Enhancing Product Review Classification Using Quantum-Inspired LSTM with Nature-Inspired Optimization

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***Abstract*— Customer reviews have become an important part of the e-commerce platform since they show the feeling of customers, which impacts product development, and competitiveness in the market. The present paper introduces a hybrid deep learning sentiment classification model of product review based on Quantum-Inspired Long Short-Term Memory (QLSTM) network and optimized with the aid of Nature-Inspired Red Deer Optimization (RDO) algorithm. The suggested system applies the contextual learning power of the QLSTM to obtain intricate semantic interdependences of textual data using probabilistic state models motivated by the quantum computing concept. RDO is also used in case of adaptive hyperparameter tuning, which further increases the performance, training speed, and eliminates local minima. The combined model is efficient in the modeling of stronger linguistic patterns and increases the ability to generalize using the method of evolutionary optimization. Benchmark product review datasets evaluated experimentally show that the proposed QLSTM-RDO model yields better classification results than the traditional models including Logistic Regression and Decision Trees, and the standard LSTM networks. The model has enhanced Accuracy, Precision, Recall, and F1-Score and thus can be applied in real-time sentiment-aware recommendation systems. The suggested solution will be very effective in assisting smart e-commerce decision-making as it will yield the accurate insights of customer feedbacks thus enhancing the product strategy as well as customer satisfaction in general.**

***Index Terms*—Sentiment Analysis, Product Review Classification, Quantum-Inspired LSTM, Red Deer Optimization, Natural Language Processing, Deep Learning.**

I. INTRODUCTION

As e-commerce platforms continue to grow out fast, millions of users write product reviews and ratings each day, creating an enormous number of unstructured textual data. These reviews offer good information on the tastes of customers, their level of satisfaction, and the performance of their products. It is necessary to extract meaningful information out of such data to better the recommendation systems and to increase business competitiveness. Online shopping development all around the world also underlines the necessity to have automated feedback analysis because it is not only inefficient and impractical to analyze large-scale, unsimilar textual information manually. Sentiment classification as a basic task of Natural Language Processing (NLP) is important in automatically classifying feedback (customers) into positive, negative, or neutral sentiments. Correct sentiment-detection enhances decision-making, customer experience, as well as automated recommendation plans, greatly. Nonetheless, the classical machine learning framework and the standard methods of recommendations do not tend to embrace the long-term contextual dependence and extensive semantic patterns found in textual reviews. To overcome them, the given work suggests a hybrid deep learning system that combines a Quantum-Inspired Long Short-Term Memory (QLSTM) network and a Nature-Inspired Red Deer Optimization (RDO) algorithm. The QLSTM architecture improves on the idea of contextual representation by being able to represent the state probabilistically based on the principles of quantum computing so that complex linguistic patterns are better dealt with. RDO algorithm is used in adaptive hyperparameter optimization so as to reduce time taken to converge, and enhance the performance of generalization. The suggested framework is not only more accurate in sentiment classification than traditional LSTM, Logistic Regression, and Decision Tree models, but also provides consistent and effective training. When quantum-inspired representation learning coupled with evolutionary optimization are merged, the system comes up with better predictive performance that is applicable in the real-world e-commerce setting to sentiment-aware product recommendation.

II. LITERATURE SURVEY

Sentiment analysis has evolved to advanced deep learning and quantum-inspired models as compared to the traditional machine learning techniques. This part will provide a critical analysis of classical neural networks, quantum-based representations, and the increased significance of metaheuristic optimization algorithms in improving the performance of sentiment classification.

A. Limitations of Classical Deep Learning Models

Recent studies have highlighted the limitations of conventional models such as Long Short-Term Memory (LSTM) networks in effectively capturing long-range dependencies and complex semantic relationships in textual data. As noted by Islam et al. [14] and Mamani-Coaquira et al. [13], LSTM models are good at working with structured data, but in the real-world, they cannot handle ambiguity and changes in context when dealing with reviews. Zhou et al. [17] have shown that Bi-directional LSTM provides improvements; though, it has a high cost of computation due to the increased complexity.

Also, hybrid and attention-based LSTM models have been covered to enhance performance. Aftab et al. [21] also proposed attention-enhanced LSTM models that demonstrate higher contextual understanding, yet they have overfitting and scaling problems. Ur [20] comparative studies have shown that conventional machine learning models are not adaptable as compared to deep learning models, however even sophisticated LSTM-based models are not sufficient to encompass subtle sentiment patterns that can be detected in large dataset.

