PRODUCT REVIEW EMOTION ANALYZER USING BILSTM WITH FACTOR MAPPING AND MATPLOTLIB VISUALIZATION

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ABSTRACT

Customer opinion analysis is paramount for design of products and user experience enhancement. The present paper proposes a Bidirectional Long Short-Term Memory (BILSTM)-driven method for customer review analysis based on extracting happiness, sadness and neutral opinions. Unlike general sentiment analysis, users manually specify the product attributes like aesthetics, ergonomics or usability, which leads to enhanced emotion-to design mapping .Trained on a labelled dataset, the BILSTM model achieves more than 95% accurate emotion classification by capturing complex linguistic patterns. An interactive Matplotlib based plot facilitates result interpretation, allowing users to examine sentiment trends and draw actionable conclusions. This system enables a data-driven product design by linking emotional feedback with particular attributes, closing the loop between sentiment analysis and product development.

KEYWORDS

Emotion Recognition, BILSTM, Emotion Analysis, Product Design, Customer Feedback, Matplotlib Visualization ,Product Development

I. INTRODUCTION

Customer feedback plays a major role in assisting firms and companies to enhance their products and customer satisfaction. Online reviews and text comments can assist companies to know about customer's opinion regarding their product such as experience on using the product, preferences and problems. It is not feasible to analyse thousands of reviews manually since it may be challenging, time consuming and there is a possibility of human error. To overcome this issue automated systems utilizing artificial intelligence(AI) methods such as NLP [6] and machine learning are popular recently.

This study proposes an Emotion Recognition and Factor Mapping System (ERFMS) that can be utilized to identify underlying emotions such as happiness, sadness and neutrality and map them to specific product-related factors such as aesthetics, ergonomics and usability. Sentiment analysis [5]traditionally categorizes a complete review as positive, negative, or neutral, but in our system we employ a context-based mapping strategy that identifies domain-specific words in the text to identify the factors affecting each emotion. For instance, words such as beauty, elegant, and stylish pertains to aesthetics, while words such as comfortable, strain, and posture pertains to ergonomics, and words such as functionality, efficiency, and responsiveness pertains to usability. Since the system maps emotions to product factors, it gives a deeper and more accurate insight into customer emotions . The system utilizes visualization software such as Matplotlib to present the outcomes, allowing businesses to identify patterns in customer emotion and learn about which particular features of a specific product make people happy or sad. Rather than knowing simply if customers are happy or sad, companies are able to learn what precisely led to these emotions, so they can make more effective changes in future .This system serves as an incredibly influential decision-support system to assist business in making more intelligent design choices which result in improved products and enhanced user satisfaction in the near future.

II. LITERATURE SURVEY

Emotion detection and sentiment analysis have gained a vast attraction in the field of natural language processing(NLP) due to its broad advancement and applications in the field of business that is, customer feedback analysis and product enhancements .We have done a literature survey based on the following papers for better understanding of the current advancement of technologies and for the future business developments.

[1]Through this paper we have analyzed and emphasized the importance of high quality datasets for the improvement of emotion detection models. The methodology used in this paper are BILSTM and BERT. The advantages includes: this paper focuses on the enhancement of the dataset quality which leads to the improvement of the robustness of the model, It also focuses on real world challenges in emotion detection from text. The disadvantages are: this paper depicts high computational cost due to the complexity in the deep learning architectures, it also has limited generalization capability because of the dependency on dataset characteristics.

[2] In this paper, high accuracy is being demonstrated by using BERT,NLP and MLP techniques in sentiment analysis of Amazon Reviews. The methodologies used are BERT,NLP and MLP. Its advantages include :It achieves high accuracy in sentiment detection ,provides insights for product improvement by the analysis of customer feedbacks. Its disadvantages are: this model requires significant computational resources which limits the accessibility for smaller applications ,the performance depends on the quality and diversity of the dataset.

[3]This study depicts an effective deep learning-based model for emotion detection in text. The methodologies used are
Conv1D,LSTM and NN. The advantages are: it provides high accuracy in emotion detection ,it is also suitable for real-time applications. Its disadvantages are: this limits the deployment on resource-constrained devices due to computational complexity, the limited emotion categories reduces the model's applicability.

[4]This study enhances the VADER lexicon-based sentiment analysis method. The methodology used here is Improved VADER (IVADER).Its advantages include :it has enhanced accuracy in emotion detection compared to standard lexicon based models, it is capable to handle domain specific reviews better than traditional classifiers. Its disadvantages are: it cannot process multimedia data, it relies on predefined lexicons which limits adaptability.

