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Attention Based Swarm-optimized Quantum CNN for Sentiment Analysis in E-commerce Products

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Abstract: In this study, a hybrid intelligent model based on deep learning techniques is presented, which exploits feature representation, optimization and enhanced feature learning capabilities. Quantum inspired Convolutional Neural Network, Efficient Dynamic Transformer, and Efficient Low-Rank Attention methods are incorporated into the design of the model to boost feature learning capabilities, context modeling capabilities and computational efficiency. First, the input data are cleaned and normalized to eliminate noise and normalize feature values. Quantum CNN is then utilized to generate feature representations, providing more efficient discriminability when compared with the traditional convolution approach. The extracted features are then used by the Efficient Dynamic Transformer to capture long-term contextual interactions, whereas Efficient Low-Rank Attention minimizes computation overheads through low-rank approximations. A series of experiments was carried out on benchmark datasets to evaluate the effective performance of the proposed method. The developed model yielded a mean classification accuracy rate of 99.47%, demonstrating superior performance to multiple state-of-the-art baseline models, including CNN, LSTM, and Transformer-based models. Other measures, such as precision, recall, F1 score and kappa score further validate the effectiveness of the proposed framework. Furthermore, experimental results show that the developed sentiment analysis model exhibits enhanced computational efficiency and generalization capabilities compared to current algorithms.

Keywords: Duck Swarm Optimization, Long-Range Attention, Elastic Decision Transformer, Distance-Based Encoding Method, Quantum Convolutional Neural Network.

1. Introduction

Due to the growth of the world wide web and internet technologies, social media has become one of the most widely used platform for public to share opinions and information about their livelihood, business, education and many more [1]. From the past few years, user ratings and reviews through online portals have often provided strong sentiment behaviors which caused strong decisions [2]. Business environments and its stakeholders have utilized the ecommerce product review data, which have great potential to decide its business in future. Customers can learn more about a product's quality by reading the reviews by the existing consumers [3]. Therefore, there is a need to present data in a form that computers and AI models can "understand" to describe and analyze it and reduces the manual effort [4]. Sentiment analysis will address it. One of the most significant and challenging tasks is sentiment analysis. Its objective is to locate and extract subjective information from texts using text mining and other methods in order to ascertain the sentiment polarity of the material [5-6]. Text mining is the process of extracting interesting and useful information from unstructured text. This approach initially preprocesses the data, followed by deep learning (DL) methods to establish polarity based on the resulting features, which are extracted from the preprocessed data [7].

Regression and pattern classification problems are addressed using a range of neural network techniques in deep learning (DL), a subfield of machine learning (ML) [8]. Deep layers that can learn to describe and quantify complex data structures and higher-order attributes are frequently used to accurately identify or quantify data qualities [9]. DL's performance on SA tasks has improved. Specialized SA systems can be made more effective by DL models driven by feature extraction and selection [10, 11]. Sentiment research shows that users' emotional orientations and perceptions of the same object frequently differ. Acknowledging this reality allows for significant usefulness in competitive and marketing analysis [12, 13]. Remaining existing approaches of SA across various industries include public review based research, e-commerce, and recommendation system for various applications, among others [14].

The exponentially growing number of online reviews for e-commerce platforms like Amazon has produced enormous amounts of unstructured, emotion-laden information that substantially affects consumer buying patterns and business decisions. But information with strong emotional content, linguistic ambiguity, domain variability, data imbalance, and natural-language context make it difficult to accurately interpret these patterns. Traditional deep learning systems tend not to ensure strong generalization across product categories and cannot handle confidence estimation, semantic disambiguation, or scalability in computation. In that regard, an effective, dependable, and quantum-enhanced framework of sentiment analysis capable of processing huge amounts of textual data and offering reasonable interpretability, versatility, and predictive reliability, even in a multi-domain environment, is much needed.

The objective behind this research work was driven by the increasing demand to enhance the accuracy, elasticity, and computational efficiency of sentiment analysis in large-scale, applications like e-commerce review systems [15, 16]. The unstructured textual data is increasing exponentially, and as a result, contemporary deep learning models often cannot learn fine language features, longer contextual interactions, and unequal sentiment patterns [17, 18]. In addition to that, traditional structures do not have adaptive mechanisms of optimization and confidence-enhanced prediction, which restricts the use of these models in decisions that are critical decisions [19]. The objective is, in turn, to develop a resource-efficient, context-sensitive, and smart sentiment analysis system capable of operating with high-dimensional data, being cross-disciplinary, and able to offer interpretable and reliable predictions. Such a system would add a lot of clarity to the automated sentiment analysis, better customer experience analytics, and enable building a more robust and transparent data-driven business intelligence.

