Real Time Emotion Recognition from text using Deep learning and Feedback Analysis

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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 has potential uses in various applications. This research paper 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 research 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.

CCS CONCEPTS

Computing methodologies →Deep Learning
Information systems → Data analytics
Social and professional topics → Customer characteristics → Customer feedback

KEYWORDS:

Deep Learning, Emotion Recognition, Bi-LSTM, Business Analysis, Customer feedback

1 INTRODUCTION

In order for living things to communicate effectively, emotional expression and emotion understanding are essential. These feelings can be expressed verbally, in writing, or through facial expressions. The relationship between an individual's emotions and interests is crucial for ideas to be implemented successfully in a variety of sectors, including social welfare and product creation.

Nowadays, most information is found in text form. This is shown in tweets from social media, expertise shared on websites, and customer reviews of products.[1] Text analysis goes beyond typical sentiment analysis, which divides sentiments into three general categories: neutral, positive or negative.[2] The difficulty is in figuring out the nuanced feelings that are hidden in words. Although sentiment analysis has its uses, it is unable to fully represent the complex spectrum of feelings that are communicated in written language.

Emotion recognition has become an important area of study in computational linguistics and natural language processing.[3] [4]Emotion recognition, in contrast to standard sentiment analysis, attempts to anticipate particular emotional states, including a wide range of emotions such as happy, sad, angry, and others. Applications like reputation management and customer feedback analysis, where a thorough grasp of human emotions is essential, benefit greatly from this change in emphasis.

The ineffective use of customer service personnel is a common problem in contemporary companies.[5] The large staff frequently becomes overburdened in reading and replying to each and every review from customers, which eventually results in the accumulation and forgetting of important issues and feedback.[6] Businesses can save time and effectively prioritize and handle critical issues by utilizing the emotions indicated in product evaluations as a helpful tactic.[7] This study examines how important emotion recognition is for improving communication, especially when it comes to customer feedback analysis and resource optimization for customer service.[8]

1.1 BRIEF INTRODUCTION OF EMOTION RECOGNITION

The capacity to interpret and understand textual expressions of human emotions is extremely important in the rapidly changing world where communication often happens through text.[9] A rapid development in the field of detecting emotions from text has been seen over few years, whose main focus was to extract the nuanced emotions from text.[10] Technology is expanding exponentially, and most communications around the globe for expressing their concerns are still in the textual format. So this makes the fact very evident that there is a need for emotion recognition from text With the help of this companies can make quick and informed decisions to increase their sales.[11] This section focused on giving a summary of the wider implications or use cases of recognising emotion from text

1.2 EMOTION RECOGNITION AND DEEP LEARNING

In this ever-growing fast-paced evolving field of artificial intelligence, emotion recognition, and deep learning have become very crucial in detecting the human emotions in a given text.[12] [13] The most important and widely used for this is the Bi-LSTM which is a deep-learning technique for finding emotion in text.[14]

The special capabilities of Bi-LSTM are discussed in this section, highlighting the ability to understand word context and extract the nuances from text.[15]Bi-LSTM stand-out feature is its capability to extract emotion from the text in both directions which helps in understanding the text even better.[16]
"Deep Learning and Emotion Recognition" demonstrates the critical role that Bi-LSTM plays in enhancing emotion recognition. Its two-way method increases accuracy and facilitates the interpretation of emotional cues in customer feedback. Bi-LSTM, which combines deep learning and emotion detection, will enable businesses to improve and comprehend the emotional impact of their products in the future, resulting in a more tailored and significant consumer experience.[17]

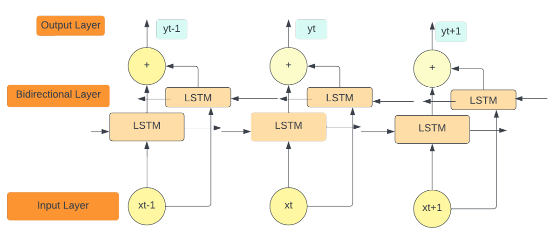

Figure 1: Architecture of bi-directional long short term memory (Bi-LSTM)

2 EXISTING PROBLEMS

There is a large gap between theoretical advances and real-world implementations in the field of emotion identification and consumer feedback analysis. [18]Although most research focuses on extracting emotions from text, there is still much to learn about how to apply these insights to practical applications. The potential advantages of using emotion recognition systems in a variety of real-world contexts are hampered by this gap. [19]

An inherent drawback of current consumer feedback analyzers is their dependence on overly simplistic emotional categorizations. The traditional method frequently assigns general names to feelings, such as positive, negative, or neutral.This oversimplified classification hinders organizations from gaining a deeper understanding of the diverse spectrum of customer opinions since it is unable to capture the subtle, nuanced aspects of human emotions.