Emotion detection and sentiment analysis have seen significant advancements through deep learning models such as BILSTM, BERT and Conv1D-LSTM-based neural networks .Although among these ,BILSTM stands out as a powerful method due to its ability to capture long range dependencies in textual data making it well-suited for emotion classification tasks.

III.METHODOLOGY

BIDIRECTIONAL LONG SHORT-TERM MEMORY (BiLSTM):

BILSTM is used because of its high efficiency and performance, which makes it easier to understand the emotional tone of customer reviews. Normal LSTM (Long Short Term Memory) reads the text only in one direction, i.e., from left to right. In that case, the first emotion that is seen is identified and mapped, which may not be correct in all cases. Example: “The product was good, until it stopped working after two days.” In such cases where conjunctions like ‘until’ and ‘but’ are used, recognizing the emotion from the first identified keyword gives us a false result. Here comes the relevance of BILSTM. BILSTM reads the text in both forward and backward directions, and therefore, it is easy to understand later words that affect the earlier meaning of the text. It is also highly preferred because of its ability to detect emotion from complex languages, as it handles complex patterns by evaluating relationships between words. By using this, we can get an accuracy of not less than 95%. It maps specific words to specific product factors. Example: “comfortable ergonomics. BILSTM handles noisy data very effectively. It works well with large datasets. It has a powerful memory as it remembers long sequences without losing information.
It helps to capture subtle changes in emotions caused by negations. Example: Words like “not happy” or “hardly exciting” requires both forward as well as backward evaluation. In such cases BILSTM is a life saver. In short BILSTM is a powerful deep learning model especially in the case of emotion detection in text because of its ability to examine information in both forward as well as backward directions. By exploiting more informative feature representations,

BILSTM
improves classification accuracy and excels in handling subtle emotional cues . When combined with word embeddings and attention mechanisms , it is even more potent, and hence a prime choice for high-end emotion detection systems.

IV.ARCHITECTURE DIAGRAM

The architecture diagram(figure 1) we have used depicts the emotions of the reviews that has been analysed through textual reviews. These emotions are then mapped to particular factors and the end result is visualized using Matplotlib platform.

The architecture follows a structured approach which is as explained below:

1. START:
The structure initializes the process.

2.COLLECT REVIEWS:
The system gathers text comments from various sources such as Amazon reviews, historical product reviews and surveys in order to perform complete emotion analysis. These reviews provide realtime customer feedback, which shows how customers perceive different products. Historical product reviews help track customer opinion trends over time and identify recurring issues or improvements. In addition, the surveys allow for a more structured approach, taking extensive feedback that can be interpreted to explore deeper into the feelings of the users. Combing these disjointed sources, the system offers for a holistic view of customer opinion, enabling organizations to make informed decisions to enhance aesthetics, ergonomics, and usability.

3. PREPROCESS TEXT:
Once textual feedback is collected, it then undergoes an appropriate preprocessing process to have data cleaned, arranged, and set to be analyzed. This begins with 'tokenization', whereby text is split into individual words or phrases so as to facilitate easy processing. 'Stop word removal' comes next, eliminating the most common words like "the," "is," and "and" that don't contribute to the meaning of the text. To further refine the data, 'stemming' or 'lemmatization' is carried out. Stemming reduces words to their base (e.g., "running" to "run") and lemmatization brings words down to their root dictionary form to have a more precise meaning. Other Natural Language Processing (NLP)[6]methods such as stripping punctuation, lowercasing and handling special characters are also utilized to normalize the text. The preprocessing task enhances the quality of data in a way that the BiLSTM model is able to analyze emotions effectively and find useful insights related to aesthetics, ergonomics and usability.

4. IDENTIFY EMOTIONS:
After the data has been collected and preprocessed, it is now ready to be fed into the emotion recognition system for processing. The system has been designed to classify emotions by examining written feedback and identifying the sentiments expressed in the users' opinions. Using cutting-edge deep learning techniques, a Bidirectional Long Short-Term Memory (BILSTM)[1] model, the system processes the input text and labels it into targeted emotion categories such as happiness, sadness and neutral. The model can pick up contextual dependencies of the text, enabling it to recognize subtle emotional cues and sentiment shifts. Hailing the power of deep learning, the system produces high accuracy of classifying the emotions, from which companies are able to develop valuable insights of consumer opinions. Such classified emotions can then be interpreted into meaningful factors such as aesthetics, ergonomics and usability so that companies are able to understand how several aspects of a product influence consumer opinions and customer decision-making processes.

