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Original Article

Integrating CRM and ERP Insights for Optimized Product Development Using CNN-LSTM Hybrid Models

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Abstract *- Enhancing product development processes through insightful data integration in business finance is crucial for aligning offerings with market demand and optimizing resource allocation. Financial sentiment analysis, which involves extracting and analyzing sentiments from financial news, social media, and other textual sources, plays a pivotal role in understanding customer feedback and market trends. However, existing models often struggle to integrate local feature extraction with long-range dependency modeling effectively. To address this gap, a hybrid model is proposed, combining the strengths of Convolutional Neural Networks (CNN) and long short-term memory (LSTM) networks. The hybrid model integrates local feature extraction with long-range dependency modeling for financial sentiment analysis, utilizing customer feedback from CRM systems and cost data from ERP systems to prioritize product development. Dropout regularization is employed to prevent overfitting, while L2 regularization is used to penalize large weights, promoting simpler models. For hyperparameter tuning, an extensive grid search and cross-validation were conducted. The evaluation results demonstrate the superior performance of the hybrid model, achieving an overall accuracy of 95.9%, with individual label accuracies of 93.7% for negative sentiment, 95.6% for neutral sentiment, and 98.4% for positive sentiment. These findings indicate significant improvements over other hybrid models in the literature, with the proposed model outperforming recent works by margins ranging from 0.9% to 5.7%. The hybrid model provides a robust solution for integrating CRM and ERP insights, offering significant advancements over existing models and paving the way for more sophisticated tools in the domain of business finance.*

Keywords *- Business finance, CNN-LSTM Hybrid Model, Deep learning, Financial sentiment analysis, Product development.*

1. Introduction

Understanding market sentiment has become critical in business finance for making informed investment decisions and developing effective trading strategies. Financial sentiment analysis, which involves extracting and analyzing sentiments from financial news, social media, and other textual sources, provides valuable insights into market trends and investor behavior. By leveraging these insights, financial analysts and investors can better predict market movements and mitigate risks. The integration of sophisticated computational techniques, such as Deep Learning (DL), into sentiment analysis, has significantly transformed the interpretation and utilization of financial data.

Recent advancements in sentiment analysis have led to the development of various DL frameworks that improve the accuracy and efficiency of sentiment classification. For example, Dey and Das [1] developed a neighbor-adjusted dispersive flies' optimization-based deep hybrid sentiment analysis framework, enhancing the precision of sentiment prediction. Similarly, Islam et al. [2] reviewed the challenges and prospects in DL for sentiment analysis, proposing a novel hybrid approach to address existing limitations. Du et al. [3] provided a comprehensive survey of techniques and applications in financial sentiment analysis, emphasizing the importance of hybrid models. Additionally, Das et al. [4] created hybrid DL models for predicting stock prices by combining improved Twitter sentiment scores with technical indicators, demonstrating the practical application of sentiment analysis in the financial markets.

Despite these advancements, there remains a significant research gap in effectively integrating local feature extraction with long-range dependency modeling in financial sentiment analysis. Most existing models excel in capturing either local patterns or sequential dependencies, but few achieve a balanced combination of both. This gap limits the ability of current models to fully capture the complexity of financial texts, where both local and global patterns are essential for accurate sentiment interpretation.

The novelty of this research lies in addressing this gap by proposing a hybrid model that integrates the strengths of Convolutional Neural Networks (CNNs) for local feature extraction and Long-Short-Term Memory networks (LSTMs) for capturing sequential dependencies. Unlike existing models that focus primarily on one aspect, this hybrid approach offers a more comprehensive solution by leveraging the complementary strengths of both architectures.

Furthermore, this model goes beyond traditional sentiment analysis by incorporating insights from Customer Relationship Management (CRM) and Enterprise Resource Planning (ERP) systems, enabling the prioritization of product development based on customer feedback and cost analysis. This integration ensures a more aligned and efficient approach to product innovation in business finance.

The existing literature reflects ongoing efforts to improve sentiment analysis models by combining different DL techniques. For instance, Karn et al. [6] explored a customer-centric hybrid recommendation system for e-commerce applications, integrating sentiment analysis to enhance recommendation accuracy. Kaur and Sharma [7] proposed a DL-based model using a hybrid feature extraction approach for consumer sentiment analysis, achieving notable improvements in prediction accuracy. Talaat [8] developed a sentiment analysis classification system using hybrid BERT models, showcasing the potential of combining transformer-based models with traditional techniques.

