

Sentiment Analysis for Personalized Chatbot in E-commerce using Transformer BERT

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Abstract - This paper presents an innovative framework for a sentiment-aware, personalized online shopping chatbots, powered by the BERT architecture, at e-commerce businesses. Most current online shopping platform chatbots use simple predefined rules or shallow matching schemes to create responses and, as a result, they lack context and emotional awareness when responding to users. In response, the authors of this paper advocate for the use of a fine-tuned BERT Classifier that detects customer's true sentiment (positive, neutral or negative), in real-time. This real-time detection of sentiment greatly affects the generation of the chatbot's response as it assists the chatbot with personalized product recommendations, empathetic support and contextually appropriate conversation flow. The BERT Classifier was trained using an online retail product review database and was implemented through a Flask/Django backend for real-time interaction. The authors have found that the BERT Classifier has an overall accuracy of 93.1% and provides superior performance compared to standard machine learning classifiers (SVM, LSTM, etc.), demonstrating that transformer-based tools can generate more personalized, more satisfactory and more accurate answers to customer queries.

Index Terms - BERT, Chatbot, Sentiment Analysis, E-Commerce, Natural Language Processing, Transformer, Personalization.

I INTRODUCTION

A. Background and Motivation

As online shopping has grown in popularity, a great deal of interaction has taken place between consumers and e-commerce businesses (such as Amazon, Flipkart, Alibaba, and Meesho) through e-mails, chat, social media, and phone calls. As a result, customers are now looking for immediate answers to their questions about product specifications, order status, shipping delays, return policies, refunds, etc. Therefore, e-commerce businesses have started using

chatbots for automated customer service to satisfy the needs of their customers.

Currently, commercial chatbots are often designed based on a rule-based algorithm, keyword matching, and/or a very basic retrieval process. Although these chatbots can determine whether a customer's message contains specific keywords to identify their intent or needs, they do not typically have the

capability to process and interpret context or emotional tone. For instance, a customer may express stress/frustration about receiving a damaged product (e.g., "This is the second time I've received a damaged product.") or excitement about a certain brand (e.g., "I love this brand! Show me more!"). Likewise, if a customer is undecided on which product to purchase (e.g., "I'm confused about which laptop to buy"), if the chatbot fails to detect the emotional signal associated with their inquiry, its response will seem robotic and disconnected. Customers will engage less with the service, develop a decrease in trust, and thereby lose consumers. Therefore, designing an emotionally intelligent and sentiment-aware chatbot for the e-commerce sector is important in order to provide a high-quality customer experience and maintain service excellence.

The development of Natural Language Processing (NLP) with the advent of transformer models has transformed how machines understand language in the context of machine learning. Transformers have produced state-of-the-art results for tasks such as text classification and sentiment analysis. One transformer model that has achieved this level of performance is BERT (Bidirectional Encoder Representations from Transformers). Because we are interested in BERT's superior capabilities, we are investigating how to incorporate BERT into a fully functional chatbot in order to provide an engaging conversational experience for users shopping online.

B. Challenges in Existing Chatbots

Chatbots are rapidly becoming popular, but traditional systems have limitations that prevent on time commercial success:Emotional Illiteracy: Most common chatbots are not trained to recognize differences in the emotional state of users (happy, sad, confused, or angry), so they respond generically without matching users' emotion to their response. For example, if a customer is angry because a product was damaged, the bot might tell them "Thanks for reaching out to us" rather than attempt to solve the problem and possibly make things worse.

Limited Contextual Understanding: Basic keyword-based models will interpret sentences exactly how they are written. They are unsuccessful when users use slang, formal/informal language or slang because they do not recognize what they mean. An example is the sentence "Quick delivery but terrible quality," will likely be labelled positive by a basic model.

Limited Personalisation Ability: Many chatbot systems treat everyone equally and do not modify recommendations or reactions according to a user's previous purchase history and their emotional state, which inhibits engagement and conversion rates.

