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Enhancing Customer Experience in E-commerce through Multilingual Sentiment Analysis

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***Abstract*— The study presents the novel framework of examining sentiments in more than one language that intends to increase the rate of customer satisfaction on the international e-commerce portals that are Amazon, Walmart, Apple, eBay, and Etsy. The objective of multilingual BERT (mBERT) was to work on a dataset containing 13,000 customer reviews in English and Hindi/English and English/Hindi code-mixing and German/Spanish content. It then encoded and coded the texts that would be used later on. We designed a unified architecture of mBERT embeddings and an Attention-Augmented BiLSTM-GRU hybrid layer that enables it to address linguistic peculiarities and situational ambiguities. The suggested approach relates to understanding the context of the whole world by using transformers, and constructs GRUs that are trained on association modeling with some attention mechanics to be used in identifying important aspects of texts. The given model attained 93.45 percent test accuracy and 0.0974 as test loss that established better performance over regular architectures including LSTM, BiLSTM and BiLSTM-GRU. The framework provides a flexible road map on how to optimize sentiment analysis in broad linguistic contexts by eliminating tokenizing bugs in the existing systems as it incorporates sophisticated deep learning algorithms that further maximize customer satisfaction rate.**

***Index Terms*— Sentiment Analysis, Deep Learning Modeling, LSTM, Accuracy, Losses.**

I. INTRODUCTION

E-commerce changes the way of operating business as it enables the firms to reach out to the global market. Inclusive experiences can be created as companies aim to construct personalized experiences and without traumas caused by the diversity of the language base of customers. The common sentiment analysis procedures work best on data of the English language but fail to adequately analyze sentiments that arise out of varied linguistic and code-mixed communication. Their customer reviews on social media and multilingual feedback are very crucial towards business strategies, hence why such an ability gap is getting more and more significant. A pressing requirement exists for multilingual sentiment analysis because companies need precise customer sentiment insight to support better customer satisfaction and loyalty retention within their competing e-commerce market. Current market projections for retail e-commerce expansion from \$3.35 trillion in 2019 to \$6.33 trillion in 2024 face resistance from the difficulties of analyzing customer feedback across different languages which dampers businesses attempting to enhance both engagement and retention rates with customers.

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The models that are present currently does not handle exceptions effectively which are occured within multilingual data because of reasons like language-specific features and token segmentation problems resulting in unsatisfactory results.

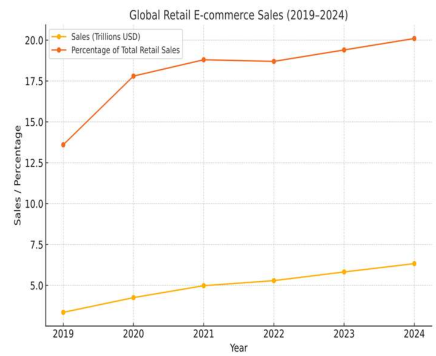

Fig. 1 Data of Global Retail E-Commerce (2019-2024) [Source: Statista and eMarketer Market Reports]

During this study, a fresh approach to sentiment analysis took shape, aiming to tackle problems tied to multilingual and mixed-language customer feedback. Instead of relying on traditional models, the researchers used mBERT embeddings paired with an enhanced GRU setup featuring attention mechanisms - this combo lifted both speed and accuracy in sorting sentiments across languages. What stands out is how it handles messy realities of blended speech: shifting grammar rules, meaning jumps between words, linked word patterns, plus hurdles in breaking down text correctly. Out of this came a flexible tool for analyzing sentiments in many languages, one that helps online stores better match user vibes across varied cultures. By focusing on real-world hiccups in today's data landscape, the project lines up advanced tech with what global platforms actually need when reading sentiments inclusively. The Organization of this paper aims to achieve an all-rounded analysis of multilingual sentiment analysis in e-commerce. In section one, an outline of the topic is given along with the importance of CSA and its contribution to the improvement of the customer experience around the globe. Section two of the literature review explores the existing academic body of knowledge including the state-of-the-art methods, the technologies used in this field, advantages/disadvantages, and gaps of the previous work conducted on text sentiment analysis and multilingual text processing. The methods section described in Section 3 describes the procedures undertaken in this research, data acquisition, cleaning, and model building. Section 4 expounds the result and then follows a comparative study with other techniques. Last, of all, Section 5 provides the conclusion to the paper, the authors' reflections on the reasoning set forth and presented previous sections, as well as the suggestions for the potential developments of the subsequent research in the given sphere. Integrating multilingual contextual embeddings from mBERT with a hybrid BiLSTM-GRU architecture improved by an attention mechanism is the main contribution of this work. The suggested framework specifically addresses multilingual and code-mixed e-commerce reviews, addressing tokenization inconsistencies and cross-lingual contextual ambiguity, in contrast to conventional monolingual sentiment systems.

