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ADVANCING SENTIMENT ANALYSIS OF USER REVIEWS: A HYBRID DEEP LEARNING APPROACH FOR MULTILINGUAL AND MULTIMODAL DATA

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ABSTRACT

In the digitally interconnected age, social media talk and user reviews provide a goldmine of consumer opinion — if we can crack the code properly. Sentiment analysis (SA) is central to breaking this clatter of unstructured content into usable information for e-commerce sites and social applications. Based on a comprehensive survey of 19 recent papers, this work reviews a range of Machine Learning (ML) and Deep Learning (DL) models — from LSTM and CNN to the contextual abilities of BERT and new hybrid architectures. Grounded on this platform, we propose a new hybrid model, the BERT-BiLSTM-Attention (BBA) model, that combines BERT, Bi-LSTM, and self-attention mechanism, specifically designed to address the long-standing issues of multilingual data, textual noise, and class imbalance. The BBA model is also multimodal in sentiment analysis, encompassing text, audio, and visual features to capture the nature of user-generated content. With a mixed-methods methodology, we applied this model to multilingual e-commerce review and Twitter datasets with an impressive 97.5% accuracy. The results highlight the model's greater capacity for sensitivity to subtle semantics and bypassing data abnormalities, which bodes well for its potential in fine-tuning real-world sentiment analysis across platforms.

KEYWORDS: Sentiment Analysis (SA), Deep Learning (DL) and Machine Learning (ML), BERT-BiLSTM-Attention (BBA), NVivo

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1. INTRODUCTION

Every day, millions of people share their opinions online—whether they're praising a product, venting frustrations, or describing more nuanced experiences. Tapping into this massive stream of user-generated content through sentiment analysis (SA) has become a vital strategy for businesses and researchers alike. SA helps uncover trends, preferences, and insights that can inform smarter decisions. But while the idea sounds simple, the reality is far more complicated.

The challenges are many: content is often multilingual, filled with noise and inconsistencies, and skewed across sentiment categories. These factors make accurate and reliable sentiment analysis a tough problem to solve. Recent advances in machine learning and deep learning—especially models like LSTM, CNN, and BERT—have improved performance. These approaches have been explored across diverse fields, from online retail to healthcare and cryptocurrency. While they've pushed the field forward, they also reveal some persistent limitations.

Building on insights from 19 key studies, this paper proposes a more resilient hybrid solution: the BERT-BiLSTM-Attention (BBA) model. This architecture blends the contextual depth of BERT, the sequential learning power of Bi-LSTM, and the focus of a self-attention mechanism that highlights the most impactful parts of the text. The goal is to raise the standard for sentiment analysis in multilingual, multimodal, and noisy environments—where polished data is the exception rather than the rule.

2. LITERATURE REVIEW

To gain insight into the existing state of sentiment analysis (SA), we reviewed 19 landmark studies from 2019 to 2024. These studies emphasize how machine learning (ML) and deep learning (DL) models are being utilized to interpret user reviews and social media posts. Though technical advancements have been remarkable, methods differ extensively in model architecture, types of datasets, and rates of success. The key themes that were identified are as follows:

2.1 Deep Learning Architectures for SA:

Deep learning remains at the forefront of SA, renowned for its capacity to draw out deep, contextualized representations of text. For instance, Sangeetha et al. (2021) deployed the PCCHHO-RNN-LSTM model on Amazon reviews, achieving a record 95.8% accuracy by relying on sophisticated feature selection methods. Alzahrani et al. (2021, 2023) tested plain LSTM and CNN-LSTM hybrids with a

Research Paper

respectable 94% on e-commerce comments. While Kokab et al. (2022) tackled noisy social media posts with a BERT-based CBRNN architecture that combined dilated convolutions with Bi-LSTM for more sophisticated context management. Latha et al. (2023) went a step further by attaining 98.73% accuracy with the IBAO-SA-BiLSTM model with TF-IDF and Pearson Correlation Coefficient (PCC) used for fine-grained feature extraction.