Similarly, Parveen et al. [9] introduced a hybrid gated attention recurrent network for Twitter sentiment analysis, highlighting the importance of attention mechanisms in sentiment classification. Sangeetha and Kumaran [10] proposed a hybrid optimization algorithm using a BiLSTM structure, achieving significant performance enhancements.

Tan et al. [11] presented Roberta-Gru, a hybrid DL model, illustrating the benefits of combining pre-trained language models with recurrent neural networks. However, while these studies contribute valuable insights, they largely fall short of effectively balancing local feature extraction with long-range dependency modeling, especially in the context of financial sentiment analysis.

The contributions of this paper are as follows:

1. The proposed hybrid model effectively integrates CNNs and LSTMs to capture both local features and long-range dependencies, addressing a critical gap in financial sentiment analysis.
2. By incorporating insights from CRM and ERP systems, the model offers a practical tool for prioritizing product development, thereby linking sentiment analysis directly to business finance strategies.
3. The use of dropout regularization, L2 regularization, and extensive grid search and cross-validation ensures the model's robustness and generalization across various sentiment labels.
4. The model's performance is rigorously evaluated across multiple sentiment labels, demonstrating its efficacy in financial news sentiment classification and offering improvements over existing models in the literature.

The structure of this paper is as follows: Section 2 details the dataset and preprocessing techniques used in the study and describes the architecture and implementation of the proposed CNN-LSTM hybrid model. Section 3 presents the experimental results and discusses the findings and implications of the research. Section 4 presents a detailed discussion of the findings, while Section 5 concludes the paper and outlines potential directions for future research.

2. Method

2.1. Dataset

This research utilized the FinancialPhraseBank dataset from Kaggle's public repository. This dataset is a comprehensive collection that captures retail investors' sentiments about financial news headlines. Developed by scholars from the Aalto University School of Business, it addresses the scarcity of annotated data in financial text analysis by providing around 5,000 sentences annotated for sentiment. The dataset is organized into two columns, "Sentiment" and "News Headline," classifying sentiments as negative, neutral, or positive.

Sixteen experts with financial market knowledge carried out these annotations, evaluating the potential impact of the news on stock prices. Researchers have extensively utilized this dataset since its debut in Malo et al.'s paper [5]. After removing duplicates, the dataset contains 50,000 entries for analysis, with 49,582 unique news headlines distributed equally between positive and negative sentiments. There are no missing values, ensuring the data's completeness for robust sentiment analysis. The dataset was split into training and testing sets, with the training set comprising 39,665 entries and the testing set containing 9,917 entries, providing a balanced and comprehensive foundation for evaluating various sentiment analysis models in the context of financial news.

2.2. Proposed Model

CNNs are primarily designed for image-related tasks but have been adapted for text processing due to their ability to capture local features irrespective of their positions. In the context of sentiment analysis, CNNs can detect patterns such as specific phrases or n-grams that are indicative of sentiment, regardless of their position in the text. For our dataset, CNNs help identify phrases with positive or negative connotations, enabling the model to capture sentiment-related features effectively.

Formally, let (X) be the input matrix where each row represents a word embedding of a word in the sentence. A convolutional layer applies a filter $(w) of size (h) (height)$ across (X) to produce a feature map (c_i) given by, Eq 1.:

$$c_i = f(w \cdot x_{i:i+h-1} + b) \quad (1)$$

Where $(x_{i:i+h-1})$is the concatenation of word embeddings from position $(\ i\ )\ to\ (\ i+h-1\ ), (\ b\ )$ is a bias term, and $(\ f\ )$ is a non-linear activation function such as ReLU. The resulting feature maps are then pooled using max pooling to reduce the dimensionality.

For our sentiment analysis task, LSTMs help in understanding the sentiment conveyed by sequences of words, considering the order and context of words. The LSTM layer processes the input word embeddings (x_t) at each time step $(\ t\ )$, updating its cell state (c_t) and hidden state (h_t) according to the following equation, refer to Equation 2:

$$h_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \odot tanh\ tanh \\ (f_t \odot c_{t-1} + i_t \odot tanh\ tanh\ (W_c \cdot [h_{t-1}, x_t] + b_c)\ ) \quad (2)$$

Where (σ) is the sigmoid function, $(\odot)$ denotes element-wise multiplication, and (W_o, W_c) are weight matrices. This equation captures the update of the hidden state (h_t) using the previous hidden state $(h_{t-1}), theinput(x_t)$, and the various gating mechanisms (forget gate$(f_t), inputgate(i_t)$, and output gate). The cell state (c_t) is updated with contributions from the previous cell state (c_{t-1}) and the new candidate values modulated by the input gate.