A significant obstacle in the present systems is the absence of reliable data analysis and proper visualization of gathered data. Although emotion detection technologies offer a basis for understanding client sentiments, the lack of comprehensive data analysis restricts the retrieval of specific insights.[20] This restriction hinders businesses from identifying certain customer trends, interests, and preferences that may guide more focused marketing and product development efforts. The inadequate promptness with which client complaints are addressed is one of the main concerns in the field of customer service.[21] A company's reputation is at stake due to the dissatisfaction that results from this slow response.

There's a noticeable gap in how companies analyze customer feedback and understand emotions from text. Right now, these two areas textual emotion analysis and customer feedback analysis are two different aspects. This divide weakens companies' ability to truly understand the emotional context of what customers are saying.[22] [23] Closing this gap is key to improving how companies respond to and understand their customers. The disadvantage is the lack of proactive customer interaction initiatives. Many businesses take a reactive stance, waiting for customers to reach out to them, This reactive approach ignores the possibility of developing deeper customer relationships through proactive interaction, in addition to limiting possibilities for development.[24] Effectively addressing these challenges will pave the way for unleashing the full potential of emotion recognition and customer feedback analysis technologies.[25] [26] [27]

3 IMPLEMENTATION

The implemented system is structured around a well-defined architecture that resolves all the existing problems and provides a well-defined solution model made up of many functional modules.The figure 2 represents the proposed solution architecture, the pictorial representation of the architecture shows the overview in more detailed fashion and is easy to understand the flow of our solution.

3.1 Overview

The described implementation includes the following modules.
1) Feedback System
2) Emotion Recognition
3) Response Generation
4) Manager's Portal for customer support
5) Data Visualization Dashboard

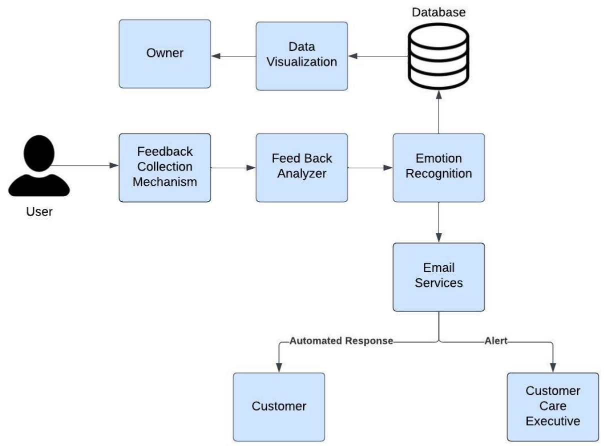

Figure 2: Architecture of Proposed solution

3.2 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.

Figure 3: Feedback System

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.

3.3 Emotion Recognition

A novel method called Bidirectional Long Short-Term Memory(Bi-LSTM) is used by the emotion recognition module.[28] 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.[29][30] By integrating consumer emotion into the whole feedback processing method, a seamless understanding of consumer preference can be noted.

3.4 Response Generation

The main problem identified is, over utilization of customer care manpower, which involves responding to every customer feedback.

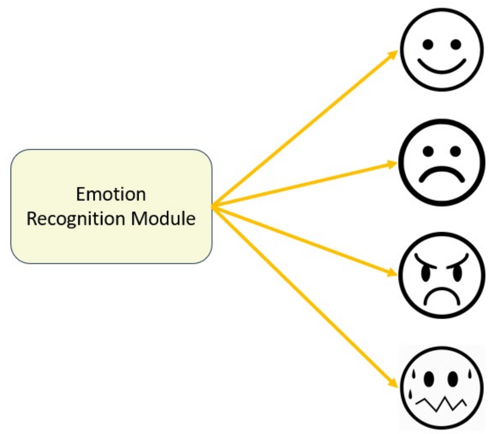

Figure 4: Recognising Emotion

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.

3.5 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.

