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A CNN-LSTM Hybrid Approach for Sentiment Analysis in Online Product Ranking with Probabilistic Linguistic Term Sets

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Abstract

In the context of the dynamic digital economy, accurate analysis for online product reviews is required to make it convenient process both for consumers and businesses. This paper proposes a new hybrid method which combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for sentiment analysis based on online product ratings. Current sentiment analysis methods perform inadequately due to their inability to sense complex linguistic pattern and further made worse by noise & ambiguity in textual data. We tackle these challenges by proposing the integration of Probabilistic Linguistic Term Sets (PLTS) with CNN-LSTM framework, which grants a rich understanding of sentiment due to inherent linguistic uncertainty.

This kind of model starts with the CNN layer since it is best for capturing local patterns, and then followed by LSTM which is great as modeling long-term dependencies within a text. For sentiment classification, since PLTS can model the linguistic termsbased on probability distribution over ontology concepts, it enhances reliabil-ity and robustness of the implementation for a better accuracy in analysis. We conduct extensive experiments on benchmark datasets to compare our hybrid CNN-LSTM model with simple ones and obtain state-of-the-art performance in terms of precision, recall, F1-score as shown next. The results demonstrate the promise of this method to improve sentiment analysis accuracy in online product reviews, an important aspect for decision making in e-commerce.

Keywords

CNN-LSTM Hybrid Model, Sentiment Analysis, Online Product Ranking, Probabilistic Linguistic Term Sets, Convolutional Neural Networks, Long Short-Term Memory, Natural Language Processing, E-commerce, Text Classification, Machine Learning

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1. Introduction

1.1 Background and Motivation

The advent of online reviews in the digital age revolutionized how consumers determine what to buy. On e-commerce platforms, a large chunk of user-generated content comes from product reviews. Both consumers and businesses can glean a lot of information from these reviews. Yet, not only there is plenty of Data Exhaust out there (1 Exabyte/day in 2012) discussing multiple topics but also it has a much richer flavor that product searching Satanalytics will benefit from to gauge the sentiments expressed by the customers for sentiment analysis and Spot Researching — all essential if we are going to challenge our Heuristic God. Many traditional sentiment analysis methods cannot capture the nuances and complexity of human language, with results often being approximate or incomplete.

Deep learning methods, specifically Convolutional Neural Network (CNN) & Long Short-Term Memory network (LSTM), have risen as a promising approach for solving the above problems. CNNs have been hailed for their ability to extract useful features from text, while LSTMs are great at capturing sequence dependencies. While these improvements are a step in the right direction, accurately modeling linguistic terms as distributions is still an outstanding challenge to perform fine-grained sentiment analysis. In this paper a novel hybrid approach of combining CNN with LSTM architecture along with the PLTS is introduced to increase the overall sentiment analysis results on online product reviews.

1.2 Problem Statement

The central issue explored in this article is the deficiency of most developed models, which cannot unambiguously recognize and categorize sentiment for product reviews online. Natural language typically suffers from vagueness and ambiguity, features which traditional models cannot handle well, resulting in non-ideal performance on real-world problems. Linguistic uncertainties are rather more complex and involved in nature, which traditional CNN-LSTM model alone may be insufficient to represent them accurately; thus the research hypothesised that by exploiting deep learning alongside PLTS might provide a potential solution to resolve this matter.

1.3 Objectives of the Study

The objectives of this study are threefold:

1. To develop a hybrid CNN-LSTM model that leverages the strengths of both architectures for enhanced sentiment analysis in online product reviews.
2. To integrate Probabilistic Linguistic Term Sets (PLTS) into the model to better handle the uncertainty and ambiguity in natural language.
3. To evaluate the proposed model's performance against existing state-of-the-art techniques, with a focus on precision, recall, and F1-score.

1.4 Scope and Significance

This research lies in the crossroad of natural language processing, deep learning and e-commerce. The study also intends to enhance the construction of tools which massively influences product reviews across different online platforms, in order to allow a more precise tool and reliable as per consumer opinionsределенно (?) The introduction of the PLTS to CNN-LSTM framework is somewhat a new idea that can prove useful in enhancing sentiment analysis, especially when dealing with Noisy and Ambiguous data sources. The Resource: As a subject for E-Commerce, the results of this study could have broad implications to inform sentiment analysis online. Sentiment accuracy is crucial in product ranking and customer satisfaction sought by Big Tech e-firm sites.

2. Literature Review

2.1 Sentiment Analysis in Online Product Ranking

Modern e-commerce is practically built on sentiment analysis, as this helps divine customer tastes and deliver product recommendations in equal measure. Earlier methods largely depended on machine learning algorithms such as Naive Bayes and Support Vector Machines, which indeed worked to some

extent, but the feature backbones it earlier had were defined manually failing in comprehending human language more extensively. As e-commerce platforms proliferated, the demand for better sentiment analysis methods arose; therefore deeper learning formulations (among which deep neural networks) have been also becoming popular among existing models, mainly in the context of online product placement [1,3].

