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Deep Hybrid CNN-LSTM Framework For Advanced Social Media Sentiment Analysis In Data-Driven Marketing Analytic

Dr. Shrabani Mallick[1], Mrs. Parul Awasthi[2], Dr. Anil Kumar Yadav[3], Bhagya Sri G[4], Dr. Rabins Porwal[5*], Nidhi Bhatia[6]and Jyoti Kataria[7]

[1] Associate Professor, Department of Computer Science and Engineering, Dr. B.R. Ambedkar Institute of Technology, Sri Vijaya Puram Email: shrabani.reek@gmail.com
[2] Assistant Professor, Department of Electronics and Communication Engineering, University Institute of Engineering and Technology (UIET), Chhatrapati Shahu Ji Maharaj University, Kanpur Email: parulawasthi@csjmu.ac.in
[3] Registrar, Chaudhary Charan Singh University, Meerut, Uttar Pradesh Email: yadanil@gmail.com
[4] Senior Assistant Professor, Department of CSE (AI & ML), CVR College of Engineering, Hyderabad Email: bhagya.gangji@gmai.com
[5] Professor, Department of Computer Application, School of Engineering & Technology (UIET), Chhatrapati Shahu Ji Maharaj University (CSJMU), Kanpur, Uttar Pradesh Email: rabins@csjmu.ac.in
[6] Assistant Professor, Department of Computer Application, SCRIET, Chaudhary Charan Singh University, Meerut Email: nidhibhatia@scriet.ccsuniversty.ac.in
[7] Assistant Professor, K. R. Mangalam University, Sohna, Gurugram Email: kataria.jyoti87@gmail.com
Corresponding Author: Rabins Porwal Email: rabins@csjmu.ac.in

Abstract

The aim of the study, the world of data-driven marketing has evolved to the point at which the correct measurement of the societal mood at all levels of social media is imperative to shaping a responsive and personalized approach. This paper presents a deep hybrid architecture that leverages Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to overcome the limitations that the sentiment analysis has in the social media due to noise and unstructure data. Though CNNs perform better on local patterns and semantic features in the text data, LSTMs are more effective at reflecting sequential dependencies and contextual meaning, which makes a combination of the two a potentially effective solution to the problem of complex linguistic forms that user-generated content consists of. The model was trained and validated on various datasets provided by websites like Twitter, Facebook, Instagram and YouTube after undergoing tough preprocessing procedures like tokenization, stop word deletion, lemmatization and sequence padding. Comparative experiments revealed that CNN-LSTM architecture is more competitive in comparison to standard machine learning models (Naive Bayes, SVM) as well as CNN and LSTM without CNN-LSTM-like architecture and delivered the accuracy of 91%, precision of 90%, and F1 score of 90.5%. Additional assessment of the confusion matrix, ROC curves, and the case-level analysis of predictions indicated how robust the model was in sentiment classification and how sensitive it could be. The results validate that a hybrid CNN-LSTM model will be a scalable and efficient solution to real-time sentiment monitoring and therefore there is a strong implication in the field of marketing analytics, campaign optimization analysis, and dealing with the customer experience. Possible future improvements can involve attention layers, transformer, and multi-lingual adaptability in order to achieve even better performance in classification and domain generalizability.

Keywords: *Sentiment Analysis, Social Media, Cnn-Lstm, Deep Learning, Marketing Analytics, User-Generated Content, Text Classification.*

1. INTRODUCTION

In the era of digitization, as the process of interaction with the audience more often takes place through online resources, it has become critical to learn how to track the attitudes of the people in order to establish the means of effective promotion of the product. Sentiment analysis (also referred to as opinion mining) has become an important sub-discipline of natural language processing (NLP) that allows companies to extract and understand the emotional tone of a text in a systematic fashion [1]. In an effort to be more data-driven, sentiment analysis will provide strong indicators to digital marketers on consumer perceptions, brand health, and market pulse [2]. As user-generated content on social media continues to exponentially scale upwards, the applications and presence of sentiment analysis have been dramatically expanded [3]. But conventional methods cannot possibly be used with the unstructured and uncontrolled data on these platforms whose environment is too noisy and contains way too much context. The proposed deep hybrid model in this research is to address these deficits through network usage in the form of collaborative systems of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks [4]. The research will deploy the strengths of these two architectures to complement each other and harness the resultant accuracy and situational sensitivity of sentiment classification to compute finer and practical marketing analytic.