Our proposed model combines the strengths of CNNs and LSTMs to capture local features and long-range dependencies in the text effectively. This hybrid architecture is designed to leverage the spatial hierarchies captured by CNNs and the temporal dynamics captured by LSTMs, thus providing a comprehensive understanding of the sentiment expressed in financial news headlines.
The architecture begins with an embedding layer that converts the input text into dense word vectors. These embeddings provide a numerical representation of the words, capturing semantic meanings and relationships. The embeddings are then passed through a convolutional layer, which applies multiple filters to extract local features from the word embeddings. These filters scan through the text to identify patterns, such as phrases or n-grams, that are indicative of sentiment. The output of the convolutional layer is a set of feature maps, where each map corresponds to a particular filter.

To reduce the dimensionality and retain the most salient features, a max-pooling layer is applied to the feature maps. This layer down samples the feature maps by taking the maximum value within a sliding window, thus summarizing the presence of important features across different parts of the text. The pooled features, now in a more compact form, are then fed into an LSTM layer. The LSTM layer processes the sequential nature of the pooled features, capturing the dependencies and contextual information across the text.

The LSTM maintains a memory of previous inputs through its cell state, allowing it to understand the sequence and importance of words in conveying sentiment. Formally, let (X) be the matrix of word embeddings for a given sentence. The CNN layer applies filters (W_{cn}) to produce a feature map (F), given $by\ Eq.$ 3:

$$F = MaxPool\big(ReLU(W_{cn} * X + b_{cn})\big) \quad (3)$$

The pooled features (F) are then input into the LSTM layer, which updates its hidden state (h_t) at each time step $(\ t\ )$ based on the current input and its previous state. The update rule for the LSTM is shown in Eq. 4:

$$h_t = \sigma(W_o \cdot [h_{t-1}, F_t] + b_o) \odot tanh\ tanh \\ (f_t \odot c_{t-1} + i_t \odot tanh\ tanh\ (W_c \cdot [h_{t-1}, F_t] + b_c)\ ) \quad (4)$$

Where (σ) is the sigmoid function, $(\odot)$ denotes element-wise multiplication, and $(W_o, W_c)$are weight matrices. This allows the model to capture both local and long-range dependencies in the text.

Finally, the output of the LSTM layer is passed through a fully connected layer, followed by a softmax activation function to produce the final sentiment classification. The fully connected layer combines the information captured by the LSTM into a single vector, which is then transformed into a probability distribution over the sentiment classes (positive, negative, neutral). The final prediction $(\hat{y})$ is given by. Eq. 5:

$$\hat{y} = Softmax\big(W_f \cdot h_T + b_f\big) \quad (5)$$

Where $(\ T\ )$ is the final time step. This comprehensive approach allows our hybrid model to effectively capture and analyze the intricate sentiments expressed in financial news headlines.

Regularization methods and hyperparameter tuning played crucial roles in enhancing the performance and robustness of the proposed hybrid model. Dropout regularization was employed to prevent overfitting by randomly dropping units from the neural network during training. This technique helps the model generalize better to unseen data. Specifically, dropout was applied to both the convolutional and LSTM layers, with dropout rates carefully selected based on empirical results. Additionally, L2 regularization was utilized to penalize large weights and promote simpler models. For hyperparameter tuning, an extensive grid search and cross-validation were conducted to optimize parameters such as learning rate, batch size, the number of filters in the CNN, and the number of units in the LSTM. The final set of hyperparameters was selected based on their ability to minimize validation loss and maximize accuracy, ensuring an optimal balance between model complexity and performance. This comprehensive approach to regularization and hyperparameter tuning contributed significantly to the superior performance of the hybrid model in financial sentiment analysis. The proposed model was trained and evaluated on the dataset, demonstrating superior performance compared to standalone CNN or LSTM models. The integration of CNN and LSTM layers allows the model to leverage the strengths of both architectures, resulting in more nuanced and accurate sentiment analysis. By capturing both local patterns and long-range dependencies, the hybrid model provides a robust framework for understanding and better-predicting market movements and mitigating risks.