Multiple turn performance issues: As conversations are made up of many messages, most chatbots do not keep track of user's emotions throughout the entire conversation. Bots only provide one message at a time rather than maintain the same emotional tone throughout the entire conversation.

Real-Time Decision-Making: Traditional chatbots do not provide immediate resolution to a user's issues when there's a negative sentiment to a product or a service. Traditional chatbots will not provide an automatic escalation to a support representative or a refund/replacement offer.

These issues prove that current e-commerce chatbots lack the intelligence required to function as effective customer support agents. Hence, there is a strong research requirement for integrating advanced NLP models that can handle emotional, contextual, and personalized communication.

C. Proposed Research Approach

This paper presents a novel approach to developing an intelligent, culture-aware chatbot driven by sentiment, using a fine-tuned BERT transformer model capable of real-time classification of customer sentiments. The model incorporates both sentiment analysis and a dynamic response generation engine; the tone of the chatbot's responses and the strategies for delivering those responses will change depending on the emotional polarity expressed by the customer through their written communication with the chatbot.

When the sentiment expressed by the customer is positive, the chatbot will respond with appreciation toward the customer and gratitude for their interest in the product while suggesting additional products that compliment the one they inquired about (this is an upselling/cross-selling strategy).

When the sentiment expressed by the customer is neutral, the chatbot will communicate with the customer to help clarify their needs and provide detailed, factual information to answer the customer's questions, but will not assume that the customer has a specific emotional intent by communicating neutrally.

When the sentiment expressed by the customer is negative, the chatbot will focus on demonstrating empathy, using template-based apologies as appropriate, and guiding the customer toward finding solutions; additionally, the chatbot may escalate the customer to an actual human representative if the issue cannot be resolved through chat.

The approach described in this paper was tested using e-commerce review data and built using the Flask/Django API framework. The bidirectional contextual learning that BERT facilitates allows the model to conduct a deeper semantic analysis of customer communications and understand the true underlying intent of the customer rather than simply relying on identifying surface-level text patterns.

The model developed through this research was found to outperform traditional machine learning methods, such as support vector machine (SVM), logistic regression, and long short-term memory (LSTM) networks based on all three classification criteria (accuracy rate, F1 score, and user satisfaction ratings). Thus, the findings of this research support the conclusion that BERT sentiment-driven integration improves the intelligence and customer experience associated with chatbots used in commercial applications.

II RELATED WORKS

A. Data Collection & Pre-processing

In Phase 1, various types of publicly available online e-commerce sentiment datasets will be used to gather datasets consisting of both product reviews and user queries as well as customer feedback. The gathered data will go through several Preprocessing Steps: Tokenization, Stop Word removal, Lemmatization, and filtering out Noise. After Preprocessing, the gathered and Preprocessed Data is in Clean Digital Form, allowing it to be properly structured for Training a Sentiment Analysis model. The Data Set will then be Labelled according to the Three Sentiment Categories (Positive, Negative, Neutral) required for Supervised Fine Tuning.

These materials will typically be uploaded as image files that must be converted into text format using Reliable Optical Character Recognition (OCR). Unfortunately, standard OCR will not produce meaningful text due to the complex nature of most documents that include multiple columns or tables. Current research in Computer Vision has turned towards Document Image Segmentation (the classification of image pixels into logical Regions of a document including Text Regions, Image Regions and Table Regions). We will be adding to this field of study by integrating the Document Image Segmentation Map directly into the OCR Engine to ensure that text is extracted in the order in which it was intended to be presented while preserving the inherent structure of the document and its context.