The proposed ABS-Q-CNN approach is unique because it uses quantum-inspired computing with an emphasis on a specific context, attention, and bio-inspired optimization to train powerful, understandable sentiment analysis. Unlike traditional deep learning models based on either classical convolution or recurrent models, ABS-Q-CNN utilizes QCNN with additional entangled features, ELRA with global contextual interactions and DSA with adaptively optimizing hyper parameters. This unique combination allows it to generalize better across product fields, have more calibrated confidence, and calculate. NDBEM also improves feature normalization and feature semantic scaling in the framework to render it resistant to highly imbalanced data. Overall, ABS-Q-CNN is a hybrid deep-learning framework based on quantum force connecting semantic intelligence with scalability in mass sentiment analysis. The main contributions are listed below,

1. Development of a novel ABS-Q-CNN framework combining attention mechanisms and swarm intelligence for robust sentiment analysis.
2. Integration of Quantum Convolutional Neural Networks (QCNN) to enhance high-dimensional, entangled feature extraction with reduced computational cost.
3. Development of an Efficient Long-Range Attention (ELRA) method to enable modeling of long-range contextual relationships in extensive review texts.
4. Use of the Duck Swarm Algorithm (DSA) for intelligent optimization of feature selection and enhanced convergence.
5. Use of the Distance Based Encoding Method (DBEM) for feature scaling.
6. Prediction framework to support confidence-based sentiment analysis to improve the sales.

The model structure can be briefly described as follows: Previous literature is discussed in the second part. Results will be presented in Section 4, while Section 3 will give details about the proposed approach. Section 5 will contain conclusions.

2. Literature Survey

This section examines a few existing works based on Sentiment Analysis. In 2022, Norinder and Norinder [20] presented predicting Amazon customer reviews with deep confidence using deep learning and conformal prediction. The study starts with the collection of product reviews on Amazon in 12 categories and then the use of NLP for pre-processing the data in order to remove unwanted elements. Further, deep learning models are created to carry out sentiment analysis on the processed data. These models are evaluated based on both in-category predictions, where data of the same category is used, and cross-category predictions, where models are evaluated with data of other categories.

For graph-based collaborative filtering in 2023, Liu, *et al.* [21] used a review-based feature-level information aggregation model. The initial stage in RFIA model proposed by Liu *et al.* [21] was the creation of an interaction graph between users and items with feedback being depicted through edges. At first, semantic review features are extracted from review texts corresponding to interaction graphs through the BERT-Whitening model. Following this, the extracted features are optimized in opposite directions by two different non-linear feature extractors to derive feature-level attention vectors.

The MAFCDR meta-adversarial framework for addressing cold-start recommendations in the year 2024 was proposed by Liu, *et al.* [22]. The first stage in the proposed MAFCDR meta-adversarial framework involves collecting user behavior data from both source and target domains. Multi-level feature attention models are used in order to generate comprehensive representations of user preferences in the source domain where the learning process involved entails estimating feature weights at both the long-term and short-term levels of each user individually. Robust and generalized user representation capabilities are then obtained via the use of the learnt feature embedding vectors within the proposed meta-adversarial network.

The system proposed by Almahmood, *et al*. [23] in 2024 is one such novel approach toward review analysis that takes into consideration the difference in rating values with respect to user preferences and balances deep reviews. The data used for this model are from several Amazon 5-score domain datasets. For the BHRQUT model recommended by the authors, the text of reviews and ratings are gathered from these datasets. Preprocessing of the text involves cleaning, tokenizing, and normalizing the text. Then, NLP methods are used to extract feature vectors, which can be optimized based on the effect of embedding size and word frequency. These feature vectors undergo transformation into dense vectors through an embedding layer and are then processed using the hybrid CNN-BiLSTM framework.

Sentiment analysis for user reviews on Amazon using a hybrid approach is proposed by Sangeetha and Kumaran in 2023, [24]. Firstly, the model proposed in this research suggests the collection of user reviews from Amazon, which then requires pre-processing, including the removal of unnecessary information, noises, and stop words. The process of feature extraction is then performed to extract relevant features from the textual data. After the feature extraction phase, Pearson Correlation Coefficient (PCC) is applied to reduce the dimensions by removing redundant or correlated features. It has been observed that using the Harris Hawks Optimization (HGO) algorithm in order to refine the selected features is a much better choice since it identifies only significant non-redundant features. Finally, the obtained RNN-LSTM classifier is able to classify the attitudes of customers as positive, negative, or neutral.