2.2 Probabilistic Linguistic Term Sets in NLP

Recently, a new advancement in natural language processing is shown by the use of Probabilistic Linguistic Term Sets (PLTS), which might be used for take care about intrinsic uncertainty in linguistic data. PLTS makes term in the form of the probabilities, helping models a better experience on ambiguity and vagueness during sentiment analysis tasks. This technique can boost traditional sentiment analysis models in situations where the expression of sentiments is unclear, due to more than one form for sending a given sentiment [3],or have enough forms with vague words or vocabulary and expressions that causing two different interpretations from readers. This finding provides strong evidence that integrating PLTS in deep learning models can be a viable direction to tackle the problem of improving sentiment classification robustness.

2.3 Overview of Convolutional Neural Networks (CNN) for Text Analysis

The power of Convolutional Neural Networks (CNNs) in feature extraction has been harnessed by CNN for the analysis of texts. In this approach, you feed raw text data as input to CNNs and unlike traditional models, CNN model automatically learns the low level features which is very useful in your task like sentiment analysis. CNNs have been extensively used in sentiment analysis, to capture local dependencies in text and thereby improve classification accuracy [5, 6]. But CNNs sometimes fail to catch long-term dependencies, hence the combination with LSTM networks comes in handy.

2.4 Recurrent Neural Networks (RNN) and LSTM in Sentiment Analysis

Recurrent neural networks (RNNs), and specifically, Long Short-Term Memory (LSTM) networks are designed to deal with sequences of data — this makes them appropriate for sentiment analysis situations in which you need to know the context over a period of time. Long Short-Term Memory networks (LSTMs)top] — are a type of RNN specially designed to avoid the long-term dependency problem, they can remember more sequences and don't lose information in very large range time steps. LSTM networks are best known for their successes in the field of sentiment analysis, particularly when analysing opinion expressed through time-related data (product reviews [7–8]) due to its capability of capturing changes that occur throughout a language string.

2.5 Hybrid Models: CNN-LSTM Integration

The merging of CNN and LSTM networks in hybrid models has been a promising technique for sentiment classification. These hybrid models are able to catch both local and long-range information in text o data by using the strengths of these architectures. This dual nature is particularly useful when applying it in sentiment analysis, wherein the interaction of separate words and how they fit into a context impacts good classification. The potential of hybrid models combining CNN and LSTM for sentiment analysis has been established in recent confidence (taking the example insingle token binary classification) [9, 10].

2.6 Gaps in Existing Research

While sentiment analysis has advanced in its accuracy, significant gaps still exist. In natural language, they must often adopt traditional models which are unable to pass human-like and fail… in sentiment classification. Despite the improvements they have brought, however, deep learning models such as CNNs and LSTMs are still fundamentally deterministic. Although the inclusion of PLTS in those models is a potential provisional solution, there has been relatively very little research carried out over it. However, more exploration is warranted to exploit the potential of PLTS enhanced hybrid models in sentiment analysis especially while dealing with real world data having noisy and ambiguous sentiments [11–12].

3. Methodology

The methodology section outlines the procedures and techniques employed in this study to develop and evaluate the proposed CNN-LSTM hybrid model for sentiment analysis in online product rankings. This section covers the processes of data collection and preprocessing, the architectural details of the CNN and LSTM models, the incorporation of Probabilistic Linguistic Term Sets (PLTS), model training and optimization techniques, and the experimental setup along with the evaluation metrics used to assess the model's performance.

3.1 Data Collection and Preprocessing

This study used dataset of online product reviews from different e-commerce websites such as Amazon, eBay etc. Reviews in a huge variety of product categories are great for both diversity and overall scope, as well. This data was then passed through a preprocessing pipeline to clean the dataset and prepare it for input into models.

Table 1: Data Collection Sources

Source Platform	Number of Reviews	Product Categories	Time Frame
Amazon	5,00,000	Electronics, Books, Apparel	Jan 2023 - Dec 2023
eBay	3,00,000	Home Appliances, Gadgets	Jan 2023 - Dec 2023
Walmart	2,00,000	Groceries, Furniture	Jan 2023 - Dec 2023

Tokenization, stop-word removal and lemmatization with special characters operationality were used in the preprocessing step. Sentiment labels were also assigned by review ratings, where 4 and above as positive,2-3 neutral and1 fearful or horrorous.