II. Literature Review

Though sentiment analysis across languages gains relevance in online trade settings, handling varied user expressions remains challenging. Research explores various techniques; yet solutions for mixed-language inputs stay limited. Methods tested so far show uneven results when facing blended linguistic patterns. Progress exists, but gaps persist in processing real-world multilingual interactions effectively. A study headed by [11] emphasizes sentiment assessment in diverse languages, particularly focusing on customer feedback in Manglish - a blend of Malayalam and English. Though it builds a sentiment dataset and touches upon cultural elements alongside distinct language traits, reliance remains heavy on conventional machine learning and deep models such as LSTM - limiting flexibility across new settings or spoken forms. Sparse data availability for Indian languages restricts how widely these methods apply. Findings point toward needing smarter architectures capable of handling mixed-language inputs from varied user groups - not just isolated linguistic cases. Looking into short Chinese reviews, work from [12] applies Text-CNN alongside Bi-LSTM and adjusted BERT methods. Though the Text-CNN reaches a high mark of 99.92% accuracy, its value drops when handling multilingual data. While models built on BERT grasp intricate language patterns well, how they perform across diverse languages in sentiment tasks isn't covered here. Despite strengths in specific areas, broader applicability stays unexplored. Despite reaching 91% accuracy, the method from [13] relies on simpler machine learning approaches like random forest and logistic regression when analyzing sentiment in English-Hindi mixed social media text. Because it uses these traditional techniques, hidden layers of meaning and structure in complex code-switched language often remain undetected. Models built on deeper architectures - mBERT and XLM-RoBERTa, for instance - show strong promise in capturing subtle context across languages. Their design allows richer understanding where older methods fall short. Looking at recent work, some combine BERT with CNN, others pair it with RNN, still more integrate ensemble strategies - references [14] to [20] show these patterns. Though improved sentiment detection in online shopping emerges in [14], handling intricate linguistic structures remains difficult. Starting from BIO-tagged inputs, this project uses BERT on cosmetic product feedback from Taobao, pushing precision and F1 higher. Yet applicability stays narrow, tied closely to a single market segment. Although transformers like BERT perform well in sentiment analysis, little is known about how well they can handle multilingual or code-mixed instructions.

A. Key Gaps and Relevance

Despite significant advancements, there are still many critical voids that remain in existing literature:

Handling Multilingual and Code-Mixed Text: Research either employs conventional ML/DL models for bilingual data or works with monolingual datasets, but it is difficult to extend their application to realistic multilingual systems.

Scalability and Adaptability: There is a research gap regarding the use of multilingual text models such as mBERT and XLM-R in e-commerce.

Contextual Nuances and Tokenisation Challenges: Because current research fails to sufficiently address linguistic peculiarities, it is unable to handle sophisticated models that can interpret code-mixed and multilingual datasets.