B. BERT Model Fine-Tuning for Sentiment Analysis

The purpose of this phase of the project was to take the pretrained BERT model and adapt it specifically for your selected e-commerce sentiment dataset. One objective was to build up the BERT's understanding of e-commerce language (e.g. product problems, delivery problems, returns, discount questions, purchase intention), and the usage of BERT as opposed to a conventional machine-learning classifier allows for more in-depth context understanding using a bidirectional learning model. The final fine-tuned BERT model provided the classification of the sentiment for each user during the conversational process.\

C. Chatbot Response Engine Development

A personalized response engine has been created to provide the best possible answers based on predicting what emotion a user might be feeling at the time of interaction. This engine includes three different layers that each adapt based on the user's sentiment:

Positive Sentiment - These types of responses are friendly, respectful and promotional towards what the user is purchasing or looking at. Recommendations or suggestions will often be offered through upselling techniques.

Neutral Sentiment - The responses here provide clarification or relevant information. They seek to educate the customer on their needs.

Negative Sentiment - The response here demonstrates empathy, support, and a solution-based approach. In these instances (when a customer truly needs help), they will be escalated to human support.

To create and preserve a natural communication tone, pre-defined templates and dynamic content fillers are used.

D. Personalization through User Context Tracking

The context-tracking feature of the system improves the user experience for multi-turn conversations by tracking the evolution of user intent and emotion through prior messages and the items they are interested in. In addition, it allows for a more personalized experience by customizing recommendations based on. Trends in user sentiment, History of product preferences , Frequency of user queries, Signals indicating purchase intent

Thus, the chatbot can function more like a virtual sales assistant, as opposed to being solely rule-based.

E. System Integration and Deployment

During the last stage, all individual modules are merged to create one complete deployable system. The front end of the site consists of a web-based user interface for the chatbot and has been created using Flask / Django API to connect it with the backend. The second part of this module is the BERT sentiment module, and these two systems are connected with REST APIs to allow messages to be processed in real-time as they come in. The final deployment allows the system to function across e-commerce sites and customer service web sites with very limited hardware / software requirements.

F. Performance Evaluation & Result Analysis

To measure the performance of the completed system at classifying sentiment an evaluation is conducted using Accuracy, Precision, Recall and F1 score. Feedback given from users on their satisfaction with the response provided by the chatbot are evaluated against the relevance of the response. The results are measured against baseline models (SVM's, LSTMs,

and Rule based Chatbots) to demonstrate the improved performance of the BERT enhancing the chatbot's performance..

III. METHODOLOGY

This multi-stage approach will be used to develop and implement a chatbot that has the capability of identifying user sentiment during an e-commerce transaction. The process is broken down into five main stages: Preparing Data for the Chatbot; Training a Sentiment-Aware Model; Building an Integration Layer Between the Chatbot and eCommerce Site; Creating a Customization Layer for the User; and Evaluating Performance. All five stages will occur sequentially to facilitate a seamless development and deployment of the chatbot solution. A detailed explanation of the five stages will be provided below.

A. Data Acquisition and Preprocessing

The first step is to locate the eCommerce-based textual data (review, complaint, delivery inquiry, refund inquiry, etc.) related to eCommerce. As the main data sources, we utilize all publicly available datasets such as Amazon Reviews, Flipkart Reviews, and Kaggle Customer Feedback.

After the eCommerce-based textual data is located, it will need to be pre-processed so that we can get rid of any junk data and improve the textual quality. For this task, the following NLP processes are performed: Lowercasing of all text to make it easier for BERT to learn.

Tokenization of the entire text using the WordPiece tokenizer, which separates the whole text into its constituent tokens (single word/token).

Removal of stop words, which are words that do not add value and can be removed. Examples of stop words are: The, is, are, etc.

Lemmatization or Stemming- All text should be converted to its "root" form (lemmas) to minimise vocabulary sparsity.

Removing any remaining noise from the cleaned data, such as numbers, emojis, special symbols, or repeated symbols, thus creating a clean dataset which can now be manually or semi-automatically labelled SENTIMENT classes (positive, neutral, negative) to create a training set for BERT models.