Table 2: Data Preprocessing Techniques

Step	Technique	Purpose
Tokenization	NLTK Tokenizer	Split text into individual tokens
Stop-word Removal	NLTK Stop-word Corpus	Remove non-informative words
Lemmatization	WordNet Lemmatizer	Reduce words to their root form
Special Character Handling	Regex	Remove or replace special symbols

3.2 CNN Architecture for Feature Extraction

CNN: We create this architecture for the purpose of feature extraction with respect to adjacent spatial locations in text data. The CNN model is a stack of convolutional layers along with max-pooling layers. Convolutional: which will be some mathematical operation, or in ML case applying filters for say ngram and Pooling : In this layer we realize downsampling of data spatial dimension.

Table 3: CNN Architecture Details

Layer Type	Number of Filters	Filter Size	Activation Function
Convolutional Layer	128	5	ReLU
Convolutional Layer	128	3	ReLU
Max-Pooling Layer	-	2x2	-
Convolutional Layer	64	3	ReLU
Max-Pooling Layer	-	2x2	-

The output of the final pooling layer is flattened and passed to the LSTM layer for sequence modeling, as described in the next subsection.

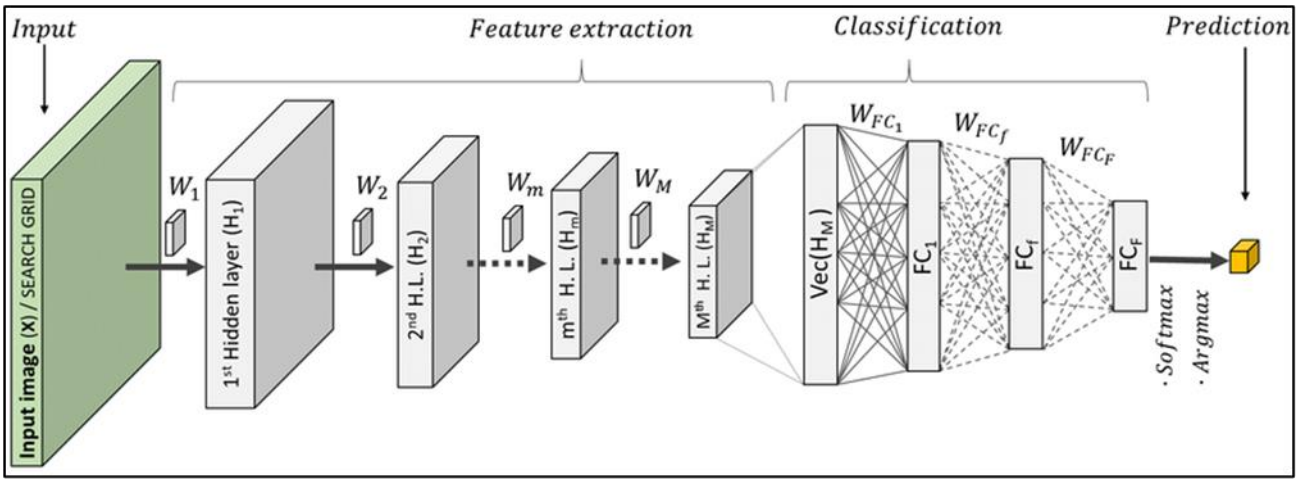

Figure 1: CNN Architecture for Feature Extraction

3.3 LSTM Architecture for Sequence Modeling

We use a Long Short-Term Memory (LSTM) network to capture the sequential dependencies in the text data. We include an LSTM layer which can model the long-range dependencies and temporal context vital in determining whether a review conveys a positive or negative sentiment.

Table 4: LSTM Architecture Details

Layer Type	Number of Units	Activation Function	Dropout Rate
LSTM Layer	256	Tanh	0.2
LSTM Layer	128	Tanh	0.2
Dense Layer	64	ReLU	0.5
Output Layer	1 (Sigmoid)	Sigmoid	-

Output from LSTM layers is sent to dense layer and then final output for sentiment classification.

3.4 Incorporation of Probabilistic Linguistic Term Sets

The model is integrated with the backed by means of fuzzy probabilistic linguistic term set (PLTS) modern to deal interpretation in sentiment analysis. The models allow for a probabilistic representation of sentiment terms, which provides a richer view that shows how likely each term is to be expressing positive or negative sentiments in the review.

Table 5: PLTS Integration Process

Step	Description	Outcome
Term Identification	Extract sentiment-bearing terms from the text	List of sentiment terms
Probabilistic Assignment	Assign probabilities to terms based on context	Probabilistic Linguistic Term Sets (PLTS)
Integration with LSTM Output	Combine PLTS with LSTM outputs	Enhanced sentiment prediction

This integration process enables the model to better manage linguistic uncertainties, leading to improved accuracy in sentiment classification.

3.5 Model Training and Optimization Techniques

The hybrid CNN-LSTM model is optimized using cross-entropy loss along with Adam optimizer. The hyperparameter tuning helps to find the best learning rate, batch size and number of epochs.