Knowledge gain-sharing knowledge (GSK) optimization process is used to fine-tune the model hyper parameters to attain efficiency and performance in convergence.

In 2022, Iqbal, *et al.* [25] presented the application of deep learning to assess the sentiment of customer reviews. Data collection is the first part of the suggested sentiment analysis process. Data is in the form of text, which was collected by accessing different social media and e-commerce websites, such as customer reviews, comments, and posts on the websites. Once the text has been smoothed out, it is converted into numerical form through a feature encoding technique so that it can be used for training the models. The feature-encoded data is then run through three distinct LSTM models in order to analyze the sentiment and context of the text.

In 2023, Atandoh, *et al.* [26] employed a single deep learning platform to perform sentiment analysis on documents. The proposed BERT-Multi-Layered Convolutional Neural Network (B-MLCNN) model of sentiment analysis of documents took into consideration the textual review of a single document. Afterward, context-based feature vector representations were derived with the help of the pre-trained BERT model that was able to identify global semantic and syntactic dependencies in the text. These embeddings are then given to the Multi-Layered Convolutional Neural Network (MLCNN) that employs a high count of convolutional layers with different sizes to provide both local and hierarchical features of sentiment. Each of the flattened extracted characteristics is then classified as positive, negative, or neutral using a softmax activation function and inputted into fully connected layers.

2.1 Research Gap

Even though deep learning models have contributed majorly in sentiment analysis, various research problems remain unaddressed in the literature reviewed. The widely available literatures were solelyoptimizes performance in a single domain or on a static dataset and offers limited flexibility for cross-domain sentiment generality and handling probability-imbalanced classes. Though other models are better at relative understanding and modeling user preferences, such as RFIA, MAFCDR, and BHRQUT, they are not as sufficiently better at standardizing confidence and uncertainty, or at quantifying them, to achieve reliable predictions in a large-scale sales prediction and review system. Also, more efficient optimization strategies, such as HHO and GSK, are more accurate but tend to be computationally more intensive and do not scale to quantum-efficient or long-range attention. A few studies have integrated conformal prediction with quantum-inspired learning paradigms to facilitate sentiment predictions that are transparent, interpretable, and mindful of confidence. As a result, it is desperately necessary to develop a quantum-effective, confidence-calibrable, and domain-generalizable sentiment analysis system capable of balancing interpretable, robust, and computationally efficient performance on multi-category Amazon review data.

3. Methodology

The proposed ABS-Q-CNN framework provides a systematic workflow for performing reliable sentiment analysis of reviews for Amazon products.

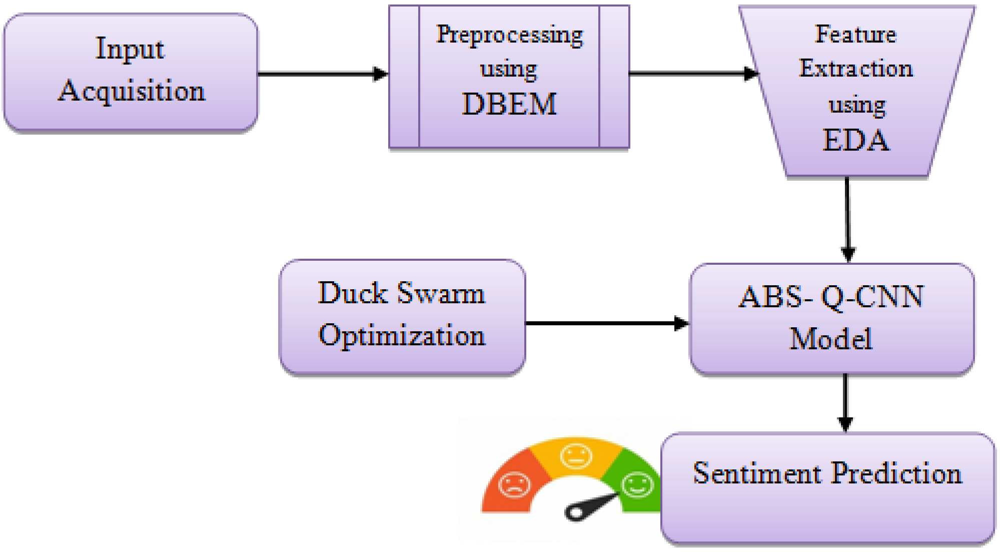


Figure 1. Block diagram of proposed Methodology.