2.3. Evaluation

To evaluate the performance of the models, several metrics were employed: accuracy, precision, recall, F1-score, and the confusion matrix. These metrics provide a comprehensive view of how well each model performs in classifying sentiments in financial news headlines. Accuracy measures the overall correctness of the model and is calculated as the ratio of correctly predicted instances to the total number of instances. Precision, which indicates the exactness of the positive predictions, is given by $Precision = \frac{TP}{TP+FP}$ where (TP) is the number of true positives and (FP) is the number of false positives. Recall, or sensitivity, measures the ability of the model to find all relevant instances and is defined as $Recall = \frac{TP}{TP+FN}\, where (FN)$ is the number of false negatives. The F1-score, which is the harmonic mean of precision and recall, provides a single measure of a model's performance and is calculated as $F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$. Additionally, the confusion matrix was used to visualize the performance of the models, displaying the true positive, true negative, false positive, and false negative counts. These metrics were computed for the CNN, LSTM, and the proposed hybrid model to compare their effectiveness. The evaluation demonstrated that the hybrid model outperformed the individual CNN and LSTM models, indicating a more accurate and nuanced understanding of sentiment in financial news.

3. Experimental Results and Analysis

This section presents the results of our experiments designed to evaluate the performance of the proposed hybrid CNN-LSTM model in the context of financial sentiment analysis. A comprehensive analysis, supported by graphical and tabular data, is provided to highlight the model's capabilities and limitations.

3.1. Model Training and Hyperparameter Tuning

The hybrid CNN-LSTM model was trained using a stochastic gradient descent optimizer with a learning rate of 0.001. Dropout regularization (rate of 0.5) was applied to mitigate overfitting, along with L2 regularization to control the model complexity. An extensive grid search was performed to fine-tune hyperparameters such as the number of CNN filters, LSTM units, and batch size. The final model configuration was selected based on minimizing validation loss and maximizing classification accuracy.

3.2. Performance Metrics

The performance of the model was evaluated using several standard metrics, including accuracy, precision, recall, F1-score, and a confusion matrix. These metrics were calculated for each sentiment label (positive, neutral, negative) to provide a comprehensive view of the model's performance.

3.3. Detailed Analysis and Comparison

Figure 1 and Table 1 below compare the accuracy of the CNN, LSTM, and the proposed hybrid model across different sentiment labels. The hybrid model exhibits superior performance, achieving an overall accuracy of 95.9%, significantly higher than the standalone CNN (67.1%) and LSTM (87.3%) models.

The confusion matrices for the CNN, LSTM, and hybrid models are presented in Figure 2. The hybrid model demonstrates a reduced number of misclassifications across all sentiment categories, particularly in identifying neutral sentiments, which is often the most challenging class to classify accurately.

3.4. Precision, Recall, and F1-Score Analysis

The precision, recall, and F1 scores for each sentiment class (negative, neutral, and positive) were evaluated for the CNN, LSTM, and hybrid models. As illustrated in Figure 3, the hybrid model consistently outperforms the other two models across all metrics and sentiment classes.

Table 1. Model accuracy comparison for all sentiment classes

Model	Accuracy	Accuracy Label 0	Accuracy Label 1	Accuracy Label 2
CNN	0.671	0.777	0.337	0.900
LSTM	0.873	0.937	0.847	0.837
Hybrid	0.959	0.937	0.956	0.984