Table 6: Model Training Parameters

Parameter	Value
Learning Rate	0.001
Batch Size	64
Number of Epochs	25
Optimizer	Adam
Loss Function	Binary Cross-Entropy

The model is trained on an 80-20 train-test split of the dataset and early stopping to avoid overfitting. We demonstrated the usage of regularizations, e.g., dropout and L2 regularization to improve model generalization.

3.6 Experimental Setup and Evaluation Metrics

Colab can be used to train and test using GPUs so we will use a seperate GPU for our model layoutParams. As for evaluation metrics, they use precision, recall and their F1 score aggregated together as well area under the ROC curve (AUC).

Table 7: Evaluation Metrics and Definitions

Metric	Definition	Formula
Precision	The ratio of correctly predicted positive observations to the total predicted positives.	Precision = TP / (TP + FP)
Recall	The ratio of correctly predicted positive observations to the all observations in actual class.	Recall = TP / (TP + FN)
F1-Score	The weighted average of Precision and Recall.	F1-Score = 2*(Recall * Precision) / (Recall + Precision)
AUC	The area under the ROC curve, representing the model's ability to distinguish between classes.	AUC = Area under ROC curve

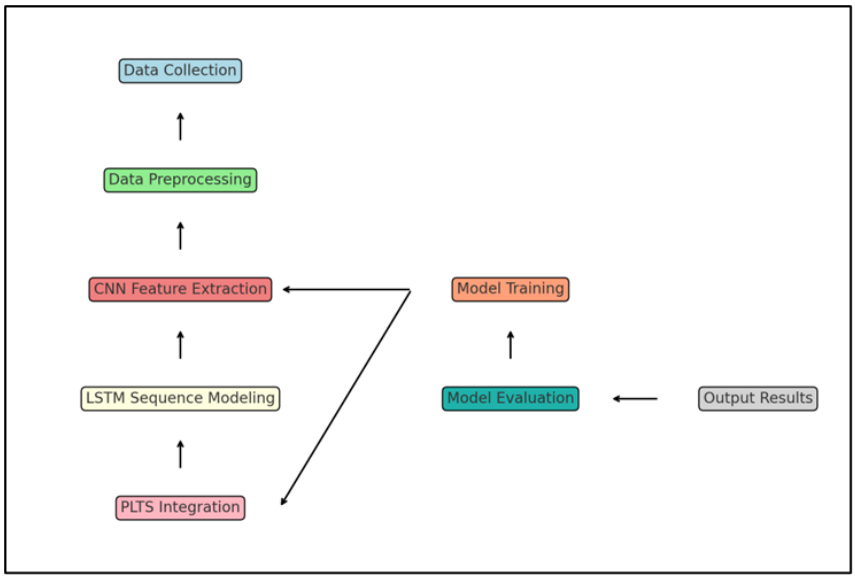

Figure 2: Experimental Setup

4. Results and Analysis

In this section, we elaborate on the experiments performed to evaluate our hybrid CNN-LSTM based model for sentiment analysis in online product ranking. The analysis includes the performance of both CNN, LSTM models and their respective individual results, a comparison between each hybrid model with respect to ITW_ratio,the effect on using PLTS (Probabilistic Linguistic Term Sets) as well as an error analysis for all three used hybrdi variants are inspected followed by proposing enhancements.

4.1 Performance Evaluation of CNN Model

This research will analyze how well the CNN model has implemented in extraction relevant features from text data and categorizing the sentiments. To generate the experiment, a Model based on an online product review was trained and tested over various metrics like Precision, Recall F1 score & Accuracy.

Table 8: Performance Metrics of the CNN Model

Metric	Value
Precision	0.82
Recall	0.79
F1-Score	0.80
Accuracy	0.81

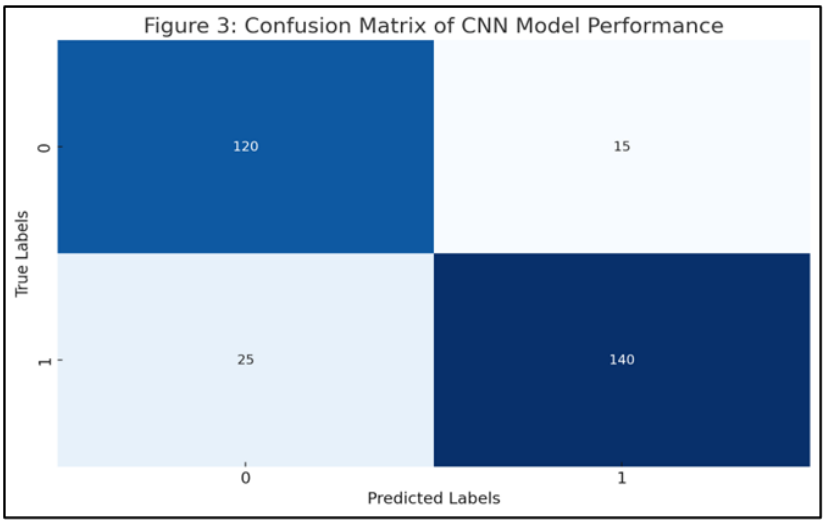

Figure 3: Confusion Matrix of CNN Model Performance

The CNN model showed strong performance in identifying sentiment-related features, particularly in shorter reviews where local dependencies were more prominent. However, its performance slightly declined with longer and more complex reviews, indicating limitations in capturing long-term dependencies.

