

Text Classification using RNN

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Abstract: Advanced text classification tasks have gained significant attention in the field of Natural Language Processing (NLP) due to the increasing need for accurate categorization of large-scale text data. Traditional machine learning methods often face challenges in handling sequential dependencies and contextual information within text. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, offer a promising solution by effectively modeling sequences and overcoming issues like the vanishing gradient problem. This article explores the use of LSTM-enhanced RNN architectures for advanced text classification tasks. LSTM networks enable the model to capture long-range dependencies in textual data, making them particularly effective for tasks such as sentiment analysis, topic categorization, and spam detection. The paper discusses the advantages of LSTM networks over conventional RNNs and other deep learning techniques, focusing on their ability to retain important information over extended sequences. Additionally, it reviews the challenges in training LSTM models, including issues related to overfitting, model optimization, and computational complexity. Through empirical analysis on standard text datasets, the article demonstrates that LSTM-based RNNs achieve superior performance in terms of accuracy and generalization compared to traditional approaches. The article concludes by highlighting the potential of LSTM-based RNNs in advancing text classification technologies, with applications ranging from automated content filtering to sentiment-driven decision-making systems.

Keywords: Recurrent Neural Networks, Long Short-Term Memory networks, text classification, machine learning.

I. INTRODUCTION

Text classification has become a cornerstone in Natural Language Processing (NLP), as it enables machines to categorize text data into predefined categories, facilitating various applications such as sentiment analysis, spam detection, and topic categorization. As the volume of unstructured text data continues to grow, particularly in the form of customer reviews, traditional machine learning models often struggle to capture the complexities of language, especially the sequential and contextual relationships between words. This challenge becomes even more pronounced when dealing with datasets like Amazon product reviews, where reviews contain varied expressions, slang, and context-specific opinions.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for text classification, thanks to their ability to handle sequential data and learn long-term dependencies effectively. LSTM networks, a specialized form of RNN, address key limitations of traditional RNNs, such as the vanishing gradient problem, by using memory cells that retain crucial information over long sequences. This ability makes LSTMs particularly well-suited for tasks like sentiment analysis, where the context of an entire review is important for determining whether a product is perceived positively or negatively.

In this study, we apply advanced text classification techniques using LSTM-based RNNs to the Amazon review dataset. By leveraging the power of LSTM networks, we aim to enhance the accuracy of sentiment analysis and product categorization, making the model more adept at understanding complex user feedback. The Amazon review dataset, with its rich diversity in product categories and user opinions, serves as an ideal benchmark for testing the efficacy of LSTM networks in extracting meaningful insights from large-scale text data. This approach offers the potential for improved automated decision-making systems, enabling businesses to better understand customer sentiments and improve product offerings based on user feedback.

II. RELATED WORK

Recent advancements in text classification have focused on enhancing the capabilities of Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks. Du and Huang et al. (2018) explored the use of attention-based RNNs for text classification tasks, demonstrating improved accuracy on various datasets [1]. Wahdan et al. (2020) conducted a systematic review on deep learning models for text classification in the Arabic language, emphasizing the challenges and solutions for Arabic text processing [2]. Zagabathuni (2021) utilized LSTM networks for spam text classification, achieving high performance in distinguishing spam messages from legitimate ones [3]. Kim et al. (2018) proposed the use of Capsule Networks for text classification, which provided significant improvements in handling complex linguistic structures [4]. Habib and Akter et al. (2022) applied deep learning techniques, specifically RNNs, for Bangla text classification, demonstrating the effectiveness of these models in low-resource languages [5]. These studies underline the continued evolution and success of RNN-based approaches in text classification tasks across diverse languages and dataset.