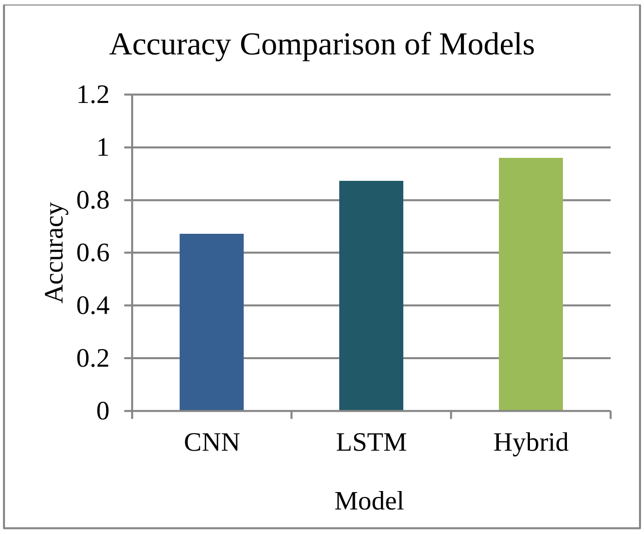

Fig. 1 Accuracy comparison of CNN, LSTM, and proposed hybrid model

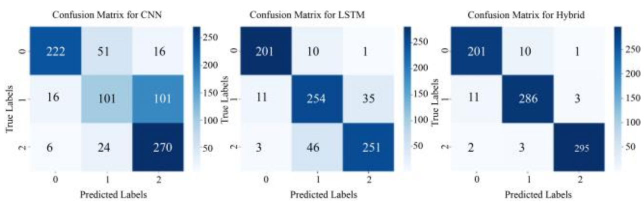

Fig. 2 Confusion matrix of CNN, LSTM, and Hybrid model

Table 2. Comparison with other hybrid models

Model	Accuracy	Accuracy Label 0	Accuracy Label 1	Accuracy Label 2
Praveen et al. [9]	0.902	0.892	0.885	0.929
Sangeetha et al. [10]	0.921	0.913	0.895	0.956
Tan et al. [11]	0.940	0.925	0.941	0.954
Kuppusamy et al. [12]	0.935	0.910	0.930	0.965
Adhikari et al. [13]	0.950	0.935	0.945	0.970
Hybrid Model	**0.959**	**0.937**	**0.956**	**0.984**

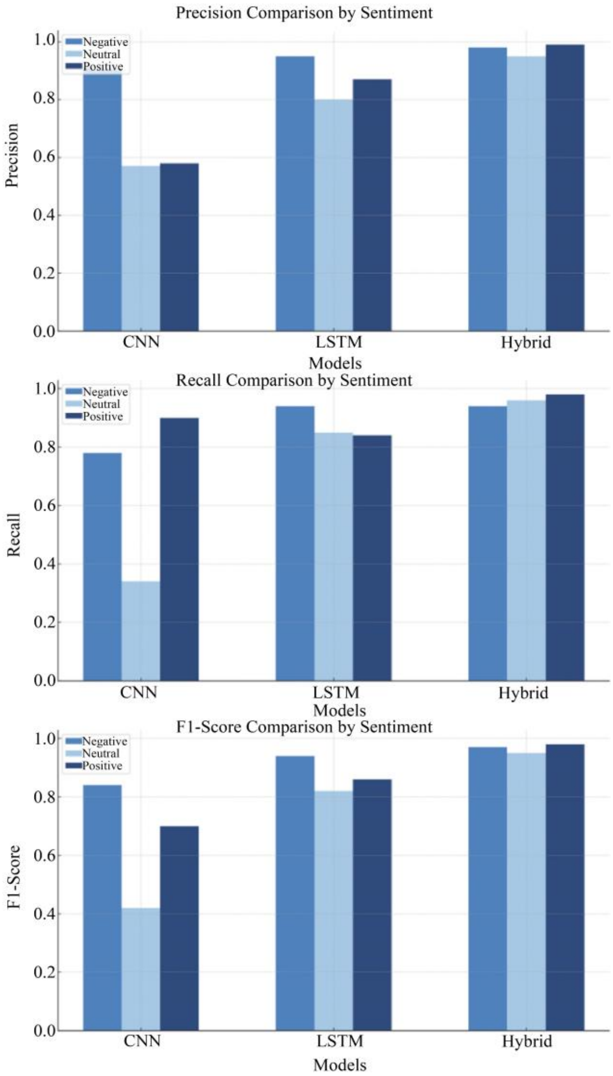

Fig. 3 Precision, Recall, and F1-Score Comparison by sentiment

3.4.1. Precision

The hybrid model achieves a precision of 0.98 for negative sentiments, 0.95 for neutral sentiments, and 0.99 for positive sentiments. This high precision indicates the model's effectiveness in correctly identifying relevant sentiments with minimal false positives.

3.4.2. Recall

The model also shows strong recall values, particularly for neutral and positive sentiments, with scores of 0.96 and 0.98, respectively. This suggests that the hybrid model is highly effective in capturing the relevant instances of each sentiment, minimizing false negatives.