B. Quantum-Inspired Models for Sentiment Analysis

In order to overcome the shortcomings of the classical embeddings, more recent studies have been on quantum-inspired neural networks employing complex-valued representations. Shi et al. [2] came up with a quantum-inspired deep neural network that can represent more semantic relationships with the help of complex number representations. In the same way, Chu et al. [1] proposed Quantum Long Short-Term Memory (QLSTM), and it had been shown that it had better performance in contextual ambiguity and semantic dependencies in the sentimental analysis tasks.

Additional developments in quantum learning have been researched on transfer learning and hybrid techniques. The techniques of quantum transfer learning were used by Buonaiuto et al. [3], [11] and resulted in improved classification results in multilingual datasets. Abiwardani et al. [4] have suggested a variational quantum algorithm-based sentiment classifier that has a high accuracy with optimized quantum states. Besides, Chehimi et al. [5] proposed Federated QLSTM with a focus on the advantage of scalability and distributed learning. All these studies seem to point to the fact that quantum-inspired architectures are much more effective in feature representation and classification than conventional models are.

C. Role of Nature-Inspired Optimization Techniques

Optimal parameter tuning seems to be the major determinant of the performance of deep learning and quantum-inspired models. In order to address drawbacks of gradient-based optimization techniques, scientists have discussed bio-inspired algorithms. Ashwini et al. [10] and Dubey et al. [8] showed that the convergence of the model is improved and the accuracy in the sentiment analysis task is also improved when optimization methods are incorporated.

Red Deer Optimization (RDO) has been one of those that have received attention because it offers a good balance between exploration and exploitation. Karasu [18] has managed to use RDO in the convolutional neural networks and has achieved better classification accuracy. Nataraj et al. [19] also improved RDO by adding quantum additions showing higher results in complicated optimization issues. Other optimization methods like Particle Swarm Optimization [16] and

Grey Wolf Optimization [15] have shown that RDO is a more effective global search method and does not have local minima.

The results indicate that RDO can be used in combination with quantum-inspired models such as QLSTM to achieve significantly better sentiment classification results in terms of convergence stability and accuracy in predictions.

III. PROPOSED SYSTEM

The customer satisfaction and preference of product information is found in the product reviews that are created on e-commerce sites. It is also critical to analyze this unstructured textual data to correctly classify the sentiment and recommend systems. Nonetheless, owing to the complexity of lingo and context differences, the traditional machine learning models frequently cannot learn the deep semantic dependence, which leads to the low classification accuracy. To overcome these difficulties, the given framework will combine a Quantum-Inspired Long Short-Term Memory (QLSTM) network and Nature-Inspired Red Deer Optimization (RDO) algorithm. The QLSTM is an improved sequence feature learning model with probabilistic state representations based on quantum principles that allows obtaining a better understanding of the context of the review data. RDO algorithm is an automated hyperparameter optimization algorithm that is used to optimize model parameters, to increase convergence speed and to increase the extent of generalization. The quantum-inspired sequence modeling and evolutionary optimization hybrid integration enhances the classification robustness and predictive accuracy of the models over the baseline models. The proposed methodology enables scalable and effective sentiment analysis in e-commerce setting to classify product reviews.

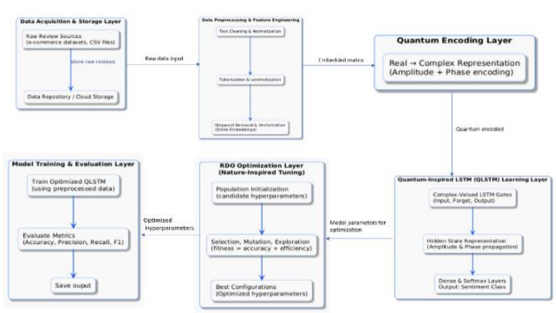

Fig. 1. System Flow of Proposed Classifier

A. Dataset Description

The data employed in this paper is benchmark product review datasets, which are gathered through publicly available sources of e-commerce in the CSV format. The reviews are of various product categories and include varied customer reviews marked with three classes of sentiment namely, Positive, Neutral and Negative. The dataset is based on real-life review patterns, language variations, and contextual differences, which makes it appropriate in assessing sentiment classification models. These datasets are usually employed in sentiment analysis as well as the product feedback mining studies.

