers experiencing difficulties.

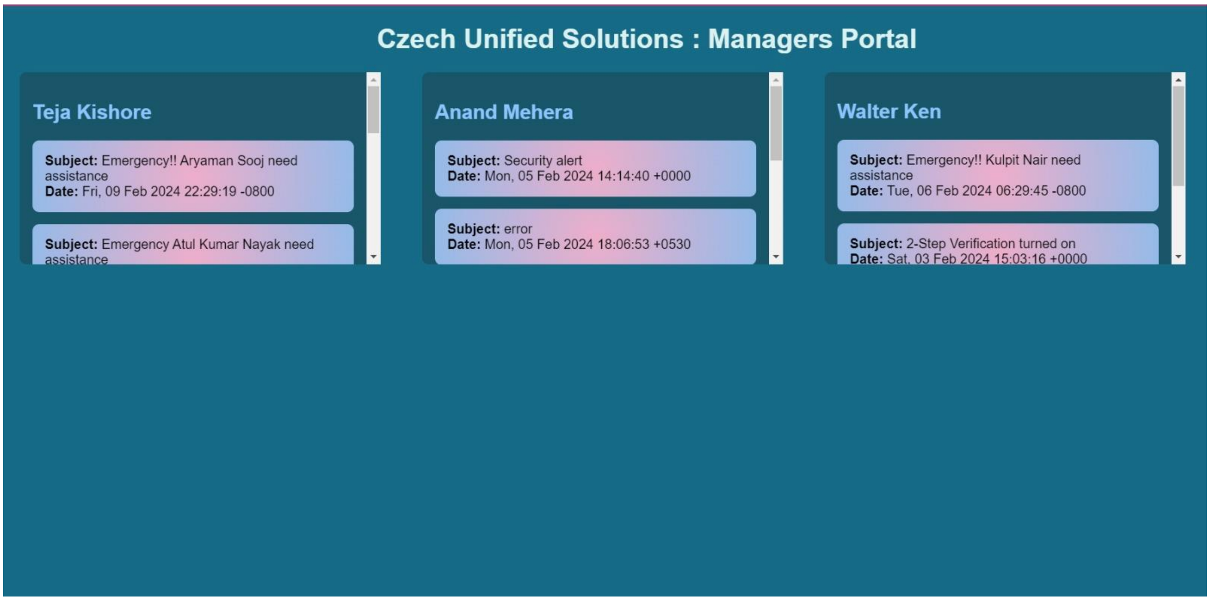



Figure 14: Managers Portal

The figure 14 displays the manager's portal, which includes details of unread emails from the customer care executives. This enables the manager to monitor their customer care executives for prompt resolution of customer problems.