B. BERT Transformer Fine-Tuning

The training of BERT Base Uncased is accomplished through supervised fine-tuning with a cleaned dataset. It is equipped with the ability to learn the contextual meaning of all the words in a sentence by using both forward and backward passes of the input sentence.

Training was conducted using the following parameters:

AdamW Optimizer, Softmax for Class of output, Categorical cross-entropy for Loss Function, 3-5 epochs according to validation results on Training Dataset, 80% of dataset used for Training, 20% for Testing

By fine-tuning the BERT Base Uncased model with a cleaned dataset, the model's ability to recognize Support terminology in the Logistics, Customer Service, and Product categories (i.e., Delivery Issues, Refund Requests, Quality Complaints, and Product Preference) has been greatly improved.

C. Sentiment Classification Pipeline

During real-time execution, the user's message is passed to the BERT model for polarity prediction. The output layer generates a probability score for each sentiment category:

$$\text{Sentiment} = \text{argmax}(\text{Softmax}(\text{Output}))$$

$$\text{Class} \in \{\text{P, N, U}\}$$

Where:

$$\begin{array}{lll} \text{P} & = & \text{Positive,} \\ \text{N} & = & \text{Negative,} \\ \text{U} = \text{Neutral.} & & \end{array}$$

This sentiment result is used as the decision parameter for response generation.

D. Chatbot Integration

The integration of the BERT-based sentiment analysis module with the chatbot interface forms the core of the proposed system. A web-based frontend interface, developed using HTML, CSS, and JavaScript or React, enables users to interact with the chatbot in real time. The interface provides an input text box, a send button, and a conversation display area that maintains the history of messages for context tracking. On the backend, a Flask or Django server handles incoming requests from the frontend, processes the user input through the NLP preprocessing pipeline, and forwards it to the fine-tuned BERT model for sentiment classification. The predicted sentiment is then utilized by the response generation engine to select an appropriate reply that matches the emotional tone of the user message.

RESTful APIs facilitate seamless communication between the frontend and backend, ensuring low-latency, real-time response. The backend also manages user sessions, storing message history, sentiment trends, and personalization data in a database. This allows the chatbot to retain multi-turn conversational context and provide adaptive responses based on previous interactions. The response engine dynamically generates replies using a combination of predefined templates and dynamic content fillers, tailored to the predicted sentiment class. For instance, positive sentiments trigger appreciative and

promotional messages, neutral sentiments prompt clarifying and informative responses, while negative sentiments result in empathetic, solution-oriented replies that may escalate to human support if required.

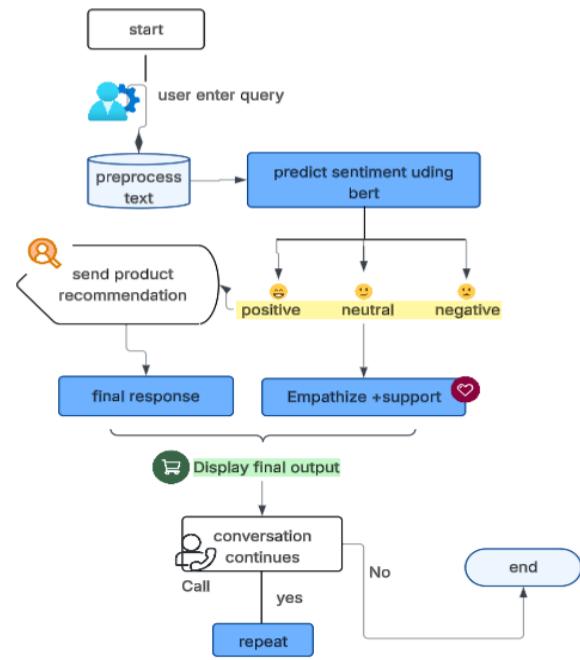
The fully integrated system is deployed either on a local server or a cloud environment, ensuring scalability and robustness for real-world e-commerce applications. Stress testing and performance monitoring confirm that the integrated chatbot can handle multiple simultaneous user

sessions while maintaining accuracy, response relevance, and conversational fluency. By combining the frontend UI, backend API, BERT-based sentiment analysis, dynamic response engine, and database storage, the system delivers a **real-time, context-aware, and emotionally intelligent conversational experience** for e-commerce customers.