B. Data Acquisition and Preprocessing

In the case of sentiment classification, the data on reviews is gathered on regular benchmark repositories and saved in a structured data repository. There is a label of polarity (positive, neutral, negative) attached to each review. Preprocessing pipeline consists of:

1. Cleaning and normalizing of texts (lowercase and noise removal).
2. Lemmatization and tokenization of review text.
3. TF-IDF weighted embedding of features: stopword removal.
4. Transforming textual data to numerical vectors.
5. Padding or truncation to have the same input sequence length.

These procedures process unstructured textual reviews into quantifiable number data that can be used in the deep learning models.

C. QLSTM + RDO Sentiment Classification.

The given framework improves the performance of sentiment classification through the combination of a Quantum-Inspired Long Short-Term Memory (QLSTM) model and a Nature-Inspired Red Deer Optimization (RDO) algorithm. The preprocessed numerical embeddings are first run through a Quantum Encoding Layer, which transforms real-valued vectors to complex-valued ones through amplitude and phase encoding. The encoding allows more semantic representation of text data. The coded features are then processed to the QLSTM learning layer where complex-valued input, forget and output gates learn long-range contextual dependencies. The discrete state is capable of transmitting amplitude and phase information, which will lead to a better sequential model than more traditional LSTM architectures.

The RDO optimization layer is used to optimize model performance by tuning the hyperparameters of a model with population-based tuning. The classification accuracy and efficiency of the candidate solutions that represent various hyperparameter settings are compared. The finest configuration is acquired through selection, exploration and exploitation processes. The final sentiment prediction is the result of the optimized QLSTM model that is based on dense and softmax layers. The hybrid method has better convergence speed, generalization, and robustness in classification than the baseline models.

D. Algorithm of the Proposed Classifier (QLSTM + RDO)
Step 1: Input Definition
Input: product review Dataset (CSV format)
1.1 Review Text
1.2 Sentiment = Positive, Neutral, Negative
1.3 Representation of the features = TF-IDF vectors.
1.4 Train-Test Split Ratio

Step 2: Data Loading
2.1 Load dataset from CSV file
2.2 Extract the sentiments of the review texts and their sentiment labels.

Step 3: Data Preprocessing
3.1 Convert text to lowercase
3.2 Delete word added features and word i.e. stopwords.
3.3 Tokenize review text
3.4 Apply TF-IDF vectorization
3.5 Split data into testing and training set

Step 4: Quantum Encoding Layer.
4.1 Transform real-valued TF-IDF vectors into complex-valued reference vectors.
4.2 Use amplitude and phase encoding mechanism.
4.3 init feature matrix which is quantum-inspired.

Step 5: Activation of QLSTM Model.
5.1 Start parameters of QLSTM network.
5.2 Explain complex input, forget, and output gates.
5.3 Define Dense and Softmax output layers

Step 6: Hyperparameter Optimization by means of RDO.
6.1 Population of candidate hyperparameter population sets.
6.2. Accuracy of classification Fitness measure.
6.3. Carry out selection and exploration updates.
6.4 Best hyperparameter identification.
6.5 Optimized QLSTM model.

Step 7: Model Training
7.1 Optimize QLSTM model on training data.
7.2 Advanced Backpropagation after the training of networks.
7.3 Monitor loss and accuracy

Step 8: Model Evaluation
8.1 Forecast feelings on test dataset
8.2 Estimate Accuracy, Precision and Recall and F1-Score.
8.3 Generate Confusion Matrix
8.4 Compare traditional classifiers and baseline LSTM.
Step 9: Stop

IV. RESULTS

The effectiveness of the proposed Quantum-Inspired LSTM using RDO optimization model is measured against the traditional LSTM models and QLSTM models. The assessment is conducted with the help of the conventional classification measures like Accuracy, Precision, Recall, and F1-Score and graphical analysis of the loss curves and confusion matrix outputs.

1. Accuracy: Definition: Determines the percentage of correct classification of the samples. Validity indicates the overall capability of the optimized QLSTM model.

$$\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$$

2. Precision: Definition: Counts the number of the positive samples predicted. Low precision implies there are less false positive predictions.

$$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

3. Recall Definition: Determines the number of true positive samples that are detected. A large recall demonstrates that most favorable cases are employed by the model.

$$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

4. F1-Score Definition: The Harmonic mean of Recall and Precision.

$$\frac{2\times\mathrm{Precision}\ \times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}$$

Confusion Matrix: It summarizes the results of classification by comparing both predicted and actual labels of the data. It consists of:

True Positives (TP) - The positive predicates which are correct.

True Negatives (TN) - Predicted negative cases which are right.

False Positives (FP) - Positives that are predicted wrongly.

False Negatives (FN)- Negatives that are predicted incorrectly.