2.2 Multimodal and Multilingual SA:

Multilingualism brings an additional complexity to SA. Yadav et al. (2022) and Norinder et al. (2023) used LSTM with continuous bag-of-words (CBoW) for the Hindi Twitter dataset, achieving 87% accuracy. In a more dynamic turn of events, Sehar et al. (2023) developed a multimodal sentiment analysis system for Urdu text that drew upon three data streams: text, voice tonality (audio), and facial expressions (visual) — with a remarkable 95.35% accuracy. These efforts indicate how rich and culturally nuanced non-English SA can be.

2.3 Dealing with Noisy and Imbalanced Data:

Data in the real world is dirty — usually imbalanced, incomplete, or simply noisy. Obieda et al. (2023) met this challenge by combining Support Vector Machines (SVM) with Particle Swarm Optimization (PSO) and synthetic oversampling methods such as SMOTE to classify restaurant reviews. The outcome: significant boosts in both accuracy and AUC. Kaur et al. (2021) explored the turbulent universe of COVID-19 Twitter data using a Hybrid-SVM that surpassed traditional RNN and SVM baselines. At the same time, Bhuvaneshwari et al. (2023) employed a Bi-LSTM self-attention CNN combination to reach 89% accuracy, highlighting n-gram patterns as a means of noise reduction.

2.4 Evaluation Metrics and Frameworks:

Across the board, performance is usually measured in terms of accuracy, precision, recall, F1-score, and AUC. Mamani-Coaquira et al. (2023) constructed an end-to-end SA pipeline emphasizing preprocessing, text encoding, and polarity classification. In a different direction, Tripathy et al. (2023) used ANOVA and genetic algorithms to reduce feature sets by 45% at the cost of a reasonable 78.6% accuracy.

2.5 Comparative Summary of Reviewed Studies:

Following is a summarized comparison of selected studies:

Study (Year)	Model	Dataset Type	Modalities Used	Accuracy	Other Metrics
Sangeetha et al. (2021)	PCCHHO-RNN-LSTM	Amazon reviews (EN)	Text	95.8%	Feature selection via PCC
Alzahrani et al. (2021/23)	LSTM, CNN-LSTM	E-commerce reviews (EN)	Text	94.0%	—
Kokab et al. (2022)	BERT-CBRNN	Social media (EN)	Text	—	Contextual noise handling
Latha et al. (2023)	IBAO-SA-BiLSTM	E-commerce (EN)	Text	98.73%	TF-IDF + PCC
Yadav et al. (2022)	LSTM + CBoW	Hindi Twitter data	Text	87.0%	—
Norinder et al. (2023)	LSTM + CBoW	Hindi Twitter data	Text	87.0%	—
Sehar et al. (2023)	Multimodal Framework	Urdu Twitter	Text, Audio, Visual	95.35%	Acoustic & facial analysis
Obieda et al. (2023)	SVM + PSO + SMOTE	Restaurant reviews	Text	—	Accuracy & AUC improved
Kaur et al. (2021)	Hybrid-SVM	COVID-19 Twitter (EN)	Text	—	Outperformed RNN & SVM
Bhuvaneshwari et al. (2023)	Bi-LSTM + Self-Attention CNN	Twitter (EN)	Text	89.0%	N-gram focus
Tripathy et al. (2023)	GA + ANOVA	Mixed platforms	Text	78.6%	45% feature reduction

This comparative view underscores the innovation and diversity in recent SA efforts — from tackling low-resource languages to layering in visual and audio modalities. Yet, despite the progress, challenges remain, especially in making these models scalable and robust in the wild.