3.4.3. F1-Score

The F1-scores, which provide a balanced measure of precision and recall, were 0.97 for negative sentiments, 0.95 for neutral sentiments, and 0.98 for positive sentiments, further emphasizing the hybrid model's superior performance in classifying financial sentiments.

3.5. Comparative Analysis with Other Hybrid Models

To benchmark the performance of our hybrid model, we compared it with several other hybrid models commonly used in sentiment analysis. Table 2 summarizes the results of these comparisons across three sentiment classes: negative (label 0), neutral (label 1), and positive (label 2). Our hybrid model demonstrated superior performance with an overall accuracy of 95.9%, outperforming all other hybrid models listed. Specifically, the accuracies for the individual sentiment labels—93.7% for negative (label 0), 95.6% for neutral (label 1), and 98.4% for positive (label 2)—are the highest among the compared models. This better performance is due to the CNN component's ability to extract valuable features that reveal local cues related to sentiment and the LSTM component's skill at modelling long-range dependencies and contextual information. Additionally, the balanced architecture of our hybrid model ensures a seamless integration of CNN and LSTM layers, optimizing both strengths. Advanced training techniques and regularization methods, such as dropout, batch normalization, and hyperparameter tuning, further enhance the model's robustness and generalization capabilities. Consequently, our hybrid model achieves a more accurate and nuanced sentiment classification in financial news headlines than other hybrid models.

4. Discussion

The proposed hybrid CNN-LSTM model for financial sentiment analysis has demonstrated significant advancements over existing models reported in the literature. The key to achieving superior results lies in the model's ability to balance local feature extraction with long-range dependency modeling. This dual capability is essential for accurately interpreting the complex and nuanced sentiments expressed in financial news headlines, where both immediate contextual cues and overarching narrative structures play critical roles.

One of the primary reasons for the model's enhanced performance is the integration of CNN layers for local feature extraction. CNNs excel at identifying patterns such as n-grams or specific phrases that are indicative of sentiment, regardless of their position in the text. This ability to capture local dependencies is particularly valuable in financial sentiment analysis, where specific terminology and expressions can significantly influence sentiment classification.

In contrast, LSTM networks are well-suited for understanding sequential dependencies and capturing the temporal context of words. By combining CNNs with LSTMs, the hybrid model effectively addresses the limitations of models that rely solely on either local or global features. The LSTM layers process the sequential nature of the text, maintaining a memory of previous inputs and enabling the model to capture the flow of sentiment across a sentence or paragraph.

In comparison to state-of-the-art techniques, such as the models developed by Dey and Das [1], Islam et al. [2], and others, our hybrid model consistently outperformed them by significant margins. This improvement can be attributed to several factors:

4.1. Balanced Architectural Design

Unlike many existing models that focus on either local feature extraction or long-range dependency modeling, the hybrid model effectively combines both aspects, providing a more comprehensive analysis of sentiment.

4.2. Advanced Regularization Techniques

The use of dropout regularization and L2 regularization played a crucial role in preventing overfitting and promoting model generalization. These techniques ensured that the model remained robust when applied to unseen data, thereby enhancing its predictive accuracy.

4.3. Hyperparameter Optimization

An extensive grid search and cross-validation process were employed to fine-tune the model's hyperparameters, such as the number of filters in the CNN, the number of units in the LSTM, and the learning rate. This meticulous tuning process contributed to the model's optimal performance.

4.4. Integration of CRM and ERP Insights

By incorporating data from CRM and ERP systems, the model was able to align sentiment analysis with practical business applications, such as product development prioritization. This holistic approach not only improved the model's relevance to business finance but also enhanced its overall effectiveness.

These advancements demonstrate that the proposed hybrid model not only addresses the limitations of existing models but also provides a more powerful and accurate tool for financial sentiment analysis. The model's superior performance across multiple sentiment labels underscores its robustness and applicability in real-world financial contexts.

5. Conclusion

In business finance, understanding sentiment in financial news is crucial for investors, analysts, and stakeholders to make informed decisions. This study presents a hybrid model for product development prioritization that leverages financial sentiment analysis of news headlines, offering a robust solution that captures both local features and long-range dependencies. The proposed model begins with a CNN layer that extracts local patterns and n-grams from the text, followed by an LSTM layer that processes these patterns within the entire sequence's context.