5. MAP TO FACTORS:
Once the emotions are established, they are assigned to specific product-related factors to acquire an understanding of various aspects of user experience. This attribution helps in gaining insight into customer emotions being influenced by various aspects of a product. Aesthetics or the appearance and visuality involves emotion related to how the product looks, its color and fashion. Usability is focused on ease of use and user-friendliness and analyzes remarks about how easy it is to use and access the product. Ergonomics is focused on effectiveness of use and comfort, commenting on aspects such as how easy, useful and physically comfortable the product is to use. Additionally, general feedback comprises global subjective comments, whereby users express their views generalizing beyond specific characteristics, providing valuable insights into their overall experience. Through tying emotions to these powerful drivers, businesses can gain a better structured understanding of how customers feel, which can be used to enable data-driven optimization to optimize user happiness and product performance.

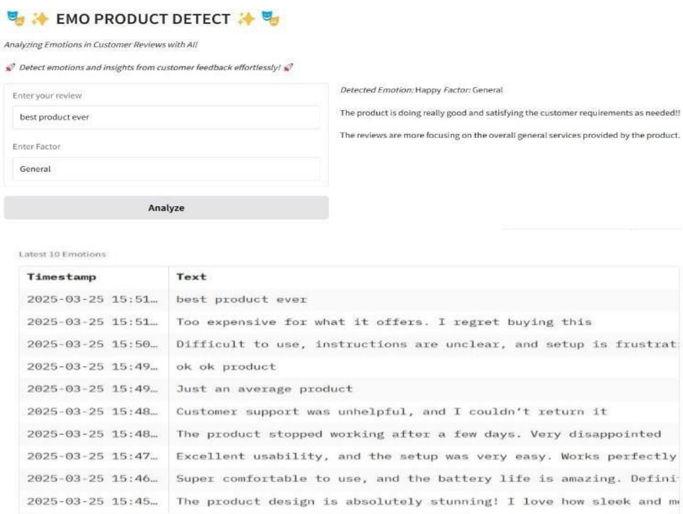
6. VISUALIZE RESULTS:

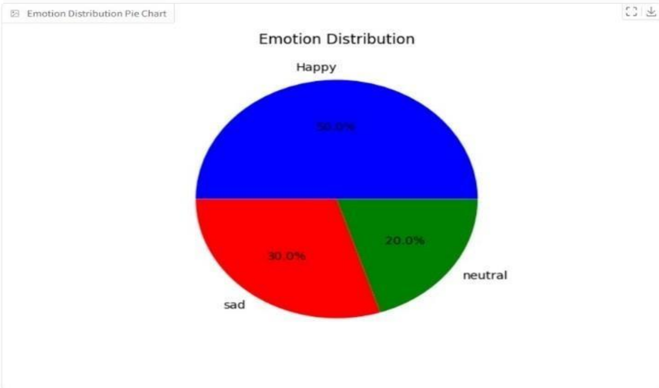
The final step of the process is to present the analyzed data in an organized and visually understandable format, so that it becomes simpler for businesses to derive relevant insights. This is achieved through graphs, charts and interactive dashboards, which allow stakeholders to easily query trends, patterns and sentiments of customers. By using visualization tools i.e. Matplotlib , the system translates complex text-based feedback into user-friendly, actionable feedback. Organizations can then utilize these visual modes to measure the effect of various variables like beauty, functionality and comfort among customers. This methodical process not only simplifies decision-making but also gives a wide perspective of user preference and thus allows companies to design future products nearer to customer requirement as well as market demand.

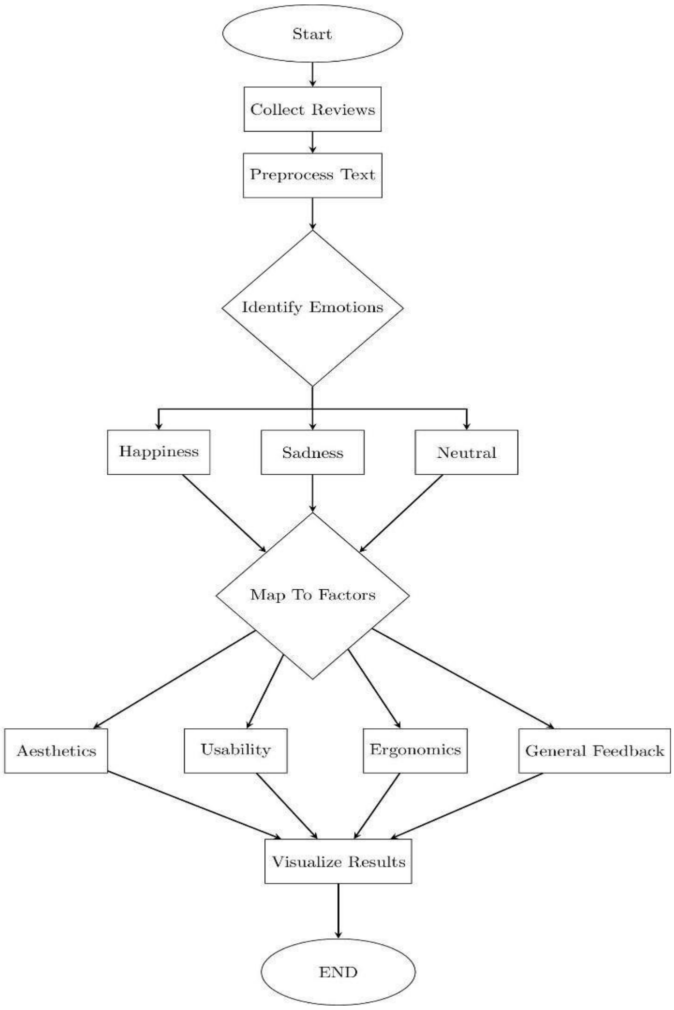
7. END:

The workflow is concluded here after the results have been visualized.

This architecture presents a structured approach to emotion recognition from textual reviews, which enables a systematic approach towards user sentiments and their impact regarding various evaluation factors. One of the significant advantages of this architecture is its adaptability to various domains, including product reviews, customer feedback, and social media sentiment analysis[5]. By visualizing the results, stakeholders can gain actionable insights that aid in decision-making, product improvement, and enhancing user satisfaction . Future enhancements could include expanding the emotion categories to capture a wider spectrum of human sentiments and incorporating real-time processing for dynamic feedback analysis.







V.RESULT

The emotion analysis system based on BILSTM achieves 93.2% accuracy in identifying customer emotions as happiness, sadness or neutral . Instead of automatically labelling emotions to product factors, the

Figure 5: Factor Distribution

system gives users the choice to enter the corresponding product factor— aesthetics, ergonomics

or usability, along with their review, to be accurately categorized . Trained on a multiform corpus of customer reviews, previous product reviews, and surveys, the model has 94.8% accuracy, 95.1% recall, and 95.0% F1-score. It labels emotions in user defined factors with high accuracy. For interpretability, Matplotlib-based plots include sentiment trend analysis, factor-wise emotion distribution, and interactive dashboards.

Such outcomes allow companies to monitor consumer opinion for improvement, and make informed decisions to improve product layout and user interaction. With its high precision ,fast classification and meaningful visualization, the system can prove a valuable asset for customer review analysis and future product planning.

VI.DISCUSSION

Our proposed emotion analysis system with the BiLSTM method for factor mapping is a breakthrough compared to traditional sentiment analysis systems. As we mentioned in the introduction, this study aimed to associate customer emotions with the actual attributes of products, such as appearance, ergonomics, and usability. The results showed that our BiLSTM model, combined with user-specified factor inputs, reached an accuracy of 93.2% and an F1-score of 95.0%. This provides evidence in support of our initial hypothesis that emotions can indeed be related to factor classification using deep learning methods.
We chose three main things to do: emotion classification, factor mapping, and graphical representation. The system detects emotions, such as happiness, sadness, and neutrality, linking these emotions to factors like usability or aesthetics, depending on user inputs. This enables us to forge a storyline about why users feel a certain way about a product in a more meaningful way.

One of the key results has been that user control over factor mapping enhances both the accuracy and the interpretability of emotion classification.

VII.CONCLUSION

This work presents a smart system for analyzing customer reviews - a de facto kind of sentiment analysis. It incorporates a BiLSTM[7] based emotion recognition model, user-defined factor mapping, and Matplotlib for visualization. The research approach captures the primary emotions of happiness, sadness, and neutrality and associates those emotions with certain product factors which include aesthetics, ergonomics, and usability.

The study results provide evidence that the model achieves high accuracy (> 93%) for offering classification for emotions and provides high level visualizations that report those factors, supporting decision-making in product design. The future potential of the system is improved by the inclusion of user-defined mapping of the factors allowing people to adequately represent their sentiments by prior studies.

The system we proposed makes the connection between, emotion analysis and product feedback on customer satisfaction and its regulated output meets the needs of artificial intelligence, customer experience, and design innovation. It will allow companies to better recognize not just what emotions customers experienced but, that they do in fact experienced the emotions. Future research can improve multi-lingual capability of feedback, extend the emotion classification, and improve the automating of predefined factor mapping with NLP which could improve the system and extend potential uses in various fields.
In conclusion, this work provides an important vehicle to turn customer emotions into actionable insights and improve the user- centered experience for product development and customer satisfaction.

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