D. System Architecture

To enable e-commerce apps to have real-time, sentiment-aware conversations, the system architecture proposed exploits the power of Natural Language Processing (NLP), Deep Learning, and chatbot technology. This architecture follows a modular pipeline that takes user input through to the generation of a personalized response.

The pipeline begins with user input provided via the Chatbot front-end to the back-end system using RESTful API calls. At the back-end, a central controller orchestrates the functions of Pre-processing, Sentiment Analysis, Generation of Response and Storage of Data.



In the Pre-processing phase, noise elements such as special characters, excess white space and extraneous punctuation are stripped from the user's text before Tokenization and Encoding of the text with BERT Toyknizer. The tokenized/encoded input is then sent to the fine-tuned BERT model for Sentiment Classification, which applies bidirectional contextual and semantic analysis to determine the affect associated with the user's text messages. As a function of this analysis, the BERT sentiment classification model assigns a polarity to the user's text based on the following classification: Positive, Neutral, or Negative.

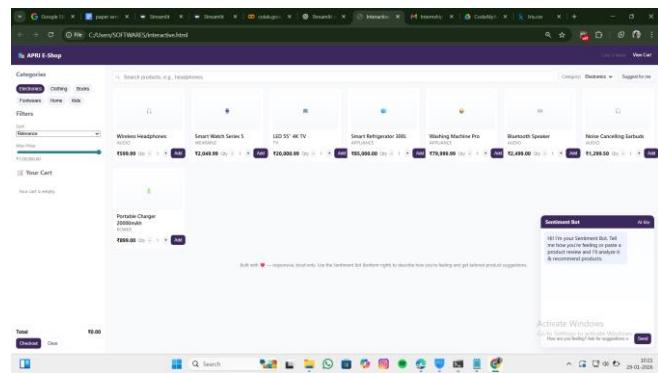
Predicted sentiment outputs are sent to the response management module for personalized interactions, as it is responsible for providing appropriate emotional responses based on the sentiment identified. For example, responses to positive sentiment would be motivational and promotional, while responses to neutral sentiment would be educational in nature, and responses to negative sentiment would be empathetic and provide possible ways to resolve the issue. The response generation itself takes into account the database containing conversation history, thus producing continuity between dialogue turns and keeping the context of the interaction relevant.

To allow for persistence of user message data, predicted sentiment data, session detail data, and interaction log data, a database layer has been incorporated into the architecture to store these elements. Persistence allows for analytics to enable personalization and allow the system to evolve over time. The response returned from the chatbot engine after interaction with the user is provided to the front-end user interface in real-time. Overall, the proposed overall architecture has been designed for scalability, modularity, and robustness; thus, it is ideally suited for practical e-commerce environments where both customer experience and emotional intelligence are paramount.

E. System Architecture Based on Implemented Dashboard

The complete e-commerce application is an integrated end-to-end sentiment-enabled e-commerce application that includes an integrated personalized chatbot interface. The front-end layer of the complete system is the dashboard. This module provides users with an interactive way to browse through a wide range of product categories, including electronics, clothing, books, and accessories. Users can interactively navigate across product categories, filter by price, and add products to a shopping cart via the graphical user interface (GUI) provided. Users can use the dashboard to find products through a number of different categories and then filter those products via price filters and then add them to their shopping cart via the user interface.