The process commences with data acquisition, during which multi-domain Amazon review datasets are gathered and categorized into 10 product groups. After that, the data underwent preprocessing and normalization via DBEM to clean, tokenize, and gain uniform semantic scaling. The refined data is further processed by EDT, which captures the deep contextual and semantic features of the encoded text dynamically. These representations are extracted and fed to the ABS-Q-CNN model, which enhances QCNN to accomplish the task of feature transformation under the effect of quantum dynamics and integrates it with ELRA to learn long-range contextual associations. This model was developed using the Diophantine Sets Algorithm to optimize its hyperparameters in order to achieve high accuracy and low uncertainty. Finally, Conformal Prediction employed sentiment classification based on confidence to obtain positive, negative, or neutral. This increases the strength, interpretability, and computational efficiency of multi-domain Amazon sentiment prediction. The block diagram of the proposed research is presented in Figure 1.

3.1 Input Acquisition

The dataset is the one obtained in this research, the Amazon Five-Core Product Review Dataset, which is publicly accessible and is also commonly used in sentiment analysis research [27]. The data set comprises reviews of products created by users of the 10 product categories, such as Movies and TV, CDs and Vinyl, Books, Electronics, Office Products, Cell Phones and Accessories, Musical Instruments, Patio, Lawn and Garden, Sports and Outdoors, Groceries and Gourmet Food, Arts, Crafts and Sewing, and Clothing, Shoes and Jewelry.

In every review record, there will be the review text, star rating (1-5), and metadata, including the product ID, reviewer ID, and review time.

To perform sentiment classification, a binary sentiment label was derived from the original five-point rating scale. Ratings of 1-2 were plotted on the negative sentiment category, whereas ratings 3-5 were plotted on the positive sentiment category. This dichotomy makes the classification process easier while maintaining the same semantic polarity of user opinions.

The data were split into training and test sets (80:20). The positive and negative samples are distributed across the product categories, as shown in Table 3.The percentage of negative reviews varies between 5% and 13%, indicating imbalance among classes. To address this disparity in model training, the binary cross-entropy loss function was class-weighted, with a greater weight assigned to the minority (negative) class.

3.2 Pre-processing using Distance-Based Encoding Method

A crucial step in converting raw, unstructured review data into a clean and consistent format suitable for training and feature extraction is preprocessing. This task is carried out with DBEM to normalize the text input, ensure semantic consistency, reduce noise, and improve compatibility with downstream methods. Normalized DBEM offers several benefits that enhance its effectiveness for preprocessing and representing sentiment analysis features. It ensures that feature sizes remain consistent while minimizing the impact of variations in word frequency and sentence length among various review types. During model training, normalization contributes to the stabilization of gradient propagation. When used prior to the Elastic Decision Transformer (EDT) step, DBEM enhances the quality of contextual embedding, leading to improved and more robust sentiment classificationon multi-domain product reviews.

Let the distances between consecutive occurrences of a feature be represented by a list $P = \{p_1, p_2, \ldots p_n\}$, where n is the total number of occurrences. The mean distance between repeated features is computed in equation (1)

$$\chi = \frac{1}{n}\sum_{a=1}^{n} p_a \quad (1)$$

where, p_a represents the Distance between the a^{th} occurrence and the previous occurrence of the same feature, χ is the Mean of the distances in the original scale. This captures the temporal or sequential distribution of feature repetition. To ensure uniformity and cross-feature comparability, each distance value is normalized to a 0–1 scale using equation (2)

$$p_a^{norm} = \frac{p_a - p_{\min}}{p_{\max} - p_{\min}} \quad (2)$$

Where, $p_{\min}$ and $p_{\max}$ are the minimum and maximum distances in P. This normalization preserves relative spacing patterns while aligning all feature scales for consistent model interpretation. The Normalized Standard Deviation (NSD) is then computed to measure the variability in normalized distances, which is expressed in equation (3)

$$\eta_{norm} = \sqrt{\frac{1}{n}\sum_{a=1}^{n}\left(p_a^{norm} - \chi_{norm}\right)^2} \quad (3)$$