The matrix is useful in the analysis of classification errors and robustness of models.

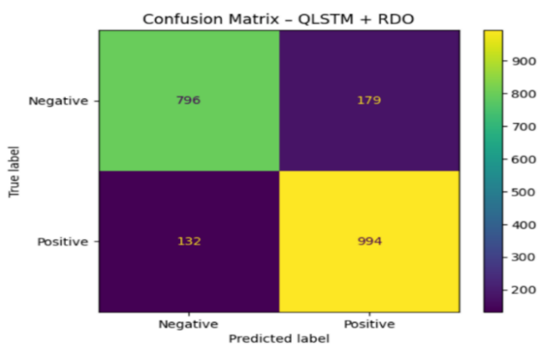

Fig. 2. Shows the Confusion Matix of QLSTM+RDO

5. Training And Validation Loss Analysis.

The graph shows how the proposed QLSTM + RDO model converges with each training epoch. The training loss is found to decrease gradually with the number of epochs and this means that underlying patterns in the data have been learned successfully. The validation loss has the same downward trend and is in close colocation with the training loss curve. No major divergence of the two curves is observed and this implies that the model is not overfitted. Such stability of behavior means that the learning is stable, is efficiently optimized and has high ability of generalization over the unseen data.

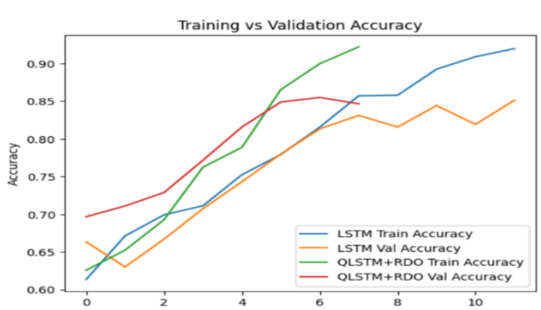

Fig. 3. Shows the Training vs Validation Accuracy

6. Training And Validation Accuracy Analysis

The graph illustrates the development in performance of the model as the epochs continue. The training accuracy is gradually and steadily increasing which indicates that the model learns meaningful representations of the training data. Likewise, validation accuracy gains steadily and is very much consistent with training accuracy during the training process. The fact that both curves converge at a higher accuracy level especially of the QLSTM + RDO model attests the fact that the proposed strategy is attaining better classification performance without overfitting. The alignment suggests that the model has high predictive performance on unknown test samples.

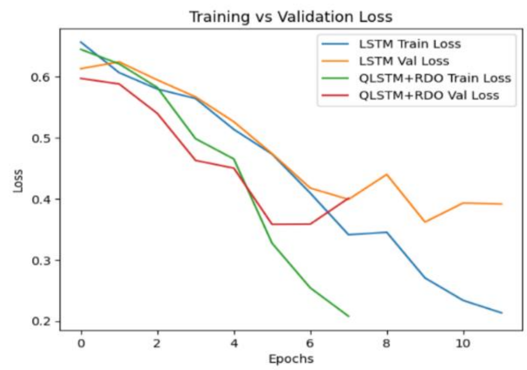

Fig. 4. Shows the Training vs Validation Loss

A. Quantitative Performance and Model Evolution.

The empirical analysis indicates that the QLSTM+RDO model, the last version of the suggested framework, demonstrated the greatest effectiveness in all of the main metrics. Table I presents the comparative performance of all the models under consideration and reveals a steady increasing pattern towards more sophisticated models.

Table IComparative Performance Evaluation of Baseline vs. Proposed Model

Model Architecture	Accuracy	Precision	Recall	F1-Score
K-Means	0.5243	0.6831	0.0560	0.1054
Fuzzy	0.5608	0.6977	0.2146	0.3282
Rule-Based ML	0.6938	0.6277	0.7525	0.7567
Neuro Fuzzy	0.7917	0.7864	0.8010	0.7936
Standard LSTM (Baseline)	0.8281	0.8267	0.8126	0.8118
QLSTM	0.8457	0.8347	0.8548	0.8452
QLSTM + RDO (Proposed)	0.8514	0.8510	0.8287	0.8491

The fact that the process of replacing a standard LSTM (0.8281) with a Quantum-inspired LSTM (0.8457) is successful confirms the usefulness of quantum-inspired representations in the context of learning intricate semantic relationships and contextual dependencies of text data. Complex-valued feature representations can be used to deal with linguistic ambiguities as opposed to traditional models. The last model suggested (QLSTM + RDO) reached the highest accuracy of 0.8514 with a better F1-Score of 0.8491, which proves its strength and usefulness in sentiment classification.