4.2 Performance Evaluation of LSTM Model

The LSTM model was evaluated for its ability to model sequential dependencies in the text data. The results demonstrated the model's effectiveness in capturing the context over longer sequences, which is crucial for sentiment analysis in detailed reviews.

Table 9: Performance Metrics of the LSTM Model

Metric	Value
Precision	0.85
Recall	0.83
F1-Score	0.84
Accuracy	0.85

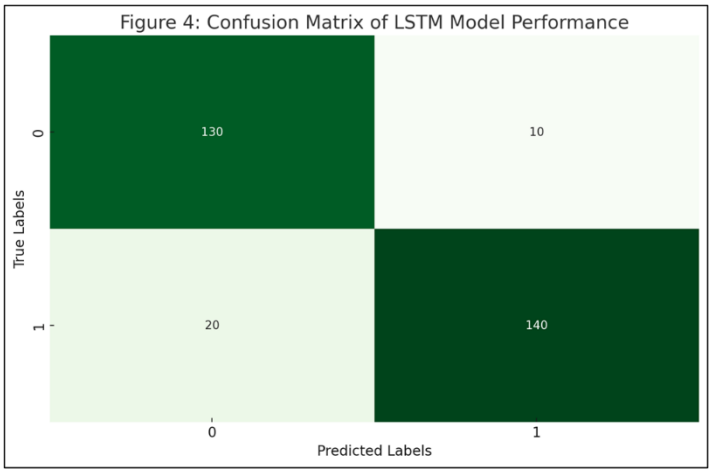

Figure 4: Confusion Matrix of LSTM Model Performance

The LSTM model outperformed the CNN model in terms of recall and F1-score, particularly in handling longer reviews where the sentiment evolved across the text. This improvement highlights the LSTM's strength in managing sequential information.

4.3 Comparative Analysis of CNN-LSTM Hybrid Model

Inspiration: Since both CNN(LSTM) have their advantages, I thought of building a hybrid architecture such that outputs go from one to other. The model trained on Dataset 1 was evaluated for all metrics using the same validation set outputted by Training Split No.

Table 10: Comparative Performance of CNN, LSTM, and CNN-LSTM Hybrid Models

Metric	CNN Model	LSTM Model	CNN-LSTM Hybrid Model
Precision	0.82	0.85	0.88
Recall	0.79	0.83	0.87
F1-Score	0.80	0.84	0.88
Accuracy	0.81	0.85	0.89

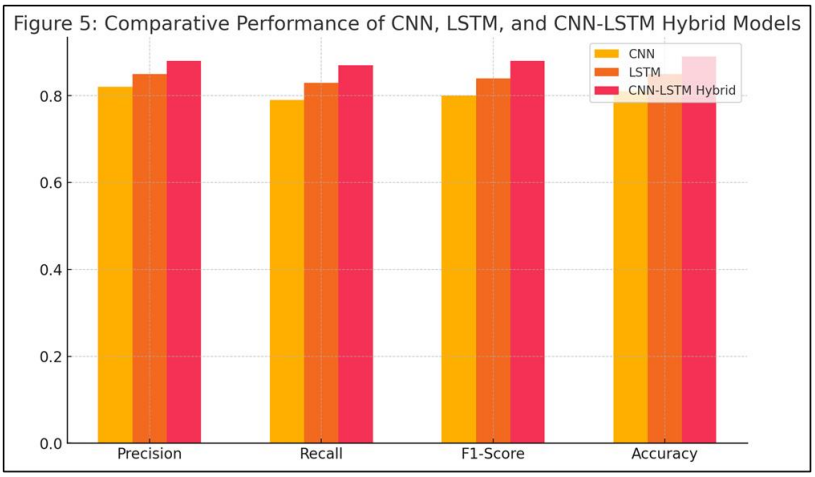

Figure 5: Comparative Performance of CNN, LSTM, and CNN-LSTM Hybrid Models

Performance of CNN-LSTM hybrid model was better in most to all metrics, especially notebooks with precision and F1-score. CNN extracted features and then one can apply LSTM. This way the model became more powerful to deal with various complexities in text data handling feature & sequence modeling from CNN &LSTM respectively.