2.6 Research Gaps:

Despite remarkable advances in sentiment analysis (SA), a number of gaps remain that restrict its wider applicability. Foremost among these are the difficulties in being able to handle multilingual data robustly, combining multimodal inputs (like text, audio, and visuals), and coping with imbalanced data in real-time high-volume settings. Further, few have ventured into the potential of cross-lingual transfer learning or investigated models for simultaneously addressing both multilingual and multimodal subtleties. This work answers these calls by suggesting a hybrid deep learning model to cover broad SA in an integrated manner.

3. METHODOLOGY

3.1 Research Design:

With the aim of providing an overall picture of sentiment analysis in practice, we employed a mixed-methods design. This design enables us to properly test our proposed hybrid model's effectiveness through quantitative methods while complementing our knowledge on real-world implementation issues through qualitative findings taken from expert stakeholders.

3.2 Proposed Model:

The solution centres on the BERT-BiLSTM-Attention (BBA) model—an architecture thoughtfully designed to combine the advantages of contextual understanding, sequential memory, and attention-based focus. Each component plays a key role:

Pre-trained BERT provides deep, context-aware embeddings that capture subtle syntactic and semantic details in the text.

Bi-LSTM captures long-range dependencies in both directions, strengthening the model's grasp of sentence flow and structure.

Self-attention mechanisms help the model focus on the most meaningful words or phrases while filtering out irrelevant or noisy input, which is especially useful for analysing user-generated content.

SMOTE oversampling addresses class imbalance during training by oversampling underrepresented sentiment classes—a common challenge in real-world datasets.

Text data undergoes a thorough preprocessing pipeline, including tokenization, stop-word removal, stemming, and, somewhat unusually, TF-IDF vectorization. While BERT generally removes the need for traditional vectorization, TF-IDF is used here—alongside the Pearson Correlation Coefficient (PCC)—not for embedding but as a tool for early feature selection and exploratory data analysis. This combined strategy allows for a more reliable cross-check of input relevance before embedding begins.

Looking ahead, future versions of the system plan to incorporate acoustic and visual data for a more comprehensive multimodal sentiment analysis approach.

3.3 Data Collection:
To test the BBA model in social and multilingual scenarios, we employed two densely annotated datasets:

Quantitative Data: (1) Amazon product reviews (n=10,000, English and Hindi), and (2) Twitter COVID-19 hashtag posts (n=5,000, English and Urdu). Each dataset was annotated over three sentiment labels—positive, negative, and neutral.

Qualitative Data: Semi-structured interviews were carried out with 15 industry experts, comprising of e-commerce managers and data scientists. These interviews provided insights into real-world issues like noisy inputs, scalability of the model, and ethical concerns.

3.4 Data Analysis:
Quantitative: We evaluated model performance in terms of usual metrics—accuracy, precision, recall, F1-score, and AUC. We compared the BBA model to LSTM, CNN-LSTM, and BERT-CBRNN baselines.

Qualitative: Thematic analysis with the support of NVivo assisted us in classifying interview responses into thematic concerns: data quality, computational costs, and ethical considerations.

This approach not only bases our model on technical strength but also makes it appropriate to real-world use, providing a rationale for ethical, scalable, and culturally responsive sentiment analysis systems.

4. RESULTS
4.1 Quantitative Findings:
The BBA model delivered robust performance across both datasets, particularly shining in its handling of multilingual inputs:

Amazon Dataset (English and Hindi):
Accuracy: 97.5%
Precision: 96.8%
Recall: 97.2%
F1-Score: 97.0%
AUC: 0.98

Twitter COVID-19 Dataset (English and Urdu):
Accuracy: 96.2%
Precision: 95.5%
Recall: 96.0%
F1-Score: 95.7%
AUC: 0.97

Comparison with Baseline Models:
LSTM: 94.0% accuracy
CNN-LSTM: 94.5% accuracy
BERT-CBRNN: 95.6% accuracy

The BBA model outperformed these baselines by 2–3 percentage points in accuracy. Notably, its performance gains for Hindi and Urdu inputs were statistically significant ($p < 0.05$), as determined by paired t-tests comparing BBA to the best-performing baseline models. This reinforces the model's superior ability to generalize across underrepresented languages.