III. METHODOLOGY

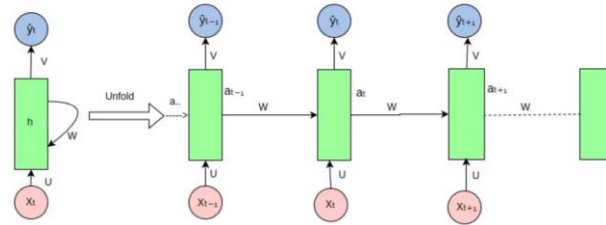


Fig. 1 RNN Architecture for Text Classification

Text Classification system leverages Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) to classify text into categories like sentiment analysis, topic categorization, or spam detection.

System Architecture:

1. Input Layer: Preprocessed text data is tokenized and represented as word embeddings (e.g., GloVe or Word2Vec).
2. Embedding Layer: Uses pre-trained embeddings to capture word relationships.
3. Recurrent Layer (LSTM): Processes word embeddings sequentially, retaining long-term dependencies.
4. Fully Connected Layer: Maps LSTM output to classification categories.
5. Output Layer: Applies softmax to convert logits into class probabilities.

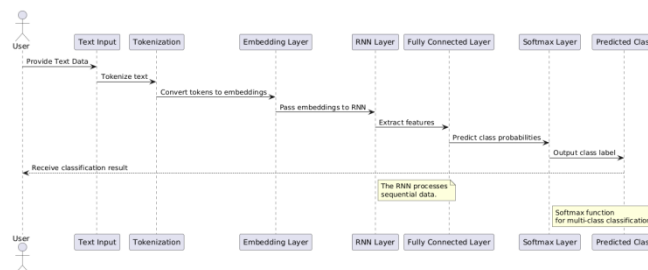


Fig.2 System Architecture

Implementation:

Using libraries like natural language tool kit (nltk), pandas, and PyTorch/TensorFlow, the model processes data, builds the architecture, and trains on datasets (e.g., Amazon reviews). The dataset is split into training and testing sets.

Advantages:

- Context-Aware: LSTM captures long-term dependencies for better accuracy.
- Scalable & Flexible: The system is adaptable to various tasks and handles large datasets efficiently.
- Automation: Reduces manual effort with automated text classification.

This approach provides an efficient and scalable solution for real-time text classification.

IV. RESULTS

Evaluating LSTM model:

Confusion Matrix:

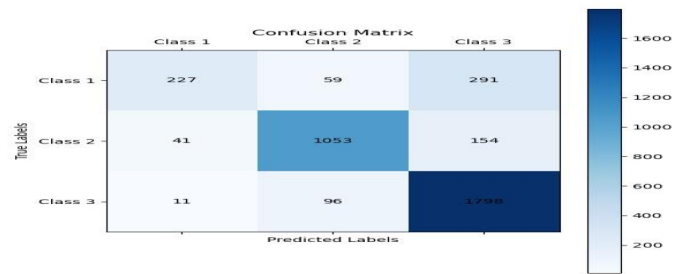


Fig.3 Confusion matrix from RNN

From Fig.3 it can be said that the 577 words belongs to neutral i.e Class 1. The Class 2 i.e (positive sentiment) has 1248 words whereas Class 3 i.e (negative sentiment) has 1905 words.

Classification Report:

label	Positive Predictive Value (PPV)	sensitivity	F1-score	Support
1 (neutral)	0.81	0.72	0.76	577
2 (positive sentiment)	0.87	0.84	0.86	1248
3 (negative sentiment)	0.91	0.94	0.93	1905
Accuracy			0.89	3730
Macro Avg	0.86	0.84	0.85	3730
Weighted Avg	0.89	0.89	0.89	3730