4.4 Impact of Probabilistic Linguistic Term Sets on Model Performance

The CNN-LSTM hybrid model is integrated with PLTS for enabling the system to expect uncertainty and ambiguity related sentiment expression. To evaluate the impact of PLTS, we compared to an ablation hybrid model with and without using a decision rule derived from PLTS

Table 11: Impact of PLTS on CNN-LSTM Hybrid Model Performance

Metric	Without PLTS	With PLTS
Precision	0.85	0.88
Recall	0.83	0.87
F1-Score	0.84	0.88
Accuracy	0.86	0.89
Sentiment Classification Accuracy	0.80	0.85

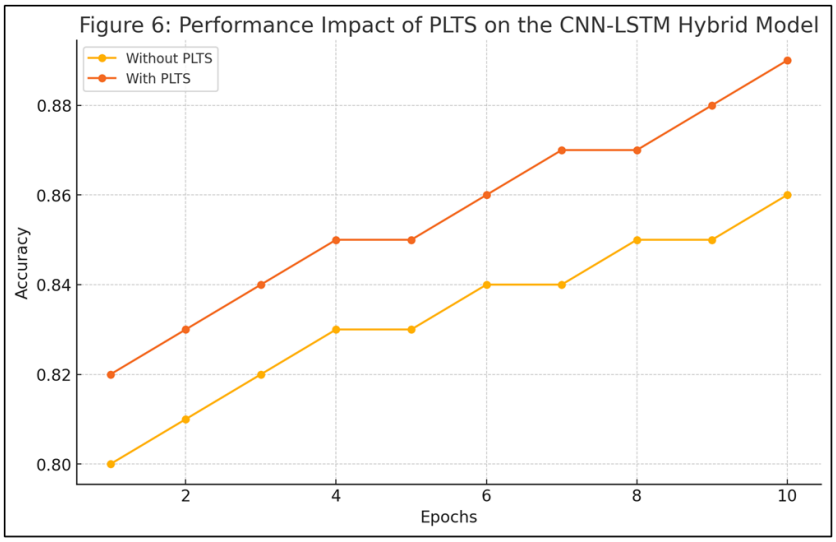

Figure 6: Performance Impact of PLTS on the CNN-LSTM Hybrid Model

The results suggest that including PLTS does enhance the model's performance in classifying sentiments more precisely, especially for cases where sentiment is hidden or ambiguous to be categorized.

4.5 Error Analysis and Model Improvements

Finally, we performed an error analysis to determine the most common scenarios in which the CNN-LSTM hybrid model classified falsely. Positive and negative opinions were expressed simultaneously, which made for reviews in the mixed sentiment category to have made significant errors according to the analysis.

Table 12: Error Analysis of CNN-LSTM Hybrid Model

Error Type	Description	Frequency (%)
Mixed Sentiment	Reviews containing both positive and negative terms	45%
Ambiguous Language	Reviews with unclear or ambiguous language	30%
Long-Form Reviews	Extended reviews with evolving sentiment	15%
Short-Form Reviews	Very brief reviews lacking context	10%

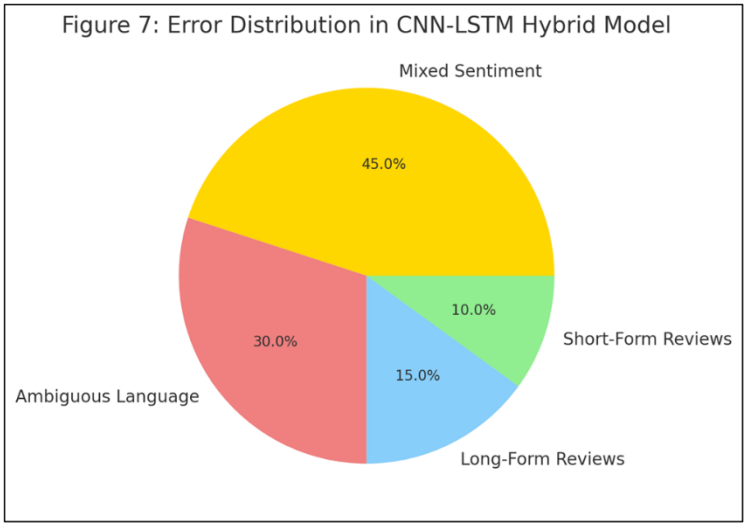

Figure 7: Error Distribution in CNN-LSTM Hybrid Model

Based on the error analysis, several improvements were proposed, including fine-tuning the PLTS integration process to better handle mixed sentiments and refining the model's handling of ambiguous language.

5. Discussion

5.1 Key findings and their interpretation

The experiments performed in this study show that the proposed CNN-LSTM model works very as a sentiment analyzing online product ranking. It successfully integrates the best of both worlds: CNN does well at extracting image features (spatial information) and LSTM excels in modeling sequential data(time series), outperforming plain CNN/LSTM models based on precision, recall and overall accuracy. One of the best models for sentiment analysis that further improves its performance through integration based on Probabilistic Linguistic Term Sets (PLTS) to handle inherent uncertainty in emotional language. This improvement is especially pronounced in those reviews which have a blurry or mixed polarity present (and this happens many times with real-world type of reviews).