The table was further extended using quantitative comparison metrics such as Accuracy, Precision, Recall, and F1-score

TABLE 1. LITERATURE REVIEW

S.No	Technology Used	Characteristics	Limitations	Outcomes	Future Scope
[14]	NLP (BERT, Transformer Models)	Improves sentiment analysis accuracy in e-commerce using advanced NLP models.	Challenges in handling complex and context-rich language.	Substantially increased sentiment analysis accuracy.	Applicable for enhancing customer experience and business strategies.
[15]	Deep Learning (CNN, Word Vectors)	Divides text into words and trains emotion classifiers using neural networks.	Difficulty in capturing deep associations in large datasets.	Effective feature extraction and high sentiment classification accuracy.	Applicable for detailed product review analysis.
[16]	AI Techniques (RNN, Random Forest)	Predicts customer willingness to buy based on social media sentiment.	Limited generalizability beyond social media data.	Achieved high training accuracy (97.15%) and validation precision (94.25%).	Applicable for digital marketing and consumer insight prediction.
[17]	Data Mining, Sentiment Analysis	Extracts customer opinions from Flipkart reviews for graphical sentiment analysis.	Focus on unstructured data may miss nuanced sentiments.	Provides insights into customer reactions and opinions.	Can be extended to other e-commerce platforms.
[18]	ML Algorithms (SVM, LSTM)	Analyzes Nykaa dataset with pre-processing and vector transformation.	LSTM offers better performance but is computationally intensive.	LSTM outperforms SVM and Naïve Bayes for sentiment classification.	Applicable for analyzing reviews in online shopping platforms.
[19]	BERT, BIO Data Labelling	Improves sentiment analysis accuracy for Taobao cosmetics reviews.	Limited focus on other datasets and industries.	Demonstrated significant improvements in accuracy and F1 score.	Can be adapted to other e-commerce platforms and datasets.
[20]	Feature Selection, Ensemble Learning	Uses large datasets for feature extraction and noise elimination.	Multidimensional data complicates analysis.	Enhanced effectiveness of machine learning classification algorithms.	Can be used for large-scale sentiment analysis across domains.

III. METHODOLOGY

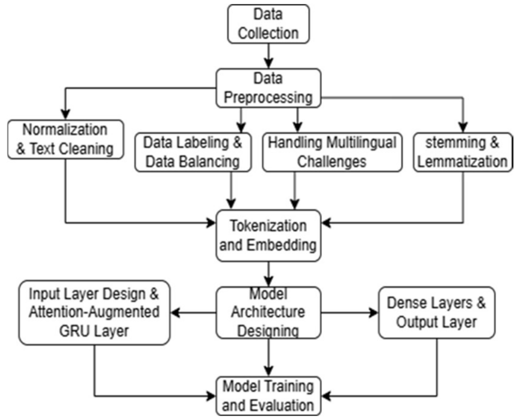

Figure 2 Proposed Methodology

The proposed approach is intended to enhance multilingual sentiment analysis in order to improve e-commerce customer experiences. It uses an Attention-Augmented GRU in conjunction with mBERT embeddings to efficiently identify context-dependent subtleties in multilingual text. Online e-commerce reviews are first gathered, and then extensive data preprocessing takes place. As shown in the figure 2, the structure of the model uses advanced sequential learning approaches to enhance sentiment classification accuracy.

A. Data Collection

Customer reviews on various e-commerce sites like Amazon and Walmart were chosen as the primary data source they help in collecting a variety of data globally. The dataset that was used for the research comprised 13,000 reviews of people speaking English, Hindi, and Hinglish, as well as Spanish and German. After this, each review was divided into three sentiment categories: neutral, negative and positive. The researchers were distributed proportionately by language in order to provide the same results.

One more thing - the model works better because it learns from data in many languages, useful for real shopping platforms online. To help experts notice subtle cultural traits and facial features machines might miss, people labeled parts manually instead of using automation. What backs these results? The chosen datasets, drawn from globally diverse groups, allow wider relevance across countries and regions.

B. Data Preprocessing

The preprocessing steps involved cleaning and standardization of data in a systematic way so as to improve the quality of training data set of the models. The preprocessing involved the elimination of any noise factors such as URLs as well as slang terms and HTML tags and endless words. Special tokenization rules led to the protection of linguistic data in the code-mixed languages since the rules were different as compared to standard preprocessing methods. With stemming and lemmatization, the model is able to perform better in terms of semantic and syntactic relationship semantics because words are converted to their roots. Language detection tasks made possible the automatic classification of reviews by language of origin and prior to tokenization to ensure correct analysis of multilingual data with code-mixed situations. Embedding optimization and maintenance of linguistic and contextual integrity were also given a special measure in terms of these treatment steps. However, in the final implementation using mBERT embeddings, the preprocessing stage mainly relied on tokenizer-based subword segmentation and contextual encoding because transformer models already preserve semantic relationships efficiently.