Where, p_a^{norm} represents the normalized distance of the a^{th} event, scaled to [0,1], χ_{norm} is the Mean of normalized distances, η_{norm} is the Standard deviation of normalized distances. Finally, the Coefficient of Variation (CV) is derived to quantify the relative dispersion of feature occurrences and it is expressed in equation (4)

$$H = \frac{\eta_{norm}}{\chi_{norm}} \quad (4)$$

where, H represents the Coefficient of variation, providing a scale-independent measure of the variability in sequential feature spacing, aiding in distinguishing stable contextual patterns from irregular or noisy occurrences. DBEM successfully converts textual raw data into semantically consistent, noise-resistant, and scale-normalized feature representations, which assure greater contextual integrity, improved convergence, and increased classification accuracy in the latter processing steps.

3.3 Feature Extraction using Elastic Decision Transformer

EDT is a dynamic feature extraction module in the proposed framework that aims to extract complex semantic dependencies and decision-relevant contextual patterns from the preprocessed Amazon review data [27]. Combining elastic attention with transformer-based encoding, EDT can learn flexible and discriminative feature representations, thereby improving the downstream effectiveness of the ABS-Q-CNN sentiment classification model. EDT makes feature extraction more efficient through adaptive contextual learning, semantic and decision-based dependency capturing, and attention to important sentiment cues. Its generalizability is high due to elastic attention, it converges faster, and it is also very interpretable, producing rich embeddings that increase accuracy and reliability.

The Enhanced Deep Transformer (EDT) module is used to extract contextual relationships from input feature representations. The EDT architecture is a combination of L stacked layers of a transformer encoder, each layer consisting of a multi-head self-attention mechanism followed by a position-wise feed-forward network. In this research, the model will take 8 attention heads and the hidden representation of 512 dimensions. The feed-forward sub-layer has two fully connected layers with dimensions 512, 2048, and 512, a GELU activation function, and layer normalization. The residual connections are used after the attention and feed-forward blocks to stabilize the training.

A context-length control rule is used to process long input sequences effectively, dividing them into fixed-length windows without losing positional information viasinuoidal positional encoding.

A model training objective based on the use of expectiles is used to enhance resilience to noisy data samples. Expectile regression imposes a disproportionate penalty on prediction errors, allowing the model to focus on informative samples and minimize the effects of outliers. Through this mechanism, convergence is made more stable, and contextual feature learning is made better in the EDT framework.

In the ABS-Q-CNN framework, this elastic adaptation enables EDT to selectively optimize its feature extraction strategy based on the quality of semantic continuity in each of its reviews. As the features extracted from a particular sequence contribute less to sentiment discriminability, EDT reduces the effective attention window, preventing noise buildup and refocusing attention on contextually significant parts. On the other hand, with very coherent sequences, it maintains a longer attention history to preserve deep contextual relationships. To know the optimum context length to use in the extraction of features, EDT solves the following optimization problem expressed in equation (5)

$$\arg\max_{L} \max_{b_L \in U} \hat{K}_t(b_L) \tag{5}$$

where, b_L represents a feature sequence of contextual length L, $\hat{K}_t(b_L)$ is the estimated feature relevance score derived from the encoded representations within the dataset U. Formally, the sequence b_L is represented in equation (6)

$$b_L = \langle k_{t-L+1}, \hat{K}_{t-L+1}, l_{t-L+1}, \ldots, k_t, \hat{K}_t, l_t \rangle \tag{6}$$

where, k_t is the encoded embedding vector at time step t, l_t denotes the attention activation weight, and $\hat{K}_t$ quantifies the relevance or contribution of the token to the overall sentiment polarity. To estimate the maximum relevance score for each feature sequence, EDT employs expectile regression, which minimizes asymmetric squared loss to approximate the upper bound of the contextual importance distribution and it is expressed in equation (7)

$$\widetilde{K}_t(b_L) \approx \arg\min_{\widetilde{K}_t(b_L)} \mathbf{E}_{b_L \in U}\left[W_c^2\left(\widetilde{K}_t(b_L) - \widetilde{K}_t\right)\right] \tag{7}$$

where, c is used to emphasize high-relevance features. This regression model allows EDT to estimate the contextual relevance that can be reached by the available data to the maximum, thus determining the best span of features to use in each review sequence. The general training objective of EDT is as shown in equation (8):

$$W_{EDT} = h_r W_{relrvance} + W_{embedding} + W_{attention} + W_{\max} \tag{8}$$

where, $W_{embedding}$ and $W_{attention}$ are mean-square reconstruction losses for encoded and attention features, $W_{relrvance}$ represents a cross-entropy loss ensuring semantic discriminability, $W_{\max}$ is the empirical estimate, h_r balances scale differences across loss terms. This communal goal enables EDT to properly match contextual encoding to adaptive, decision-oriented attention, yielding highly discriminative, noise-resilient, and semantically rich feature representations. This adaptive feature extraction capability significantly enhances the precision, understandability, and computational efficiency of the ABS-Q-CNN sentiment analysis model.