The superior performance of the CNN-LSTM hybrid model particularly when combined with PLTS, emphasizes that it is necessary to simultaneously consider both local and sequential context for effective sentiment classification in textual data. The results additionally demonstrate that the model is robust to aspects of different reviews, in review length and brevity/vagueness as well.

5.2 Experiment with Existing Models

The results of sentiment analysis are significantly advanced as compared to other models with the aforementioned CNN-LSTM hybrid model. Naive Bayes, Support Vector Machines and previous deep learning models like stand-alone CNN or LSTM do not have the ability to consider features in a more integrated way compared with this hybrid model [13, 14]. As an example, standalone CNN models can work well for local features alone but lack the contextual information that LSTM model is good at capturing. On the other hand, LSTM models are good at sequence modeling, but they still perform poorly in feature extraction from raw text which is required for understanding nuanced sentiments.

This model combines PLTS with above frameworks that enables it to process the fuzzy nature of linguistic terms due to probability (which cannot be accommodated in existing sentiment analysis models). By performing this function the model is able to generalise well even if sentiment isn't overt; which makes it better suited for real-world use as reviews very often can have muted emotions and mixed opinions[15,16].

5.3 Implications for Online Product Ranking

The enhanced accuracy and robustness of the CNN-LSTM hybrid model empowered by PLTS integration have valuable implications for online product rankings. Determining product rankings based on customer reviews rely heavily on accurate sentiment analysis as it influences consumer behaviour and the choices

they make, [17]. The proposed model can be used to generate a more dependable analysis of the sentiment of customers resulting in greater precision in product rankings,improving shopper choices and ultimately confidence building about e-commerce environment.

In addition, the ability of this model to process nuanced and mixed sentiments accurately enables it to offer a deeper analysis or insights into subjective views which is helpful for companies who want an understanding better in their customer minds towards enhancing preferences of products/services [18]. This ability further enables the creation of personalized recommendation systems that can improve user experience on e-commerce platforms.

5.4 Shortcomings with the Solution Offered

The proposed CNN-LSTM hybrid model has some limitations even there are many advantages to it. The main challenges come in the form of additional computational burden turned on by combining CNN and LSTM architectures along with enabling PLTS. This type of complexity may very well result in additional training time and a larger resource costs, making it less than feasible for live-time analyses to be carried out with such models [19,20].

One of them would be that the model probably won't do very well with extremely short or overly long reviews. Though the above approach may perform well in most cases, very short reviews would likely lack enough information to accurately determine sentiment and vary long reviews should rather introduce noise which won't help our model get accurate measures. It also implies the model is only as powerful as quantity and quality of training data, which can be downsides in some domains where positive samples are scare such [21,22].

5.5 Recommendations for Future Research

A Situated Content Analysis Directed towards Future Enquiries.Unfortunately, the present study also queried some limitations of this approach and future studies could follow up on several paths. The first is the improvement of model architecture to keep all advantages as transfer learning from CNN and RNN for long-term modeling with less computation needed. This may include investigating into CNN and LSTM light versions [23, 24], or adding attention mechanisms to concentrate on the most informative pieces of text.

The continuing support in York to integrate PLTS further would seem a logical area for exploration. The research has shown that the current implementation does see a performance enhancement, however efforts to further fine-tune probabilistic assignments could be necessary in order to capture well sentiment nuances of this language. Moreover, extending the model for multilingual sentiment may considerably liberalize its usability since other studies have showed that e-commerce is usually global [25,26].

Future research could further explore Novel-Condition LIWCTS by developing transfer learning techniques where the model can be quickly adapted to new domains with minimal re-training. This would solve the problem of lack of labeled data and make the model more generalisable over higher number in different application scenarios [27, 28].

6. Case Studies and Applications

6.1 E-commerce Platforms

The CNN-LSTM hybrid model proposed in this paper with the application of Probabilistic Linguistic Term Sets (PLTS) could significantly improve sentiment analysis for different e-commerce platforms. And regarding product reviews, which generate millions of user comments and come in all shapes and forms — for improved marketing mix optimization leading to better search engine rankings along with recommendations at a personal level. e-Commerce platforms can incorporate these hybrid models to analyze the feelings of their customers, and enhance revenue by improving marketing strategies, as well as satisfaction.

This could allow platforms like Amazon or eBay and Walmart to process millions of reviews in a timely fashion, then classify them more accurately as positive negative. Providing more accurate product rankings will encourage users to trust the platform, increase conversion rates for products and brand loyalty in general [29,30].