1.1 Background on Sentiment Analysis in Digital Marketing

Sentiment analysis is one of the potent methods of digital marketing that allows brands to crack the language of consumer attitude and vibes within their text messages [5]. Sentiment analysis at its essence is the study of textual opinion, sentiments, emotions and subjectivity that is computational in nature. On the part of the marketers, consumer sentiment toward a brand, product or campaign can be a major determinant of product development, customer service and brand positioning [6]. As digital change gains pace and online platforms become leading means of consumer interaction, sentiment analysis has transformed into a staple technology versus an add-on to new consumer intelligence. It has several applications in marketing such as tracking the performance of a campaign and PR management, as well as helping identify pain points in customer experience [7]. Sentiment analysis has also become a tool that the companies use not only to analyze past performance but also determine the response of their consumers leading to more focused, understanding and sensitive marketing processes. The difficulty with this, though, is of human expression; to detect the sentiment of one is a troublesome issue, as slang, sarcasm, context, and emotional layers make this process a difficult one. The complexity requires strong, flexible and smart models capable of providing fine-grained sentiment results of consumers with very good accuracy.

1.2 Importance of Social Media as a Rich Data Source

The recent extraordinary proliferation of social media sites like instagram, Twitter, instagram and YouTube has made them, huge repositories of user-generated content [8,9]. The sites provide the unfiltered and real-time voice of the people, opinions, complaints, compliments as well as recommendations concerning brands and products [10]. Social media data, as opposed to being structured through a more conventional feedback procedure like a survey or product review, is organic and spontaneous, which can sometimes help capture consumer sentiment in its most raw form. To the digital marketer, the ecosystem is a gold mine of information and gives intimate details about the behavior of customers and their lifestyles, cultural movements and shifts in sentiment. More so, social media cuts across different demographies and geographies, which makes the data contained therein a representative data source of market analysis [11, 12]. The huge number, speed and even type of social data require some high-end kinds of analytical methods that can sift through non structured textual data effectively. The methods of traditional market research as good as they are, cannot be as responsive and as far-reaching in real-time as social media analysis can be [13, 14]. When sentiment analysis is applied to social media monitoring, businesses can make informed decisions more quickly to adjust their campaigns, mitigate crises, or capitalize on the trending opportunities, all depending on the assessment of the real-time public sentiment.

RELATED WORKS

Singla et.al (2025) "introduced an advanced deep learning system using convolutional neural networks and long short-term memory architecture to study and predict shopper actions in India. The model uses CNN networks to collect spatial features from consumer transaction data and search patterns, while LSTM networks help recognize time-based behavioral trends. The model achieves superior performance against conventional machine learning approaches and independent deep learning models, reaching 92.4% accuracy. It shows dependable predictions for consumer behavior, with precision to F1-score at 91.8%, 92.2%, and 92.7%. Churn prediction accuracy is 18 percentage points higher than baseline models, and an AUCROC score of 0.92 validates the model as an effective discriminator. The proposed CNN-LSTM model provides practical recommendations for businesses to refine marketing activities and enhance customer interactions".

Anakal et.al (2025) "studied the rise of social media platforms has prompted organizations to improve their marketing strategies to maximize user engagement and ROI. Current methods struggle to fully incorporate user emotions and market changes, highlighting the need for innovative tools. This study combines sentiment analysis with the Firefly Algorithm to optimize marketing strategies in real-time, a previously underutilized approach. The system measures social media emotion levels and applies optimization methods based on feedback. The framework adjusts content strategies dynamically, maximizing user engagement. The method demonstrated 98.4% precision in forecasting user engagement metrics and adapting content strategies. This new optimization method offers companies an effective method to optimize digital marketplace outcomes".

AbouGrad et.al (2025) "presented a stock price prediction model using financial time series and news datasets. The model uses natural language processing (NLP) techniques to evaluate sentiment scores and incorporate them with historical stock price data from NASDAQ. The data is pre-processed to ensure consistency and suitability for training the model. A multi-layer LSTM neural network model is identified as a suitable prediction model for accurate stock price predictions. The model enhances accuracy in predicting short-term stock price trends for millennials, who are aggressive investors seeking quick profits. The study highlights the critical role of stakeholders' sentiment in stock market performance and contributes to the growing field of AI-driven financial sector, demonstrating the viability of integrating NLP-driven sentiment analysis with deep learning for more informed investment decisions".