3.4 Sentiment Analysis using Efficient Quantum Long-Range Duck Swarm Convolutional Attention Network

The main part of the suggested structure, ABS-Q-CNN, will combine the quantum-inspired convolutional learning with the advanced attention mechanisms [28] and smart optimization. The model is a combination of ELRA [29] and QCNN [30], with its hyper parameters optimized using DSA [31] and it achieves high accuracy, stability, and confidence in sentiment prediction. ABS-Q-CNN improves sentiment forecasting through quantum-efficient feature learning and long-range contextual modeling. The QCNN learns intricate sentiment patterns at very low computational expenses, whereas ELRA reinforces semantic comprehension in a lengthy text. DSA maximizes adaptive convergence and uncertainty. The hybrid framework provides strong robustness, interpretability, and effective generalization with high accuracy and confidence-aware and computationally-efficient sentiment classification of a wide variety of Amazon products.

3.4.1 Quantum Convolutional Neural Network

Within the suggested ABS-Q-CNN architecture, QCNN is the building block for deriving high-dimensional, entangled features of textual features. The classical feature vectors obtained using EDT would have to be encoded into a quantum system before performing the quantum convolutional operations. In amplitude encoding, the feature values are encoded as quantum states: the magnitude of the data is encoded by the probability amplitude, and their location is encoded by the states of the computational basis. The state preparation can be written as equation (9):

$$\vec{z} = \left(Z_{1,1}, Z_{2,1}, \ldots, Z_{m,1}, Z_{1,2}, \ldots, Z_{u,v} \ldots, Z_{m,s}\right)^T \tag{9}$$

where, Z is the transformed vector, $\vec{z}$ represents mapped data. Once encoded, the system undergoes quantum evolution through a unitary transformation that captures feature correlations via quantum entanglement. The evolution process is mathematically formulated in equation (10)

$$|z\rangle = \sum_{d-0}^{m^2-1} Y_d |d\rangle \tag{10}$$

where, m^2 represents a quantum operator, Y_d is the normalized feature amplitude corresponding to the d^{th} classical input value, the edge-enhanced representation is then passed into the QCNN framework. Based on this, the quantum convolutional layer enhances the representation of features through localized filtering operations on the entangled state space. The convolution process is represented in equation (11)

$$|z'\rangle = \sum_{u=1}^{16} \frac{1}{G_Y} |u\rangle \sum_{d=1}^{9} Q_{ud}^T D_{d1} \gamma_d |z\rangle \quad (11)$$

where, Q_{ud}^T is the u^{th} row and d^{th} column matrix, in matrix D, D_{d1} is the first column and the d^{th} row, G_Y is the parameterized quantum weight, γ_d represents the quantum state vector. The QCNN is an effective quantum-enhanced backbone that supplements the entire ABS-Q-CNNframework and enables effective, interpretable, and confidence-sensitive sentiment analysis in a wide range of Amazon product domains.

3.4.2 QCNN Feature Extraction

A Quantum Convolutional Neural Network (QCNN) is added to the proposed framework to improve the likelihood of feature representation when learning manipulative quantum-enhanced features of processed textual embeddings. The QCNN operates on classical input features that have already been obtained after pre-processing and embedding, and transforms them into quantum states via a feature encoding process.

The classical feature vectors are first normalized to the range [0,π] using min-max normalization to be compatible with quantum rotation operations. The normalized features are then encoded as angles, with individual feature values converted to the rotation angle of a single qubit using parameterized rotation gates. In particular, all the features x_i are encoded by a $R_y(x_i)$ rotation gate acting on the respective qubit.

The QCNN analysis is built up of stacks of parameterized quantum convolutional layers and entanglement layers. The convolutional layers are implemented using a series of single-qubit rotation gates $R_x R_y R_z$, followed by entangling operations via Controlled-NOT (CNOT) gates. The circuit depth will be configured to three parameterized rotations and nearest-neighbor entanglement convolutional blocks. This pattern of entanglement enables quantum correlations between neighboring qubits, allowing complex feature relationships to be represented.