Table 1: Classification Report obtained from RNN

All the three classes i.e Class 1 (neutral), Class 2 (positive sentiment), and Class 3 (negative sentiment) have higher positive predictive value (PPV) and lower sensitivity. The Class 1 has PPV value of 0.81, 0.72 for sensitivity, and 0.76 for F1-score labels. The Class 2 (positive sentiment) has PPV value of 0.87, sensitivity of 0.84, and F1-score of 0.86. Next, the Class 3 (negative sentiment) has PPV value of 0.91, 0.94 for sensitivity, and 0.93 for f1-score labels respectively. The metric macro average is calculated by taking the average of all three classes for PPV, sensitivity, and f1-score labels. The macro average is 0.86 for PPV, 0.84 for sensitivity, and 0.85 for f1-score labels. The metric weighted average is calculated by taking the average of macro average versus micro average for all three classes on PPV, sensitivity, and f1-score labels respectively. The weighted average is 0.89 for PPV, 0.89 for sensitivity, and 0.89 for f1-score labels. The overall accuracy of the RNN model is 0.89.

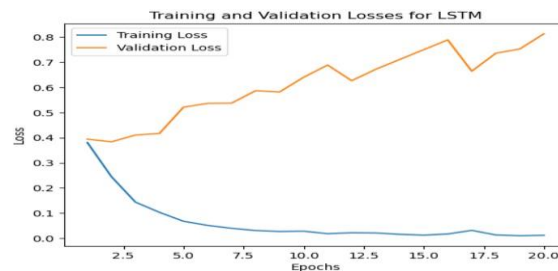


Fig 4: Loss curve on training and validation sets from LSTM

From Fig.4, it can be said that the training error is decreasing and validation error is increasing. The margin between training error and validation error is more. Therefore, it can be said that the deep neural network is over fitting.

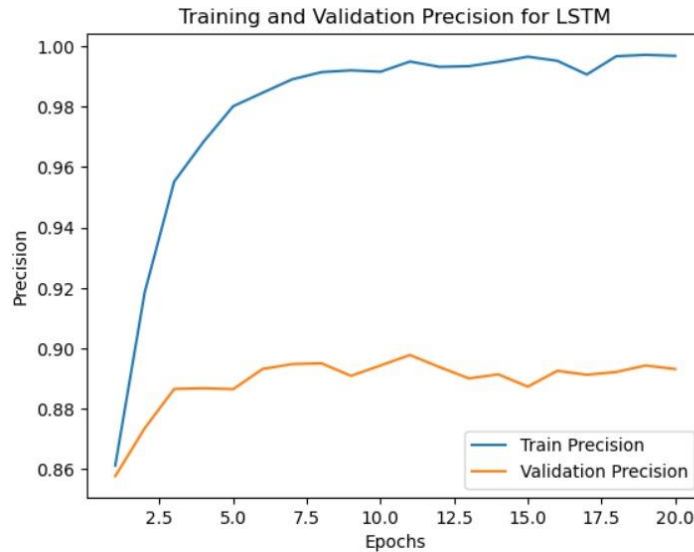


Fig 5: positive predictive value (PPV) curve on training and validation sets from LSTM

From Fig. 5, it can be said that the training PPV is increasing and validation PPV is also increasing and then becomes constant after ten epochs. The margin between training PPV and validation PPV is also more. Therefore, the deep neural network is over fitting.

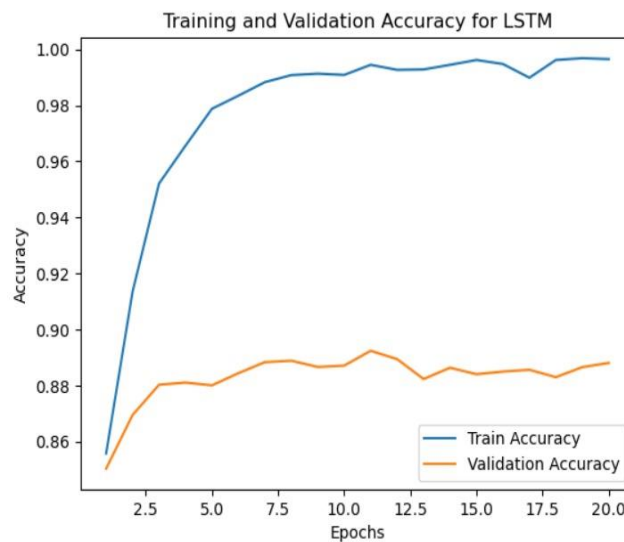


Fig 6: accuracy curve on training and validation sets from LSTM

From Fig. 6, it can be said that the training accuracy is increasing and validation accuracy is increasing initially and then becomes constant after ten epochs. The margin between training accuracy and validation accuracy is more.