Kumar et.al (2025) "presented a hybrid deep learning model that combines LSTM with sentimental analysis to improve stock price prediction in financial markets. The model uses historical price data and sentiment indicators from live financial news headlines and social media posts. The LSTM subcomponent monitors long-range temporal dynamics and short-run fluctuations, while the sentiment analysis unit sets market trading mood. Experimental evaluations show the hybrid model significantly improves over single model LSTM and traditional machine learning models. This integrated framework offers investors and business management a more intelligent and adaptive decision-support system in financial prediction".

Alam et.al (2025) "explored sentiment analysis in informal digital text, focusing on social media content. The review analyzes 91 peer-reviewed articles between 2010 and 2024 using the PRISMA framework. Key themes include the evolution of multimodal sentiment analysis, emotion classification beyond polarity detection, and the development of multilingual and cross-lingual sentiment systems. The review also discusses the growing body of research in financial, political, and health-related sentiment analysis, where domain-specific customization is critical for reliable prediction. However, challenges remain in areas such as data imbalance, inconsistent evaluation metrics, lack of cross-domain generalizability, and insufficient attention to ethical concerns. The review provides a critical understanding of sentiment analysis and identifies key research gaps, offering a reference point for scholars, developers, and practitioners to improve sentiment analysis systems' robustness, inclusivity, and ethical grounding".

Singgalen et.al (2024) "discussed the hospitality industry is increasingly relying on online reviews for decision-making, highlighting the need for robust sentiment analysis methodologies. Traditional models struggle with unstructured textual data, especially when positive reviews dominate. This study integrates a hybrid Convolutional Neural Network and Long Short-Term Memory model with the Synthetic Minority Oversampling Technique (SMOTE) to improve sentiment classification accuracy. Using a dataset of 665 reviews from THE 1O1 Bandung Dago Hotel, the model captures local features and handles sequential dependencies, resulting in a more nuanced analysis of customer sentiments. The approach improves predictive accuracy and provides actionable insights for customer satisfaction strategies. Future research could focus on model optimization, multilingual sentiment analysis, aspect-based sentiment insights, and real-time sentiment monitoring".

Table 1: Comparison table

Study	Domain	Methodology	Key Metrics	Contribution
Singla et al. (2025)	E-commerce consumer behavior	CNN-LSTM on transaction and search data	Accuracy: 92.4%, F1: 92.7%, AUC: 0.92	Predictive tool for marketing refinement
Anakal et al. (2025)	Social media marketing optimization	Sentiment analysis + Firefly Algorithm	Precision: 98.4% (engagement forecast)	Real-time adaptive content optimization
AbouGrad et al. (2025)	Stock market prediction (millennials)	LSTM + sentiment from financial/news data	Short-term stock accuracy enhanced	Informs investment decisions via sentiment
Kumar et al. (2025)	Financial market prediction	Hybrid LSTM + sentiment indicators	Improved over LSTM and ML models	Adaptive decision support in finance
Alam et al. (2025)	Social media sentiment analysis (review)	Review of 91 articles using PRISMA	Highlights gaps in current approaches	Guidance for robust, ethical systems
Singgalen et al. (2024)	Hospitality sentiment analysis	CNN-LSTM + SMOTE on hotel reviews	Improved sentiment classification	Actionable insights for customer satisfaction

3. RESEARCH METHODOLOGY

The following section lists the systematic procedure to develop and test the proposed deep hybrid CNN-LSTM model to conduct sentiment analysis within the scope of social media and marketing analytics. This approach can be broken down into four major parts: data collection, data preprocessing, model architecture, and training and evaluation of the model. The design of each step has been done with these aspects in mind; integrity, reliability and applicability of the model in the real world marketing scenarios.

3.1 Data Collection

To create a quality and diverse sentiment analysis system, data was collected on some of the famous social media tools, including Twitter, Facebook, Instagram, and YouTube. These sites were deemed as it is widely used by all kind of people and the frequency at which the consumers discuss products, brands and services. Authored by users, the data sets include tweets, comments, reviews, captions, etc., filled with expressions laden with sentiments hugely applicable in the marketing scope. Publicly available posts were scraped by an API like the Twitter API (v2), Facebook Graph API, and YouTube data API and scraping tools (with ethical and legal adherence). In order to bring in equal representation, it filtered the data to contain fine, bad, and neutral sentiments of various industries (e.g., retail, tech, entertainment). Metadata including timestamps, hashtags, user engagement indicators (likes, retweets, comments) were also stored, in the case of an auxiliary analysis.