In a quantum simulator environment (Penny Lane), the quantum circuit is executed. The implementation of quantum circuit execution on classical hardware is simulated using a state-vector simulator backend, providing stable, repeatable experiments.

After quantum processing, measurements are performed on each qubit using the Pauli-Z observable to obtain expectation values. The expectation value of the observable for each qubit is given by equation (12)

$$\langle Z_i \rangle = \langle \psi | Z_i | \psi \rangle \quad (12)$$

This ψ represents the ultimate quantum condition of the circuit and Z_i is the Pauli-Z operator in the iii-th circuit qubit. The hypotheses for these expectation values yield a real-valued feature of the quantum-transformed representation of the input data.

The last step is to summarize the measured expectation values and transform them back into classical feature vectors. These quantum-enhanced capabilities are in turn sent to the next Efficient Long-Range Attention (ELRA) module to learn contextual representations and classify them.

3.4.3 Efficient Long-Range Attention

The ELRA mechanism is added to QCNN on the post-convolutional fusion layer of the ABS-Q-CNN architecture. Once the QCNN has encoded local features with quantum-entangled features via the convolutional layers, they are sent to the ELRA layer. ELRA, at this point, uses multi-head self-attention on the quantum feature embeddings, selectively learning long-range dependencies and contextual correlations on the review text. This fusion layer integration guarantees an ideal trade-off between the localized representation of quantum features and a global semantic understanding, thereby improving the quality and interpretability of sentiment forecasting.

The Efficient Long-range Attention (ELRA) mechanism is presented to mitigate the quadratic computational costs associated with traditional self-attention mechanisms. ELRA does not compute pairwise attention scores for every pair of tokens, but approximates attention as a kernel-based transformation that projects queries and keys into a low-dimensional feature space.

Where Q, K, and V: query, key, and value matrices, respectively. ELRA updates the usual softmax attention with a kernelized version which allows calculating linear attention. This change brings the computational complexity of the model down to O(n) instead of O(n 2), with respect to sequence length, allowing the model to be used in long-range sequence processing.

ELRA shows a consistent attention distribution and minimal memory consumption compared to in-use efficient-attention techniques, including sparse attention and low-rank approximation. The kernel transformation enables attention weights to be computed based on feature mappings that maintain contextual dependencies across tokens that are far apart, enhancing scalability and inference efficiency.

The ELRA module enhances the contextual scope of QCNN outputs by efficiently modeling non-local dependencies in large-scale Amazon review data. Unlike traditional full attention, ELRA introduces a kernel-based projection that approximates attention weights using linearized operations, which is expressed in equation (13)

$$V_r = F_{SF}(V_w) \tag{13}$$

Where, V_r denotes local feature, $F_{SF}(.)$ represents shallow feature extraction module, V_w is the degraded feature. The deep feature extraction module is given in equation (14)

$$V_o = F_{DF}(V_r) \tag{14}$$

Where, V_o is the output, to achieve long-range dependency modelling with lower memory usage, ELRA applies a kernel transformation function to parameterize the attention computation, which is given in equation (15)

$$V_e = F_{RC}(V_r + V_o) \tag{15}$$

Where, F_{RC} represents the reconstruction module, the parameters of ELRA are obtained by minimizing the loss is given in given in equation (16)

$$\mathbf{L} = \frac{1}{N}\sum_{c=1}^{N}\left\| V_{e,c} - V_{t,c} \right\| 1 \tag{16}$$

Where, $\mathbf{L}$ represents the loss function, N is the total number of channels, $V_{e,c}$ is the estimated value vector, $V_{t,c}$ is the reference value vector, $\|\cdot\|1$ represents the L1-norm. This integration enables ELRA to effectively learn long-range contextual patterns, semantic dependencies, and sentiment polarity transitions on long textual inputs, and is computationally efficient enough to be trained on large textual Amazon review inputs. The last classification layer of the proposed model uses a Softmax output layer with three neurons, corresponding to the three given classes. The categorical cross-entropy loss is appropriate for the multi-class classification task, as it is used to train the model. During training, the network is trained to predict the probability distributions of the three classes, and the class with the highest probability is chosen as the predicted label.