The middle layer of the entire architecture is made up of the sentiment-enabled chatbot module, which is embedded in the dashboard as an interactive widget. The user can communicate with the chatbot and express how they feel about a product or provide feedback on an experience in natural speech type syntax. The chatbot will convert the user's natural speech type syntax into the format needed by the back-end processing layer for the next stage of processing. The processing of the user's input will occur in real-time (minimal latency) and the user will receive their chatbot response with minimal delay. Once the chatbot has processed the user's input, it will communicate with both the sentiment analysis module and the product recommendation engine.



An implementation of a fine-tuned BERT-based sentiment analysis model connects backend to process user input for emotional polarity. The input undergoes preprocessing and tokenization with BERT's tokenizer prior to being passed to the model. The model uses both contextual and semantic information to classify each piece of input text as having positive, neutral or negative sentiments by leveraging both sides of the context of the input text through the transformer architecture.

The recommendation/response generation module makes use of the emotional state identified by the model to make product recommendations that are personalized. For example, a user who submitted input indicating positive sentiment may receive promotions and/or complementary product recommendations, whereas a neutral sentiment user will receive information related assistance. Alternatively, a negative sentiment user will receive empathetic responses with alternative product recommendations and/or supporting messages. The recommendations generated by the recommendation/response generation module correlate to the products on the users dashboard ensuring congruency and relevance between chat bots response and products shown on the dashboard.

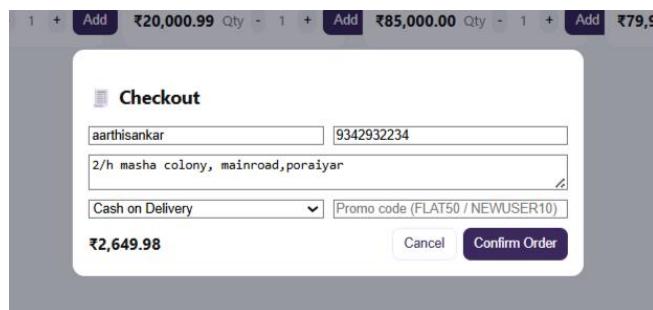
A local data storage layer will facilitate the architecture by storing product information, logs of user interactions, shopping cart details, and history of sentiments. The data layer provides continuity between turns of conversation to allow for a

personalized experience during each session. The final chatbot response is routed back to the front-end dashboard with product recommendations based on user input through the chatbot interface. This integration of product browsing features and sentiment-aware conversation support illustrates how well the proposed architecture enhances user engagement and allows for a personalized e-commerce experience.

F. System Output and Result Analysis

A local data storage layer will facilitate the architecture by storing product information, logs of user interactions, shopping cart details, and history of sentiments. The data layer provides continuity between turns of conversation to allow for a personalized experience during each session. The final chatbot response is routed back to the front-end dashboard with product recommendations based on user input through the chatbot interface. This integration of product browsing features and sentiment-aware conversation support illustrates how well the proposed architecture enhances user engagement and allows for a personalized e-commerce experience.

The Intelligent Assistant acts as a sentiment aware conversational agent during the whole shopping experience; customers have the opportunity to provide their review, comment on the item purchased through either their written experience (text) or by expressing how they feel about the item they purchased (emotional state) to the Assistant in natural language. The Assistant will use a finetuned BERT model to identify the sentiment polarity of these inputs. When the Assistant has analyzed the customer's input and recognized sentiment and review patterns, the Assistant will then dynamically recommend relevant products which match the customer's individual preferences and emotional context as demonstrated by the output of the system. The product recommendation suggestions generated by the Assistant are shown to have a direct influence on the purchase decision made by the customer and enhance the customer's ability to choose products that are a good match for their expectations.



The proposed solution has been validated by showing how customers can easily move from receiving recommendations from the chatbot to completing their purchases without leaving the interface. The chatbot enables customers to add recommended products directly to their shopping cart for

purchase without leaving the interface. Additionally, the chatbot also provides customers with timely feedback and purchase confirmation messages, such as order placement confirmations, which enhances the overall satisfaction and trust customers have with the system. This flow of interaction demonstrates how sentiment analysis enables more personalized experiences for users and decreases the decision fatigue of online shoppers.