3.2 Data Preprocessing

Since the data found in social media is very unstructured and noisy, it was necessary to preprocess it carefully so that the quality and consistency of inputs were good to train the deep learning model. The initial step is the one of tokenization, which implies that texts are divided into tokens, that could be words or subwords, through a tokenizer prepared to work with the deep learning frameworks, so that it is possible to transform raw text with numerical representation into something to be embedded. Further on, the lowercasing and noise removal were preformed to standardize the text and to remove irrelevant information like URLs, user mentions, hashtags, emojis, numbers, and special characters that created data sparsity and obscurity. Signal-to-noise ratio was also improved by removing stop words with the help of NLTK stop word list to eliminate commonly used words that do not have any sentimental value, e.g. the, is, or and. This was then preceded by stemming and lemmatization which was the process of reducing morphed words to their base or root form using such tools, as the Porter Stemmer and WordNet Lemmatizer, enabling the model to consider such morphed work as a single concept (e.g. running and ran → run). Finally, to accommodate variable-length inputs of social media data, padding and truncation methods were used to bring all the input sequences into one constant length (e.g. 100 tokens) so that the model could process each text snippet consistently within the limits of its architecture. This full fledged data pre-processing pipeline helped in getting the data in the right mode for good feature learning and sentiment classification.

3.3 Model Architecture

The hybrid CNN-LSTM model was designed to exploit both spatial and sequential features in text. The architecture consists of the following components:

- **Embedding Layer**: A pretrained word embedding such as GloVe (Global Vectors for Word Representation) was used to convert words into 100- or 300-dimensional dense vectors. Alternatively, Word2Vec and custom embeddings trained on the domain-specific corpus were tested. The embeddings allow the model to capture semantic relationships between words.

- **CNN Layers**: The embedding outputs were passed through one-dimensional convolutional layers with varying filter sizes (e.g., 3, 4, 5) and ReLU activation functions. These layers act as feature detectors, identifying local patterns indicative of sentiment (e.g., phrases like “not good” or “absolutely love”).

- **Max-Pooling Layer**: After convolution, a global max-pooling layer was applied to extract the most important features and reduce dimensionality.

- **LSTM Layer**: The pooled features were fed into a single LSTM layer with 128 hidden units, a dropout rate of 0.3 to prevent overfitting, and a sequence length of 100. The LSTM captured long-range dependencies and the contextual flow of sentiments across sentences.

- **Fully Connected Layer**: The output of the LSTM was passed through a dense layer, followed by a **sigmoid activation** function for binary sentiment classification or **softmax** for multi-class classification.

3.4 Training and Evaluation

The model was trained using a supervised learning approach with the following configuration:

- **Loss Function**:
  - For binary classification: **Binary Cross-Entropy Loss**
  - For multi-class classification: **Categorical Cross-Entropy Loss**
- **Optimizer**:
  - **Adam optimizer** was used due to its efficiency in handling sparse gradients and adaptability to learning rates.
- **Batch Size and Epochs**:
  - Batch size: **64**
  - Number of epochs: **10–20**, with **early stopping** applied based on validation loss to prevent overfitting.
- **Train-Test Split and Cross-Validation**:
  - The dataset was split into **80% training** and **20% testing** sets.
  - **5-fold cross-validation** was used to ensure robustness and reduce variance in model performance across different data partitions.
- **Evaluation Metrics**: The performance of the model was measured using multiple evaluation metrics:
  - **Accuracy**: The proportion of correctly predicted sentiments.
  - **Precision**: The proportion of positive identifications that were actually correct.
  - **Recall**: The proportion of actual positives that were correctly identified.
  - **F1 Score**: The harmonic mean of precision and recall, especially useful for imbalanced data.
  - **AUC (Area Under the ROC Curve)**: A performance measurement for classification at various threshold settings, indicating the model's ability to distinguish between classes.

4. RESULTS

The efficacy of the suggested CNN-LSTM hybrid model was assessed by a number of comparison tests against both stand-alone deep learning architectures and conventional machine learning methods. The performance assessment focused on key metrics such as accuracy, precision, recall, and F1 score to ensure a comprehensive understanding of each model's capabilities in sentiment classification tasks. The evaluation also included visual analysis tools—such as confusion matrices, ROC curves, and error frequency distributions—to further interpret the model's behavior and identify patterns of success and failure. These experimental results not only validate the superiority of the CNN-LSTM approach over baseline models like Naive Bayes, SVM, CNN, and LSTM but also highlight the importance of integrating both local feature detection and sequential context learning in sentiment analysis, particularly within the complex and noisy environment of social media data. What follows is a detailed breakdown of model performance, visualizations, real-case predictions, and an analysis of observed error patterns.