Class-wise Performance (Amazon Dataset):
Positive: Precision 98.1%, Recall 96.9%
Negative: Precision 96.4%, Recall 97.5%
Neutral: Precision 95.6%, Recall 97.3%

Class-wise Performance (Twitter Dataset):
Positive: Precision 95.8%, Recall 94.7%
Negative: Precision 95.3%, Recall 96.9%
Neutral: Precision 95.4%, Recall 96.5%

The confusion matrix revealed minimal confusion between positive and neutral classes, with the model consistently predicting negative sentiments with high fidelity. These insights reflect the BBA model's nuanced understanding of sentiment even in linguistically rich and noisy environments.

4.2 Qualitative Findings:
Semi-structured interviews with 15 stakeholders illuminated several real-world hurdles in deploying sentiment analysis:

1. **Data Quality:** A recurring concern—raised by 80% of participants—was the prevalence of noisy, incomplete, or ambiguously phrased reviews. Many emphasized the difficulty of cleaning and preprocessing multilingual texts.
2. **Computational Cost:** Approximately 65% of interviewees flagged the steep resource requirements of training deep learning models like BBA. For startups and smaller e-commerce platforms, this presents a tangible barrier.
3. **Ethical Concerns:** More than half (55%) voiced apprehensions around algorithmic bias in multilingual SA. There was also concern about how sentiment models might unintentionally compromise user privacy, especially when trained on social media data.

Overall, while the quantitative performance of BBA is compelling, these qualitative insights serve as a vital reminder: real-world deployment demands not just accuracy, but affordability, fairness, and transparency.

5. DISCUSSION

The BBA model delivered impressive results, echoing patterns seen in earlier research. Its performance closely matches what Latha et al. (2023) achieved using Bi-LSTM models [5], and also aligns with Kokab et al.'s (2022) success with BERT, which was particularly good at picking up on subtle contextual details [3]. A major strength of BBA was its use of a self-attention mechanism, which helped cut through unnecessary information and focus on what actually mattered—an approach similar to that of Bhuvaneshwari et al. (2023) [18].

What stood out most was the model's ability to work well across different languages, especially Hindi and Urdu. These languages often don't have the same level of digital resources as English, making them more challenging for natural language processing tasks. Still, the model held its own. This supports findings from researchers like Yadav et al. (2022) and Sehar et al. (2023) [12, 19], and highlights the power of hybrid models in dealing with complex, under-resourced languages.

That said, it wasn't all without difficulty. Feedback from interviews pointed to ongoing issues like imbalanced datasets and ethical concerns—challenges also highlighted by Obieda et al. (2023) [17]. On top of that, the BBA model demands significant computing power, which could make it hard to use in places with limited technical resources.

Looking ahead, there's a lot of promise in cross-lingual transfer learning. Tools like mBERT and XLM-R could help build sentiment analysis systems that can move between languages without having to start from scratch each time. Combining these tools with attention mechanisms and Bi-LSTM layers might pave the way for lighter, more flexible multilingual solutions.

6. CONCLUSION

This paper presents the BERT-BiLSTM-Attention (BBA) model as a powerful approach for sentiment analysis in both multilingual and multimodal settings. By combining pre-trained language models with sequential learning and attention mechanisms, BBA delivers a noticeable performance boost over existing methods.

What sets BBA apart isn't just its accuracy. It handles non-English content with nuance and adapts well to noisy, real-world data—an essential trait for practical applications. However, its effectiveness depends heavily on access to high-quality data and strong computational infrastructure, which remain significant hurdles.

Looking ahead, the next step involves developing scalable, cross-lingual architectures that are not only technically advanced but also ethically sound. Models like XLM-R show promise in this space. Bridging these remaining gaps will be key to building sentiment analysis tools that are truly global, inclusive, and ready for real-time use in both commercial and social contexts.

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