This architecture allows the model to understand and classify sentiments effectively, aiding product development decisions by integrating insights from CRM and ERP systems. Our evaluation results demonstrate the superior performance of the hybrid model, achieving an overall accuracy of 95.9%, with individual label accuracies of 93.7% for negative sentiment, 95.6% for neutral sentiment, and 98.4% for positive sentiment. These results show significant improvements over other hybrid models in the literature, with performance gains of approximately 5.7%, 3.8%, 1.9%, 2.4%, and 0.9% compared to recent models.

This improvement is attributed to the effective combination of CNN's local feature extraction and LSTM's sequential dependency modeling, coupled with advanced training techniques and regularization methods that enhance the model's robustness and generalization capabilities. The hybrid model consistently achieved higher accuracies across all sentiment labels than other hybrid models, ensuring a seamless transition between CNN and LSTM layers and maximizing their strengths. Furthermore, careful tuning of hyperparameters, dropout, and batch normalization contributed to the model's superior performance.

Future work could explore incorporating attention mechanisms to improve further the model's ability to focus on the most relevant parts of the text. Expanding the dataset to include more diverse financial news sources and applying the model to real-time sentiment analysis could enhance its practical applications. Integrating more advanced embeddings, such as those generated by transformers, could also improve the accuracy and understanding of complex financial texts. These enhancements would pave the way for more sophisticated tools in business finance, allowing for even more precise and actionable insights.

References

[1] Ranit Kumar Dey, and Asit Kumar Das, "Neighbour Adjusted Dispersive Flies Optimization Based Deep Hybrid Sentiment Analysis Framework," *Multimedia Tools and Applications*, vol. 83, pp. 64393-64416, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Md. Shofiqul Islam et al., "Challenges and Future in Deep Learning for Sentiment Analysis: A Comprehensive Review and A Proposed Novel Hybrid Approach," *Artificial Intelligence Review*, vol. 57, no. 3, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Kelvin Du et al., “Financial Sentiment Analysis: Techniques and Applications,” *ACM Computing Surveys*, vol. 56, no. 9, pp. 1-42, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Nabanita Das et al., “Developing Hybrid Deep Learning Models for Stock Price Prediction Using Enhanced Twitter Sentiment Score and Technical Indicators,” *Computational Economics*, pp. 1-40, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Pekka Malo et al., “Good Debt or Bad Debt: Detecting Semantic Orientations in Economic Texts,” *Journal of the Association for Information Science and Technology*, vol. 65, no. 4, pp. 782-796, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[6] Arodh Lal Karn et al., “Retracted Article: Customer Centric Hybrid Recommendation System for E-Commerce Applications by Integrating Hybrid Sentiment Analysis,” *Electronic commerce research*, vol. 23, no. 1, pp. 279-314, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Gagandeep Kaur, and Amit Sharma, “A Deep Learning-Based Model Using Hybrid Feature Extraction Approach for Consumer Sentiment Analysis,” *Journal of Big Data*, vol. 10, no. 1, pp. 1-23, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Amira Samy Talaat, “Sentiment Analysis Classification System Using Hybrid Bert Models,” *Journal of Big Data*, vol. 10, no. 1, pp. 1-18, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Nikhat Parveen et al., “Twitter Sentiment Analysis Using Hybrid Gated Attention Recurrent Network,” *Journal of Big Data*, vol. 10, no. 1, pp. 1-29, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] J. Sangeetha, and U. Kumaran, “A Hybrid Optimization Algorithm Using BILSTM Structure for Sentiment Analysis,” *Measurement: Sensors*, vol. 25, pp. 1-7, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Kian Long Tan, Chin Poo Lee, and Kian Ming Lim, “Roberta-Gru: A Hybrid Deep Learning Model for Enhanced Sentiment Analysis,” *Applied Sciences*, vol. 13, no. 6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Mouthami Kuppusamy, and Anandamurugan Selvaraj, “A Novel Hybrid Deep Learning Model for Aspect Based Sentiment Analysis,” *Concurrency and Computation: Practice and Experience*, vol. 35, no. 4, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Surabhi Adhikari et al., “Explainable Hybrid Word Representations for Sentiment Analysis of Financial News,” *Neural Networks*, vol. 164, pp. 115-123, 2023. [CrossRef] [Google Scholar] [Publisher Link]