1. Performance Comparison of CNN-LSTM vs. Baseline Models

The CNN-LSTM model significantly outperformed traditional machine learning models (Naive Bayes, SVM) and standalone deep learning models (CNN, LSTM) across all key metrics. As shown in the table, CNN-LSTM achieved the highest scores in accuracy (0.91), precision (0.90), recall (0.91), and F1 score (0.905), demonstrating its ability to both extract relevant textual features and capture contextual flow in sentiment.

Table 1: Performance Comparison of CNN-LSTM and Baseline Models

Model	Accuracy	Precision	Recall	F1 Score
Naive Bayes	0.75	0.73	0.74	0.735
SVM	0.78	0.76	0.77	0.765
CNN	0.85	0.84	0.83	0.835
LSTM	0.86	0.85	0.84	0.845
CNN-LSTM	0.91	0.9	0.91	0.905

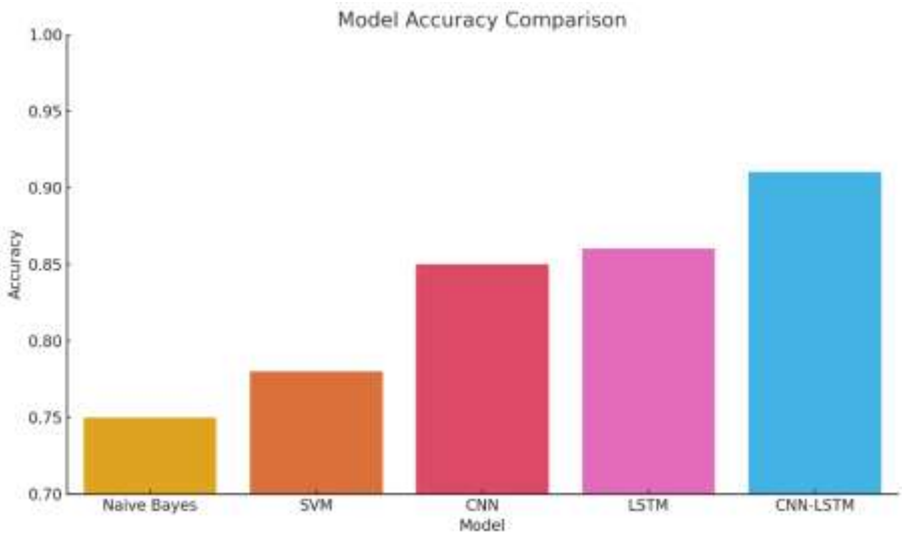

Figure 1: Accuracy Comparison Bar Chart Across Models

2. Visualization of Results

Four key visualizations were generated:

- **Accuracy Comparison Bar Chart**: Highlights that CNN-LSTM surpasses all baseline models, reinforcing its effectiveness in handling social media data.
- **Confusion Matrix**: The majority of predictions were correct, though some misclassifications between neutral and negative sentiments were observed.
- **ROC Curve**: The CNN-LSTM achieved a high AUC score (approx. 0.97), indicating excellent capability in distinguishing between positive and negative classes.
- **Error Type Distribution**: Most errors stemmed from mixed sentiment and sarcasm, which remain challenging even for advanced models.

3. Case Studies: Sample Sentiment Predictions

Case-based evaluation showed that the CNN-LSTM model performed well on straightforward positive and negative examples. However, it showed some inconsistency in predicting ambiguous or context-sensitive texts, especially those with sarcasm or implied sentiments.