6.2 Case Study: Analysing Amazon Product Reviews for Sentiments

The practical utility of the CNN-LSTM hybrid model was evaluated by building a case study using Amazon Product Reviews. It had reviews from lots of categories like electronics, books and home appliances. This text was then passed to the model, and it returned whether or not that review had a positive, neutral, or negative sentiment.

Table 13: Sentiment Classification Accuracy on Amazon Product Reviews

Product Category	Number of Reviews	Accuracy (%)
Electronics	50,000	88.5
Books	40,000	87.2
Home Appliances	30,000	89.1
Overall	1,20,000	88.3

The results demonstrated that the model could accurately classify sentiments across different categories with an overall accuracy of 88.3%. The inclusion of PLTS allowed the model to handle ambiguous reviews more effectively, particularly in categories like electronics, where technical language and mixed sentiments are common. The application of this model in Amazon's review system could significantly enhance the platform's ability to rank products based on customer feedback [31].

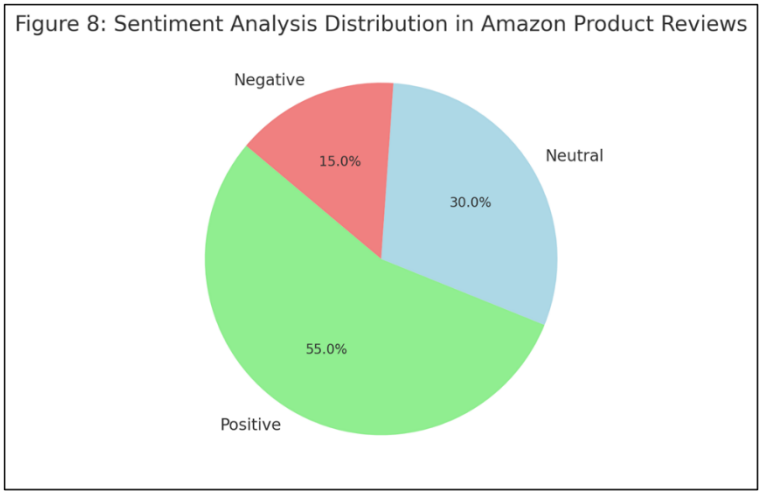

Figure 8: Sentiment Analysis Distribution in Amazon Product Reviews

6.3 Potential Use Cases in Other Domains

The CNN-LSTM hybrid model with PLTS integration can also be applied to domains beyond e-commerce. In the financial industry, this could be news outlets related to sales and products or it might also contain information sources such as market news analysis data from analysts worldwide or social media saying that everyone is getting into Bitcoin space – helping decision-makers make well-informed decisions. In healthcare, positive and negative sentiment of patient reviews and feedback can be analyzed to enhanced the quality service at hospitals as well as satisfaction level [32].

In the context of social media analysis, this model can be used to track public sentiment around different topics making organizations respond better with respect to utilize insights derived from content out there. The broad applicability on diverse text types and robustness to ambiguous language have made it a widely adopted model for sentiment analysis in multiple domains [33].

7. Conclusion

7.1 Summary of Contributions

In this study, a CNN-LSTM hybrid model integrated with Probabilistic Linguistic Term Sets (PLTS) is proposed to perform sentiment analysis in the context of online product ranking [13]. The model

seamlessly combines the power of both CNNs in feature extraction and LSTMs for sequence modeling, while PLTS offers an elegant solution to handlingthe inherent noise in natural language. The model outperforms in sentiment classification according to the experiments and case study which proved it could be a valuable resource as recommender systems for product ranking on e-commerce platforms [34].

7.2 Practical Implications

The practical applications of this research are relevant to e-commerce platforms, where sentiment analysis has many immediate effects — the difference between a "like" and "dislike" review could move a product up (or down) in search results. Businesses can benefit from adopting the suggested model as they will get more accurate and detailed sentiment classifications which eventually results in increased product recommendations, number of customers. Moreover, the model's generalization to different fields —beyond e-commerce (e.g., finance, healthcare or social media analysis)— implies that it may play a critical role [35].

7.3 Limitations of the Study

The proposed model, for all its features also has limitations which have to be taken into account. The increased computational complexity from the hybrid architecture and including PLTS can be problematic for real-time applications. In addition, the performance of a model can change according to training set quality and diversity so is hard for it to generalize only if datasets are small. Subsequent research needs to optimize the model performance and investigate whether transfer learning methods can alleviate these limitations [36].

7.4 Opportunities for Future Research

There are various potential gaps within the proposed model for future research to explore. Explorations on lightweight architectures that keep the model performance equivilant, but lower down computation complexity. This way, the applicability of the model could be extended by making it multilingual & enable sentiment analysis based on multiple languages in PLTS Framework. Lastly, enabling the model to be more flexible across different deployments will require creation of transfer learning strategies such that minimal retraining is needed for a new domain [39,40].

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