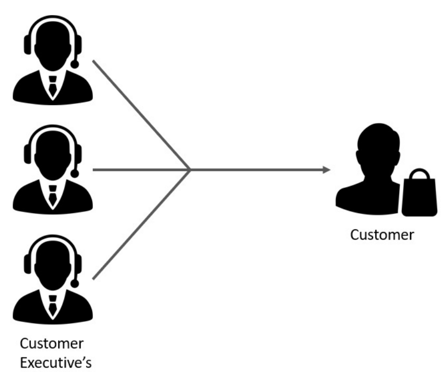

Figure 5: Assigning an executive to customer

3.6 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.

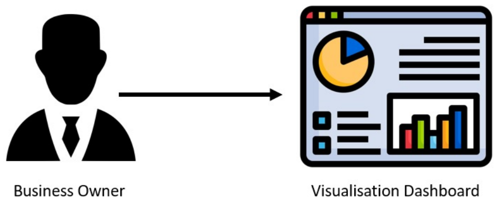

Figure 6: Data visualisation

4 SOLUTION TO THE PROBLEM

The below figure describes the flow of the entire proposed solution, including all the necessary modules.

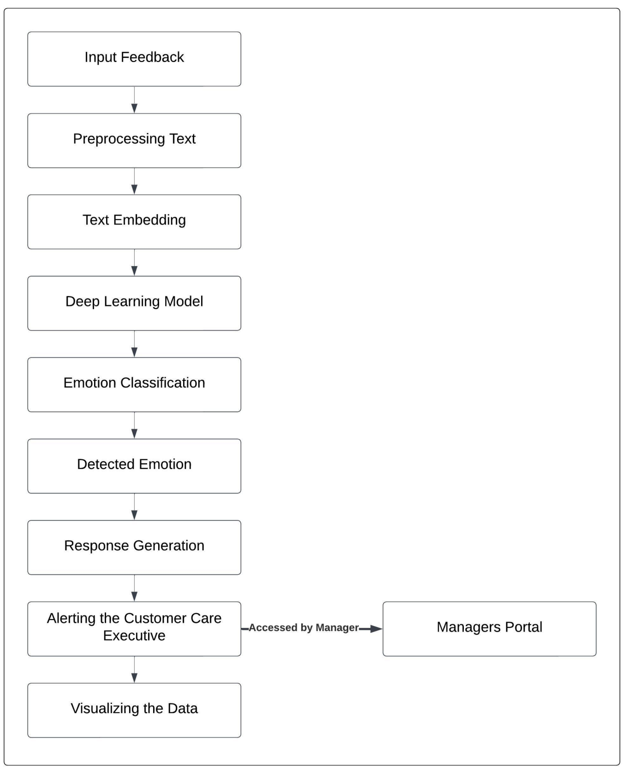

Figure 7: Flowchart of the Proposed Solution

4.1 Integrating Frontend with Backend and Database Storage

Here this pseudocode explains a Flask application that uses MySQL to store data and integrates both frontend and backend. The home page, form submission, and response will have their own paths. Data is gathered, and emotion recognition is done, and data is stored in the database upon successful form submission. At last a thank-you page is generated.

```
# Import Flask and other libraries
# Configure Flask app
# Set template folder
# MySQL database config
# Create MySQL connection object
# Home page route
@app.route('/')
def home():
    # Render home page template
# Global dictionary to store form data
# Form submit route
@app.route('/submit', methods=['GET','POST'])
def submit():
    if request.method == 'POST':
        # Get form data
        # Call emotion detection function
        # Insert form data into the database
        # Redirect to the response page
# Response page route
@app.route('/response')
def response():
    # Render thank-you page template
# Emotion detection function
def EmoDet():
    # Logic to detect emotion
    # Store emotion in the global dictionary
# Printing function
def printing_data():
    # Print the global dictionary
# Main function
if __name__ == "__main__":
    # Run the Flask app
```

4.2 Emotion Recognition

This pseudocode explains a program that detects the emotion of provided input text using a trained model and pre-trained GloVe word embeddings. It includes routines for preprocessing input text, encoding emotions, loading the model, loading the embeddings, and emotion prediction that can be angry, disgusted, happy and sad.

```
# Import required libraries
# Load pre-trained GloVe word embeddings
def load_glove_embeddings():
    # Load embeddings dictionary
    return embeddings_dictionary
# Load trained and saved model
model = load_model("trained_model.h5")
# Define sentiments/labels
sentiments = ['Happy', 'Disgusted', 'Sad', 'Angry']
# One hot encode sentiments
def encoding():
    # Encode sentiments
```

```
    return encoded_labels
# Preprocess input text
def preprocess():
    # Clean and tokenize text
    # Correct the spelling errors in the sentence
    return tokenized_text
# Main prediction loop
while True:
    # Take user input
    input_text = input()
    # Preprocess input
    text = preprocess(input_text)
    # Encode text using GloVe embeddings
    encoded_text = encoding(text)
    # Predict using loaded model
    predictions = model.predict(encoded_text)
    # Get predicted label index
    label = argmax(predictions)
    # Print predicted sentiment
    print(sentiments[label])
```