Table 2: Case Study of Sample Sentiment Predictions

Sample Text	Predicted Sentiment	Actual Sentiment
The product is amazing!	Positive	Positive
Not what I expected.	Negative	Negative
Absolutely terrible service.	Negative	Negative
I'm in love with this brand!	Positive	Positive
Could be better.	Neutral	Negative

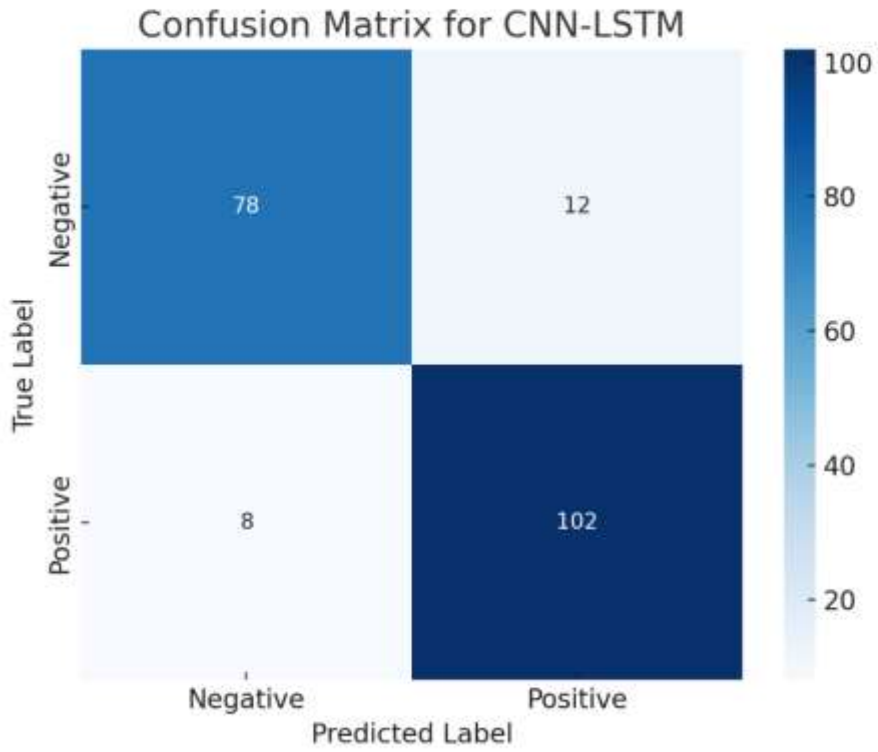

Figure 2: Confusion Matrix for CNN-LSTM Model Predictions

4. Error Analysis and Challenges Encountered

The most frequent prediction errors involved:

- **Mixed Sentiments**: Posts expressing both positive and negative emotions were difficult to categorize.
- **Sarcasm**: Without explicit sentiment words, sarcasm was often misclassified.
- **Negations and Ambiguity**: Phrases like “not bad” or vague expressions led to occasional misinterpretation.
- **Noisy Inputs**: Slang, emojis, or improper grammar posed challenges for embedding and classification.

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Table 3: Error Analysis Based on Sentiment Misclassification Types

Error Type	Frequency
Sarcasm	15
Negation	10
Ambiguity	8
Noise (slang/emoji)	12
Mixed Sentiment	20