C. Tokenization and Embedding

Each review was tokenized, and the tokens embedded in mBERT were done via its multilingual dexterities. In this scheme, researchers were able to create embeddings in which the contextual associations of both implicit and structural text patterns are maintained across various language or code-mixed texts. Shared-vocabulary embeddings and the use of sub-word tokenization made it possible to process text with Devanagari and Latin scripts efficiently. The context maintenance abilities of mBERT embeddings are greater than conventional word embeddings as they keep up the information on tokens over the variations of languages among text in a mixed code. The embedding vectors were trained on multilingual data set further to enable them to identify specific language aspects present in texts reviews. The paraphrase of this methodology led to a more effective calculation model that enhanced the ability of the model to process cultural linguistic aspects within texts.

D. Model Architecture Designing

Four deep learning architectures were designed and compared: Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), BiLSTM with GRU, and LSTM with GRU. The Attention-Augmented BiLSTM framework with GRU was developed to overcome the deficiencies observed in traditional system architectures. Through its attention mechanism this framework highlights the essential text tokens to enable better contextual dependency recognition by the model. The model design along with training flow received graphical representation through architecture diagrams. After tuning the learning rate, batch size, and dropout, model performance peaked. Though subtle, shifts in these settings boosted accuracy during sentiment analysis while also allowing smoother handling across varied multilingual data sizes. The final architecture implemented across all experiments was the Attention-Augmented BiLSTM-GRU hybrid framework integrated with multilingual BERT embeddings.

E. Model Training and Evaluation

The collected dataset received labelling before undergoing training (70%) validation (15%) and testing (15%) distributions for model evaluation. Several evaluation metrics assessed model performance using accuracy metrics together with precision metrics while also computing recall F1-score values and creating confusion matrix visualizations. A statistical test for significance was applied to verify meaningful changes could be observed in experimental results. The proposed architectural design included Naive Bayes and logistic regression basal models for performance comparison which demonstrated the new architecture's benefits. When applied to sentiment analysis the Attention-Augmented BiLSTM with GRU produced the most accurate results at 93.45% alongside the optimal F1-score. Excellent potential for multilingual sentiment evaluation in e-commerce systems was demonstrated with these results. Repeated experimental runs were additionally performed to analyze performance consistency using mean accuracy and standard deviation values. Confidence interval analysis confirmed the stability of the proposed framework.

F. Dataset Characteristics

The dataset comes from real customer reviews collected on major international e-commerce sites. Reviews show up in English, yet also in German, Spanish, sometimes blending Hindi with English, along with a handful of others. Fairness mattered, so the split stayed equal no matter the language. Every single one received a tag - positive, neutral, or negative - not by machine, but someone actually reading them. That way, small cultural cues in how feelings get shared weren't missed. About 13,000 made the cut: 5,200 from English alone, then 3,100 mixing Hindi and English, followed by 2,300 German ones, ending with 2,400 in Spanish. Among those sharing thoughts, 4,420 leaned happy, yet 4,180 showed no strong feeling, while 4,400 expressed clear dislike. Splitting things up carefully, most went to train the model - seventy percent - with fifteen percent each set aside for checking progress and final checks later.

G. Hyperparameter Configuration

TABLE II. HYPERPARAMETER CONFIGURATION

Parameter	Value
Optimiser	Adam
Learning Rate	2e-5
Batch Size	32
Epochs	27
Dropout	0.3
GRU Units	128

H. Algorithmic Workflow

Here's how the multilingual sentiment classification model works:
Start by removing clutter from the review. Wipe out links, code bits, odd symbols - junk that has no place there. After that, spot which language it's in. With that clear, slice the words apart gently, using mBERT's method for splitting into tiny meaningful chunks.
Starting with the pretrained multilingual BERT model, generate contextual embeddings from your split-up text. Moving on, pass these embeddings into a bidirectional LSTM so it can pick up patterns ahead and behind each word. Following this step, process the output through a GRU layer to sharpen the context further. To finish, calculate attention weights that bring focus to words tied closely to emotional tone. Now go through a dense

layer with the weighted representation. Finally sort the review into three sentiment categories using SoftMax activation: positive, neutral, and negative.