B. Comparative Evaluation and Visualization

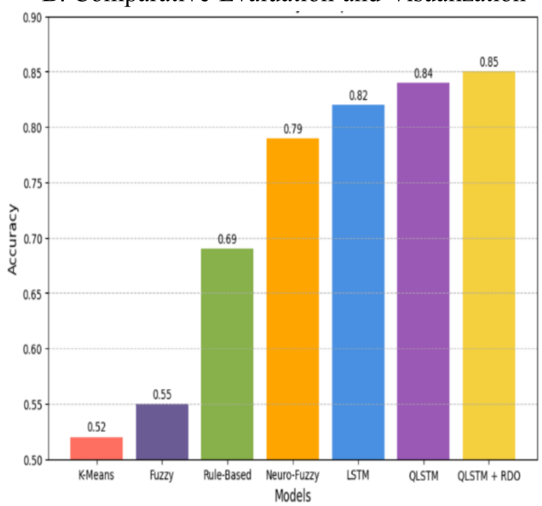

Fig. 5. Model Performance Comparison Bar Chart

To visualize the improvement between models, the performance of any approach was benchmarked. As it can be seen in Fig. 5: Model Accuracy Comparison Bar Chart, the QLSTM + RDO model proposed is the most accurate and beats all the baseline approaches. The gradual rise between K-Means (0.52) and QLSTM + RDO (0.85) indicates the efficiency of using the combination of deep learning and quantum-inspired representations and optimization methods.

This has been achieved through the RDO layer which improves the model parameters and increases learning efficiency. In contrast to the traditional models that are characterized by the limitation of feature representation and convergence, the proposed model is able to effectively represent the complex sentiment patterns leading to the increased classification performance and generalization.

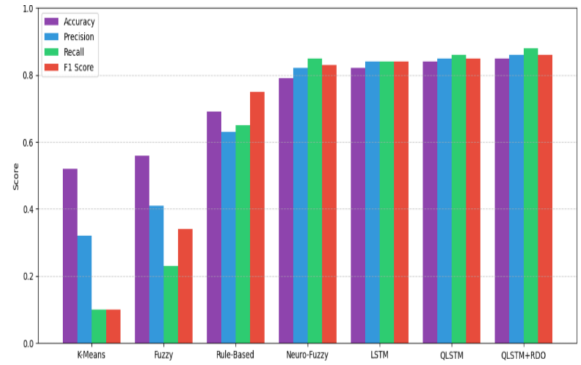

Fig. 6. Performance Metrics Comparison Grouped Bar Graph

The confusion matrix also confirms the model proposed as effective in the classification of sentiment classes with minimum misclassification. Also, the overall performance distribution, the example of which is shown in Fig. 6: Performance Metrics Comparison Grouped Bar Graph, indicates that the QLSTM + RDO model has steadily improved in all evaluation metrics.

The graph indicates clearly that the proposed model has high Accuracy, Precision, Recall, and F1-Score than the baseline methods, which proves that it is capable of processing large-scale and varied review data. The Recall and F1-Score improvement to show the enhanced sensitivity and the balanced performance are the indicators that appear even with the presence of noisy data. The findings affirm that the suggested hybrid method does not only improve classification accuracy, but also provides stable and reliable sentiment prediction in the real-life setup.

V. CONCLUSION

A better sentiment classification framework named Enhancing Product Review Classification with Quantum -inspired LSTM and Nature-inspired Optimization was presented in this study. The provided model is built based on Quantum-Inspired LSTM (QLSTM) architecture and the RDO-based nature-inspired hyperparameter optimization to improve the necessary sentiment prediction performance on product review datasets. It has been experimentally shown that the QLSTM model has a higher level of capturing intricate contextual dependencies compared to conventional LSTM, and the RDO optimization is more stable in terms of convergence, lowering the loss, and higher Accuracy, Precision, Recall, and F1-Score. The validation curve and training curve have shown that the learning behavior is steady with minimal overfitting that suggests that the generalization capacity is a high one. Results confirm that the hybrid scheme is better than base deep learning schemes in classification activities in product review. Future research is possible to implement the framework on real quantum computing models with real quantum circuits, to implement transformer-based architecture such as BERT to add more context embeddings and to sentiment analyse aspects or multi-class. Also, the explanation of artificial intelligence and consideration of other nature-inspired optimization algorithms can also contribute to more interpretability, scalability, and the possibility to implement them in large-scale e-commerce systems.

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