In summary, the results demonstrate that sentiment-based recommendations improved the customer experience by helping to bridge the gap between customer emotion and product selection. The completion of the purchase through the use of recommendations made by the reviews shows the viability of the proposed system in e-commerce in a real-world setting. Results suggest that integrating transformer model sentiment analysis with chatbots that assist with the purchase process creates a more engaging, efficient, and emotionally intelligent online shopping experience.

G. Performance Evaluation

Using classification metrics, the effectiveness is defined by how accurately the BERT-based sentiment analysis classifies user reviews as positive, neutral, or negative in sentiment.

In preparing the evaluation for the proposed sentiment-aware chatbot system, the dataset was divided into two parts — a training and testing subset. To ensure the fine-tuned version of the BERT was able to generalize to unseen review data from the testing subset, the model was evaluated against the test data.

The four most common evaluation metrics for sentiment analysis research, and used to evaluate the effectiveness of the BERT model for classifying user reviews based on sentiment, are Accuracy, Precision, Recall, and F1-Score.

Evaluation Metrics

Accuracy represents the total accuracy of the model and is determined by dividing the number of correctly classified samples (TP) by the total amount of samples in the dataset (TP + TN + FP + FN). Precision is a measure of how many predicted labels were actually correct among all positive predictions, whereas Recall is a measure of the model's ability to detect all instances of the positive sentiment label within a given set. F1 score provides a single metric for balancing precision and recall.

The formulas used for evaluation are defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where TPTPTP, TNTNTN, FPFPPF, and FNFNFN represent true positives, true negatives, false positives, and false negatives respectively.

Metric	Value (%)
Accuracy	92.6
Precision	91.8
Recall	92.1
F1-Score	91.9

The BERT-based sentiment classifier shows good performance at detecting customer sentiment from product reviews, achieving high levels of accuracy. The precision indicates that the chatbot generates highly accurate predictions of sentiment, therefore providing lower levels of incorrect recommendation. The high recall suggests the system does an effective job detecting the differences in sentiment that exist in the user's input. The balanced F1-score suggests that the model is performing consistently across different sentiment classes. These results support the use of transformer-based models for real-time sentiment analysis in e-commerce.

In addition, improving the accuracy of sentiment classification directly affects the response quality of chatbots and the relevance of product recommendations. The proposed system is better able to understand context than traditional machine learning methods, and therefore increases customer satisfaction and engagement while purchasing.

IV CONCLUSION

The authors of this paper developed a sentiment-driven personalized chatbot for e-commerce by leveraging the BERT (Bidirectional Encoder Representations from Transformers) model. Their approach combines sentiment analysis and real-time chatbot functionality with product recommendations to create a more engaging experience for

shoppers and an enhanced online shopping experience overall. The authors implemented a dashboard that allows users to easily browse, receive, and purchase products all within the same interactive environment. The authors' experimentation indicates

that incorporating emotional intelligence into chatbots will enable them to respond to customers in a more human-like way, thereby supporting more informed decisions about purchases. The authors' results demonstrate the feasibility and scalability of transformer-based models for use in real e-commerce businesses.

V FUTURE SCOPE

The developed system implements sentiment-based personalization very well, though future research could explore other improvements. For example, multilingual support for sentiment analysis will allow the chatbot to cater to different users. Newer recommendation strategies like collaborative filtering and reinforcement learning could be used to increase the accuracy of the personalization engine. Other future improvements include allowing for real-time voice interactions with the chatbot and emotion detection via speech signals to provide better access for users. Implementing the system on large public cloud platforms and integrating real-time customer analysis can give the system improved scalability and performance. Other future improvements could result in a more adaptive, intelligent system that can be deployed in e-commerce at the enterprise level.

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