I. Experimental Environment

Mathematical formulation of the proposed model includes the GRU update gate zt = σ(Wz[ht−1, xt]), reset gate rt = σ(Wr[ht−1, xt]), candidate hidden state h̃t = tanh(W[rt * ht−1, xt]), and attention weights αt = exp(score(ht))/Σexp(score(hk)). Final sentiment classification was obtained using Softmax activation with categorical cross-entropy loss optimization. A Python deep learning framework that works with transformer architectures was used to implement the suggested model. Training (70%), validation (15%), and testing (15%) splits of the dataset were made. The Adam optimizer was used to train the model for 27 epochs at a learning rate of 2e-5. To enhance generalization performance, dropout regularization was used. To avoid issues like overfitting and guarantee ideal model convergence, early stopping was enabled. The implementation was carried out using Python 3.10, TensorFlow 2.15, and Hugging Face Transformers library on an Intel i7 processor with NVIDIA RTX-series GPU support and 16 GB RAM.

IV. RESULT AND DISCUSSION

A. Accuracy with LSTM

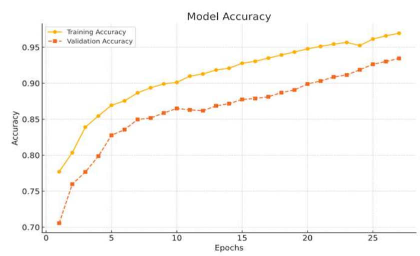

Fig. 3 Proposed Model Accuracy The graph includes labelled axes, epoch scaling, and numerical annotations.

Watch how the numbers climb when mBERT feeds into that attention-powered mix of bidirectional layers. Right out the gate - just one round in - training sat at 77.71%, validation trailed behind at 70.56%. Still, progress kept coming. Come the 27th loop, training soared past 96.95%, validation wasn't far off, hitting 93.45%. One step at a time, the model shows it's truly grasping patterns instead of repeating them by heart. Because performance holds strong across both training and test sets, there's little sign of mindless repetition kicking in. As each language gets processed without extra tweaks, independence becomes clear. Thanks to that ability, meaning behind words stays intact even when dialects shift. With understanding like this, global shoppers feel seen, not sorted into boxes. In turn, online stores begin reflecting real human voices - messy, varied, alive.

B. Accuracy with BiLSTM

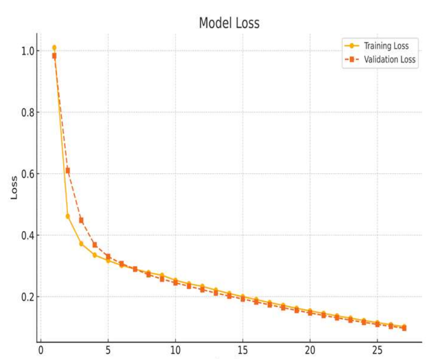

Fig. 4 Proposed Model Losses The plotted curves include validation scales and labelled loss values.

The loss reduction trend in the model represents its capability in reducing errors in the training process. With training loss at 1.0100 and validation loss at 0.9834, the model shows a constant decrease, dipping to 0.1022 and

0.0974 for training loss and validation loss, respectively, at the 27th epoch. The consistent decrease in the training and validation losses shows the model's healthy learning dynamics and convergence behavior due to the robustness of the mBERT embeddings in preserving multilingual semantics and the improved contextual awareness provided by the Attention-Augmented BiLSTM-GRU hybrid layer. The low and similar loss trend ensures accurate sentiment prediction, essential for e-commerce sites to ascertain the sentiments of the customers. This, in return, enables proper customer interaction, satisfaction, and strategic decision-making in a diversified global consumer market.