4.3 Automated Response

This pseudocode defines a function that sends an email to a customer based on their detected emotion (happy, sad, angry, or disgusted). If the emotion is not happy, it will send an email to a randomly select customer executive. The function takes three arguments: name , receiver email, and emotion.

```
#Import required libraries and modules
#Define function to send email
def send_email(name, receiver_email, emotion):
    # Get the script directory path
    if emotion == "Happy":
      # Set the happy email template path
      # Set the subject for happy email
    else (emotion=="Sad" or emotion=="Angry"
    or emotion=="Disgusted"):
      # Randomly select a customer executive
      # Unhappy email template customer
      # Unhappy email template customer executive
      # Set subject for unhappy customer email
      # Set subject for customer executive email
      # Render the executive email template

    # Render the customer email template
    # Set up email server and credentials
    # Connect to the email server

    if emotion != "Happy":
        # Create email data for customer
        # Send email to customer

        # Prepare email data for executive
        # Send email to customer executive
        # Close the email server connection
    else:
        # Prepare email data for happy template
        # Create email message
        # Attach HTML content to email
        # Print and send email
        # Close the email server connection
# Main execution
if _name_ == "_main_":
    # Sample values
    name = 'CUSTOMER_NAME'
    receiver_email = "customer@mail.com"
    emotion = "emotion"
    # Call send_email function
    send_email(name, receiver_email, emotion)
```

4.4 Data Visualisation

This pseudocode explains about the data visualization task using the data considered from MySQL database. Navigation options such as Home, Location, Gender, and Age Group are involved. The application filters data and creates bar charts for the distribution of emotions across various categories, including items, places, age groups, and genders, based on the option selected.

The business owner needs to select a product with the emotion which he wants a visual representation and one of the parameters among location, age group, and gender.

```
# Load data from MySQL database
data = fetch_data()
#Navbar to navigate between different pages
# Home page
if menu_option == 'Home':
   # Bar chart for emotion distribution
     across products
# Location page
elif menu_option == 'Location':
   # Get selected emotion and product
   # Filter data
   # Bar chart for emotion distribution
     across locations
# Age group page
elif menu_option == 'Age Group':
   # Get selected emotion and product
   # Filter data
   # Bar chart for emotion distribution
     across age groups
# Gender page
elif menu_option == 'Gender':
   # Get selected emotion and product
   # Filter data
   # Bar chart for emotion distribution
     across genders
# Bar chart function
def create_bar_chart(filtered_data, x_axis, title):
   # Create bar chart using Plotly
   # Set axes and title
   # Display chart
```

5 RESULT ANALYSIS

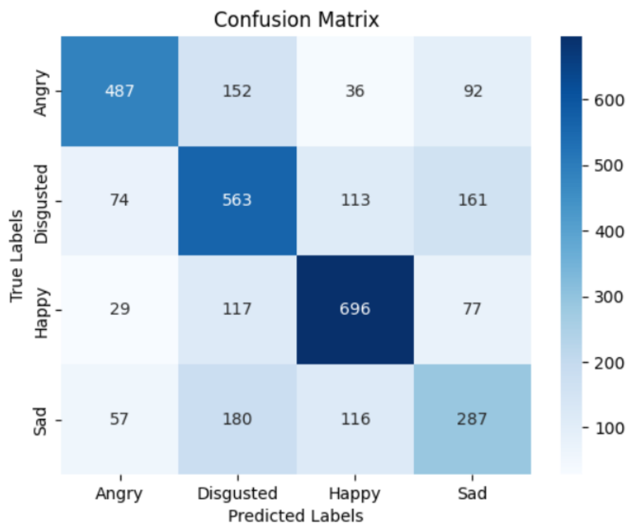

Figure 8: Confusion Matrix

The figure 8 represents the confusion matrix of the model. This is used to know the number of right and wrong classifications done by the model.