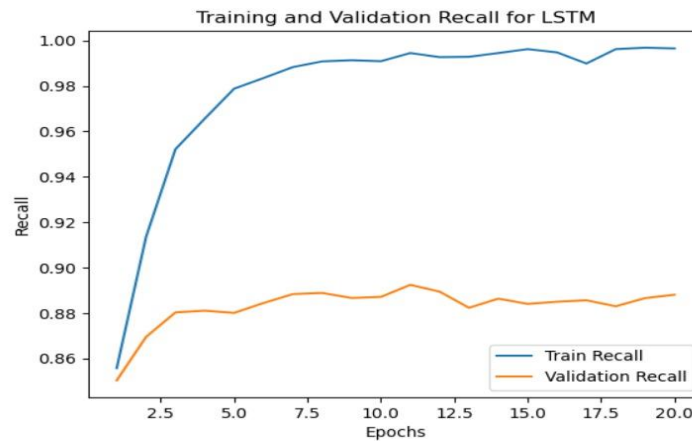


Fig 7: sensitivity curve on training and validation sets from LSTM

From Fig. 7, it can be said that the training sensitivity is increasing and validation sensitivity is increasing initially and then becomes constant after ten epochs. The margin between training sensitivity and validation sensitivity is more.

V. CONCLUSION

LSTM-based Recurrent Neural Networks (RNNs) have proven highly effective for advanced text classification, capturing long-range dependencies and handling the complexities of sequential data. Their success in tasks like sentiment analysis and topic categorization, especially with large datasets such as Amazon reviews, highlights their superiority over traditional methods. Looking ahead, further advancements in multimodal integration, real-time processing, and cross-domain transfer learning will enhance LSTM models' versatility. Additionally, improving interpretability and handling ambiguous language will expand their application. Overall, LSTM-enhanced RNNs will continue to play a crucial role in shaping the future of text classification across various industries.

VI. FUTURE SCOPE

The use of RNNs, particularly Long Short-Term Memory (LSTM) networks, in text classification has shown remarkable success, but there are several areas where further advancements can significantly enhance performance and applicability. As natural language processing (NLP) continues to evolve, the future scope of LSTM-based RNN models in text classification includes several key directions:

- **Multimodal Text Classification:** Combining text with other data types (images, audio) for more accurate and context-aware classification, such as in Amazon reviews that include both text and product images.
- **Real-Time Classification:** Adapting LSTM models for real-time, streaming data to enable immediate decision-making based on fresh user feedback or social media inputs.
- **Cross-Domain and Cross-Language Transfer Learning:** Enhancing LSTM models to generalize across different domains and languages, improving performance on diverse datasets.
- **Explainability and Interpretability:** Developing methods to make LSTM models more interpretable, particularly in high-stakes fields like healthcare or law, to increase trust in model predictions.
- **Resource Optimization:** Making LSTM models more efficient for use in resource-constrained environments (e.g., mobile devices) through techniques like model pruning and quantization.
- **Integration with Reinforcement Learning:** Combining LSTM models with reinforcement learning to enable dynamic adaptation based on feedback, improving performance in applications like customer sentiment analysis.
- **Handling Ambiguity and Sarcasm:** Improving LSTM's ability to interpret ambiguous, sarcastic, or ironic language, which is common in product reviews and social media.

These advancements will enhance LSTM models' capabilities in text classification across various applications and industries.

VII. REFERENCES

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