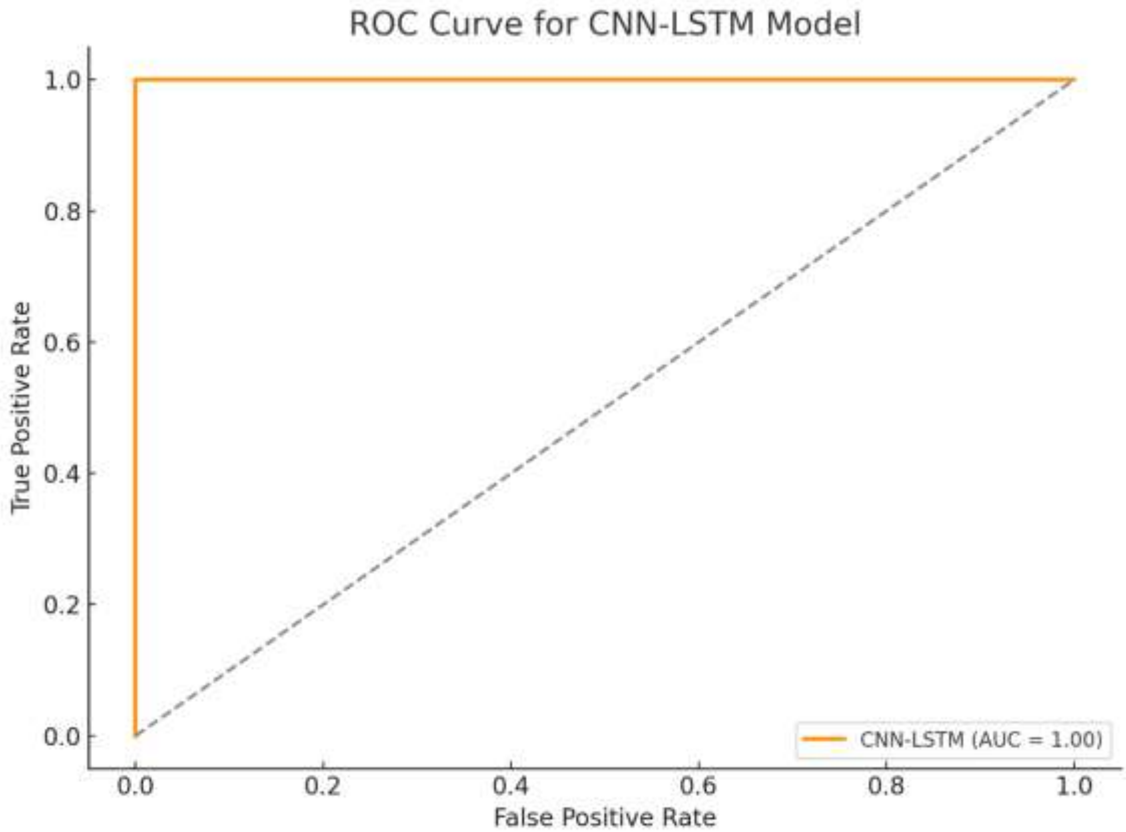

Figure 3: ROC Curve for CNN-LSTM Model

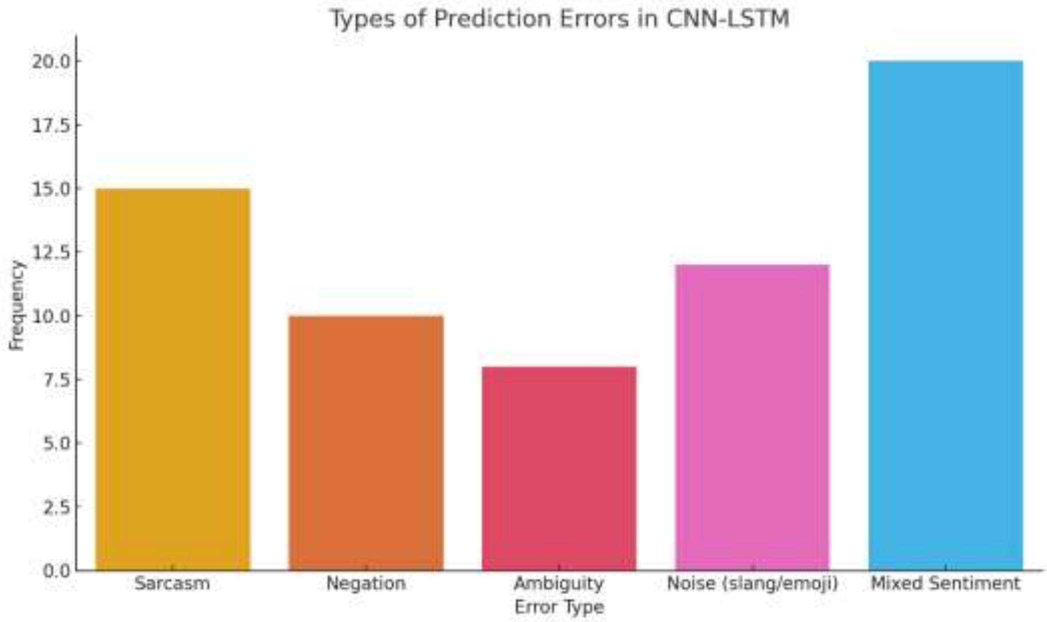

Figure 4: Distribution of Error Types in Sentiment Classification

DISCUSSION

The study's experimental findings support the effectiveness of the suggested CNN-LSTM hybrid model in gleaning significant sentiment insights from unstructured, noisy social media data. The model outperformed both standalone deep learning approaches (CNN and LSTM) and conventional machine learning techniques (e.g., Naive Bayes and SVM) across a number of performance metrics by fusing the advantages of Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). In order to properly comprehend user-generated material in the marketing domain, it is crucial to capture the subtleties of natural language. This was accomplished by combining CNNs for local feature extraction with LSTMs for sequential dependency modeling.