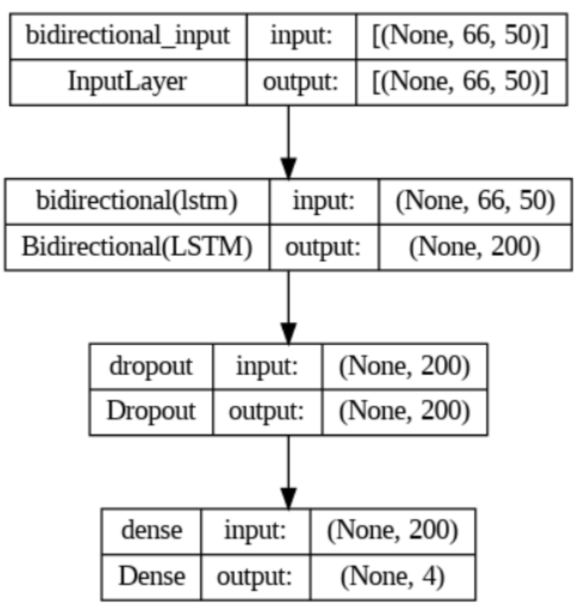

Figure 9: Model Flow Diagram

The figure-9 represents the model flow diagram where we can see our model has an input layer followed by a bi-directional long short-term memory layer, drop layer to avoid overfitting and dense layer to map with a classification and show output.

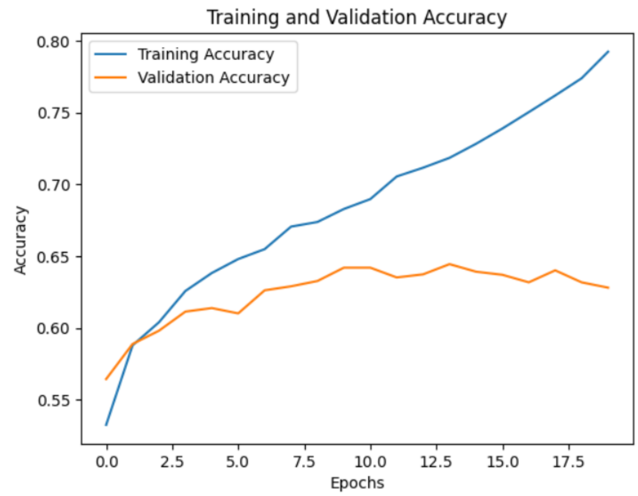

Figure 10: Training And Validation Accuracy

The figure 10 is a graph that shows the training and validation accuracy. The graph is a comparison between epochs and their respective accuracy with respect to training and validation.

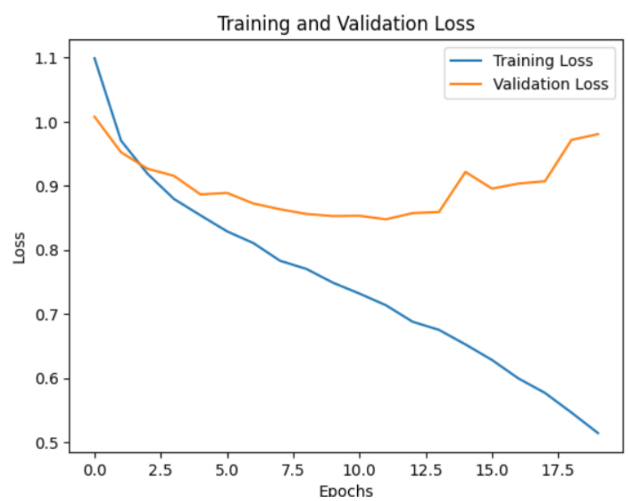

Figure 11: Training And Validation Loss

The figure 11 is also a graph that shows the training and validation loss. The graph is a comparison between epochs and their respective loss with respect to training and validation.

6 CONCLUSION AND FUTURE SCOPE

Our work demonstrates deep learning application for emotion recognition from text for customer feedback analysis. By predicting varied emotions such as happy, sad, angry, or disgusted, we can automate personalized email responses, enhancing customer satisfaction. Future research could extend our work to include more complex emotions and improve accuracy. Exploring other advanced deep learning techniques and real-time data modes could help the feedback analysis system. Integrating emotion analysis with other streams will be helpful in providing more clear understanding of customer emotions and improving the overall customer experience.

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