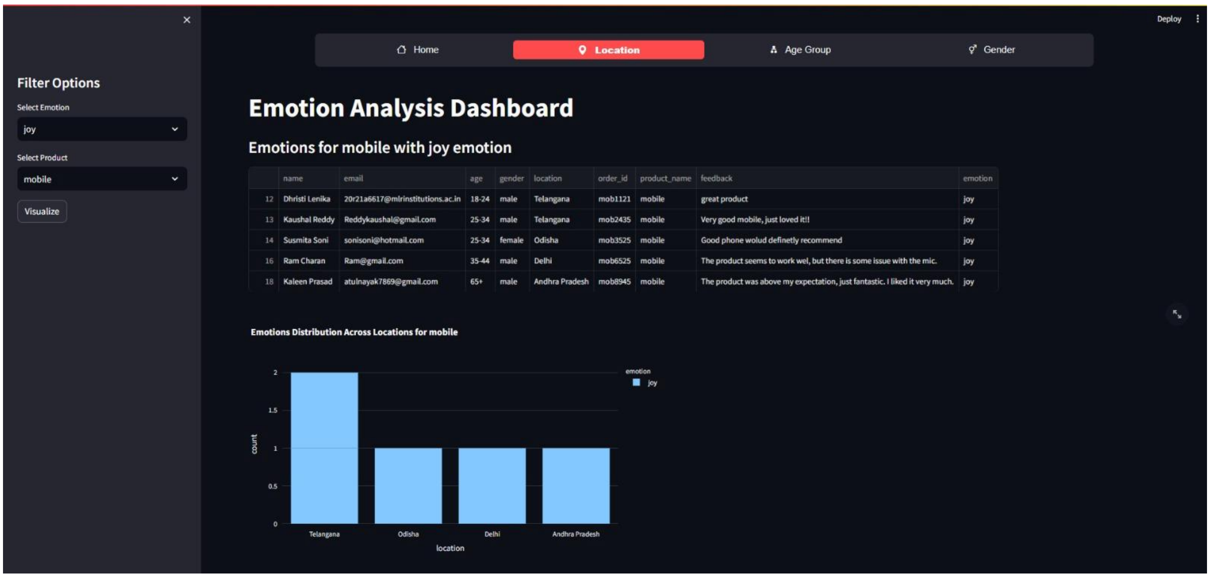



Figure 15: Owners Dashboard

The figure 15 illustrates the owner's dashboard, providing a visual representation of data for a faster and better understanding of customer emotions regarding their products.


Figure 16: Model Loss and Accuracy

The figure 16 represents the training and validation loss and accuracy with respect to the number of epochs.

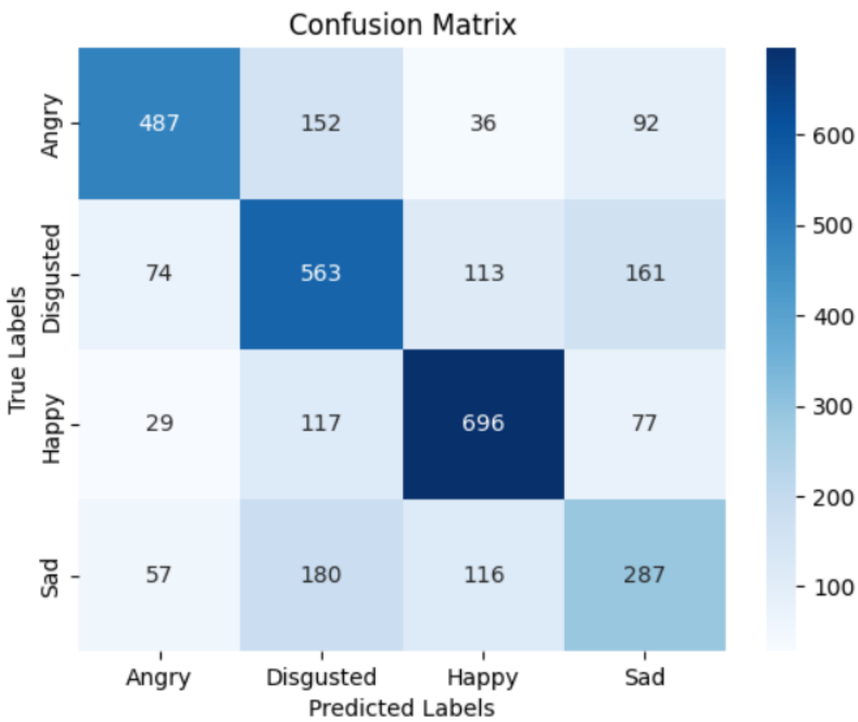



Figure 17: Confusion Matrix

The figure 17 represents the confusion matrix of the model. This is used to know the number of right and wrong classifications done by the model.

# CHAPTER 7

# CONCLUSION

The proposed system offers an innovative and comprehensive solution for businesses to analyze customer feedback effectively. By leveraging the power of deep learning and natural language processing techniques, the system accurately recognizes emotion expressed in customers' reviews, enabling personalized and targeted responses. The automated response generation and customer support allocation modules streamline the feedback handling process, improving customer satisfaction and loyalty. Furthermore, the data visualization dashboard empowers stakeholders with valuable insights into customer emotion trends, facilitating data-driven decision-making and product enhancements. Overall, this system bridges the gap between businesses and customers, fostering a better understanding of customer emotions and paving the way for improved customer service and product innovation.

## FUTURE ENHANCEMENTS AND DISCUSSIONS

While the proposed system provides a robust foundation for emotion recognition and customer feedback analysis, there is potential for further enhancements and extensions:

a. **Incorporation of multimodal data:** The system can be expanded to analyze multimodal data, such as images, videos, or audio, in addition to text, providing a more comprehensive understanding of customer emotions.
b. **Integration with social media platforms:** The system can be integrated with popular social media platforms to collect and analyze customer feedback from a wider range of sources rather than making them enter in a particular website or form enabling businesses to monitor and respond to customer sentiments across multiple channels.
c. **Multilingual support:** Extending the system to support multiple languages would enable businesses to cater to a global customer base and analyze feedback from diverse linguistic backgrounds.