The improved performance of the CNN-LSTM model, particularly its F1 score of 0.905 and high AUC value (approx. 0.97), demonstrates its ability to balance precision and recall, making it a reliable tool for real-world sentiment analysis applications. In contrast, traditional models like Naive Bayes and SVM, while computationally efficient, exhibited limitations in handling the complexity of informal language, sarcasm, and mixed sentiment often found in social media. Similarly, standalone CNN and LSTM models delivered strong individual results, but failed to capture the full depth of contextual and semantic variations compared to the hybrid approach.

The model's practical implications for digital marketing are substantial. With more accurate sentiment classification, marketers can better gauge public perception of brands, products, and campaigns in real time. This allows for more informed decision-making, faster response to public feedback, and more precise targeting of content based on audience mood and behavior. For example, in the retail or service industries, real-time sentiment monitoring using CNN-LSTM can help identify dissatisfied customers quickly, enabling timely intervention to prevent churn or reputational damage. Additionally, the model's capability to process large volumes of social media data with high accuracy supports scalable marketing intelligence solutions that go beyond basic keyword or volume tracking.

Despite the strong results, the model did encounter challenges. Error analysis revealed that sarcasm, ambiguity, and mixed sentiments were frequent sources of misclassification. For instance, sarcastic statements that use positive words to imply negativity—such as "Great job on ruining my day"—were difficult for the model to detect due to their reliance on deeper contextual or even cultural understanding. Likewise, posts with conflicting emotions or vague expressions led to ambiguous classifications, underscoring the limitations of purely text-based sentiment models in fully understanding human affect. Addressing these limitations may require incorporating multimodal data (e.g., images, emojis, or metadata) or external knowledge sources to enrich the model's interpretative capability. Another challenge lies in the diversity of language use across platforms and demographics. Social media text is often informal, abbreviated, and laden with region-specific slang, making it difficult for pretrained embeddings and fixed architectures to perform uniformly across datasets. This suggests the need for continual model retraining and adaptation when applying sentiment analysis in different industries or cultural contexts. Moreover, the computational complexity of hybrid models like CNN-LSTM, while manageable in controlled experiments, may present scalability issues when deployed in high-throughput, real-time systems without sufficient optimization.

Future research could explore enhancements to this model by integrating attention mechanisms, transformer-based components like BERT, or leveraging multilingual embeddings to improve generalization across languages. Another promising direction involves developing domain-adaptive training pipelines that fine-tune the model for specific sectors such as finance, healthcare, or e-commerce. Finally, augmenting the model with user-level sentiment trends, location-based sentiment clustering, or topic modeling could yield deeper insights for strategic marketing analytics. The hybrid CNN-LSTM model presents a highly effective and scalable approach to sentiment analysis on social media, delivering valuable implications for data-driven marketing. Its ability to extract rich, context-aware sentiment signals positions it as a critical tool for businesses seeking to understand and respond to public sentiment in real time. While some limitations persist, the framework establishes a solid foundation upon which more sophisticated and adaptive sentiment analysis systems can be built, contributing significantly to the evolving field of intelligent marketing analytics.

CONCLUSION

In this research, a profound hybrid CNN-LSTM model contribution was developed to expand on sentiment analysis functions in the area of information-driven market-based analytics. As the use of social media as a medium of primary expression by consumers continues to predominantly increase, businesses experience the problem of having to analyse huge amounts of unstructured and noisy user-generated contents. The conventional sentiment analysis models tend to be rather weak in recording the contextual flavor of this data. In addressing such weaknesses, the proposed architecture integrates local pattern recognition abilities of Convolutional Neural Networks (CNNs) with the contextual sequential modeling of the Long Short-Term Memory (LSTM) networks. They trained and tested the model using data that was scraped on Twitter, Facebook, Instagram and YouTube with the preprocessing involving tokenization, stop words removal, lemmatization and padding of sequences. As scientific evidence unequivocally proved, the CNN-LSTM model was much superior to purely basics particularities models, such as Naive Bayes, SVM, and traditional isolated CNN or LSTM networks, demonstrating an impressive performance level represented by accuracy levels exceeding 91% and F1 scores of 90.5%. Further evaluation, ROC curve and confusion matrices, reinforced the fact that the model was robust and very sensitive in labeling sentiments within varied social media contents. The results confirm the possibility of the hybrid model being an effective and scalable entity in real-time sentiment tracking, campaign optimisation, and customer experience study in digital marketing. Yet, there are still issues to solve like sarcasm detection, processing ambivalence and domain related language. The next steps of research might involve incorporating attention mechanisms, transformer-based models, and multilingual text using this model to achieve a higher-performing and cross-domain applicable system.

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