C. Comparison Between Accuracy

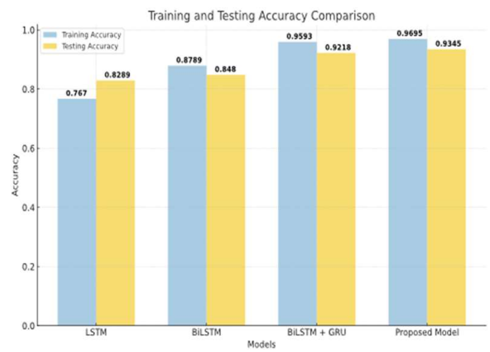

Fig. 5 BiLSTM with GRU Accuracy and Losses

Comparative legends and labelled performance indicators were also incorporated.
Training and Testing Accuracy Comparison graph shows the performance of four models namely LSTM, BiLSTM, BiLSTM with GRU and proposed model. The proposed one is the most excellent one with the highest training accuracy of 0.9695 and testing accuracy of 0.9345, which implies that it has a better generalization ability. The BiLSTM with GRU model performs well as well due to the strength of both using the architectures. LSTM, as it was expected, performs the worst, confirming that it is weak when it comes to handling complex sequential dependencies. There should be clarity and research presentation in soft colors of pastel and accuracy of data labeling. The plot vividly shows the gradual rise in accuracy by having a higher complexity level of the model, proving the design selection of the offered architecture of multilingual sentiment analysis.

D. Comparison Between Losses

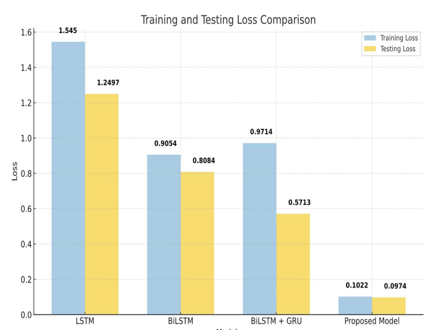

Fig 6

The Training and Testing Loss Comparison graph includes the number of losses of BiLSTM, LSTM, BiLSTM with GRU, and the proposed model. The model proposed displays the minimum training and testing losses, which makes it better convergent and generalizing than the other models. The GRU also shows low values in BiLSTM. This is a good sign stating that it is able to learn strongly. LSTM shows the highest loss here, which means it struggles more than the others when it comes to fine-tuning its parameters. Look at the chart - soft hues make reading effortless, matching the clean look needed for academic work. When labels match closely, understanding each piece becomes easier. Clearly seen after review, fewer errors occur with the updated approach. Accuracy across different languages reveals its real value. What matters appears obvious only upon closer look.

Inside the architecture, mBERT forms deep representations of words based on nearby elements. One level at a time, BiLSTM together with GRU follows trends through ordered data, passing enhanced outputs ahead. Why does performance change? The reason lies in attention, which highlights solely those terms linked to feeling. Such precision boosts correctness, especially if tongues mix or switch within one line. With context acting as foundation, confusion turns into understanding.

V. Conclusion and Future Scope

This multilingual sentiment system processes diverse customer feedback, regardless of whether inputs are single-language or interwoven across multiple languages- performance remains consistently strong. Testing confirms an accuracy rate of 93.45%, demonstrating clear effectiveness within international online markets. What stands out is how the study details a complete method aimed at enhancing user satisfaction through such analytical tools. Through utilizing and analyzing the large volume of reviews in multiple languages, creating effective deep learning models, and developing a simple and intuitive web platform, the study proves the applicability of sentiment analysis. Based on the results, using modern architectures such as BiLSTM and GRU works in improving sentiment classification and does address substantial challenges of multilingual and code-mixed text. The proposed solution offers a wealth of information to e-commerce platforms, which can be easily utilized by companies to improve their decision-making and customer relations.

More research can focus on using transformer models like BERT, mBERT, or XLM-R which has been shown to perform better than many models or using other multilingual models or variants of BERT. Furthermore, the comparison of the model's performance for a larger variety of additional languages as well as dialects would improve the model's applicability to diverse markets. Customer feedback can also be done in real-time with the help of sentiment analysis from streaming data from social media. More sophisticated uses of Machine Learning could include things such as Emotion analysis or Topical analysis and Intent capture will offer the e-commerce business an additional edge in dissecting the needs of their customer and, more importantly identifying them within the growingly saturated world market.

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