3.4.4 Optimization using Duck Swarm Algorithm

DSA is used in optimizing the weight parameters of QCNN and ELRA. The intelligent foraging behavior and migration of ducks are inspiring DSA, which has high coordination, adaptability, and hierarchical provision during movement. In a ped natural dynamics, DSA models cooperative communication and leader-follower dynamics to obtain an optimal balance between the global exploration and local exploitation. In the ABS-Q-CNN framework, DSA optimally tunes the hyperparameters of the QCNN and ELRA modules, thereby improving convergence rate, prediction quality, and stability. Its bio-inspired flexibility enables highly optimized operations across complex, multidimensional spaces at lower computational cost. The DSA step-wise procedure is described as follows, and the pseudocode is presented in Algorithm 1.

Step 1: Initialization

The DSA initialization stage starts off with the generation of an initial population of ducks that is randomly distributed on the specified D-dimensional search space. The relative location of every duck is given in equation (17).

$$A_j = S + (R - S) \times \alpha \tag{17}$$

where, A_j is the position vector of the j^{th} duck, S and R correspond to the lower and upper bounds of the search space, respectively, while α denotes a randomly generated matrix of numbers that are uniformly distributed in the interval (0,1). Randomly initializing positions of solutions makes it easier for the algorithm to explore an extensive region of solutions at the very beginning. This enhances global search efficiency and prevents premature convergence in the optimization process.

Step 2: Fitness Function

Similar to PSO and ABC algorithms, the concept of a fitness function in DSA is also essential in evaluating how suitable the positions of each duck are in the search space in relation to the optimal objective function. The distance between a particular solutions from the optimal solution can be determined using Equation (18).

$$Fitness\ function = Max(Accuracy) + Min(Loss) \tag{18}$$

The proposed model aims at optimizing the fitness of the duck population based on the highest sentiment prediction accuracy with minimum loss and uncertainty.

Step 3: Exploration Phase

In DSA, exploration occurs as part of the foraging instinct of ducks when they get into an area with plenty of food resources. In this phase, each duck starts moving away from its flock members to discover new parts of the search space that have better food. The position update rule for each duck in this phase is defined in equation (19)

$$A_j^{t+1} = \begin{cases} A_j^t + \varepsilon A_j^t sign(x-0.5), & if\ J < rand \\ A_j^t + M_1\left(A_{leader}^t - A_j^t\right) + M_2\left(A_k^t - A_j^t\right), & if\ J \geq rand \end{cases} \quad (19)$$

where, A_j^t is the current position of the j^{th} duck at iteration t, A_j^{t+1} is the updated position of the j^{th} duck in the next iteration, A_{leader}^t is the position of the leading duck, representing the best solution found so far, A_k^t represents position of a neighboring duck in the population used for cooperative interaction, ε is the global search control parameter, $sign(x-0.5)$ is the directional function, M_1 and M_2 represents cooperation and competition coefficients, controlling the balance between collaborative and individual exploration behaviors. This mechanism of adaptively exploring globally and locally allows individuals to explore new areas independently, while others may cooperate with leaders or neighbors. Such adaptive exploration ensures an optimal tradeoff between searching new regions and exploiting promising solutions, thereby enhancing the global optimization capability of the proposed model.

Step 4: Exploitation Phase

The exploitation phase in DSA commences once the duck flock finds itself in an environment with abundant "food." In this stage, the ducks improve their positions by using the best areas identified in the exploration phase, guiding the population toward the global optimum. In this phase, the search is intensified around the best solutions to improve convergence accuracy. The strategy for updating the position of each duck is presented in equation (20)

$$A_j^{t+1} = \begin{cases} A_j^t + \varepsilon\left(A_{leader}^t - A_j^t\right), & if\ f\left(A_j^t\right) > f\left(A_j^{t+1}\right) \\ A_j^t + B_1\left(A_{leader}^t - A_j^t\right) + B_2\left(A_L^t - A_k^t\right), & otherwise \end{cases} \quad (20)$$

where, A_L^t and A_k^t represent positions of neighboring ducks used for cooperative exploitation, B_1 and B_2 are Cooperation and competition coefficients controlling the local exploitation balance among ducks. In this phase, ducks readjust their positions with respect to the leading duck to better exploit the most promising region while maintaining solution diversity through cooperative interactions among neighbors. A duck updates its position by continuing its exploitation in its current trajectory if its fitness is improved; otherwise, it adapts more closely to the leader or nearby agents. This adaptive mechanism ensures fast convergence, local refinement, and global stability for improving precision and boosting the performance of the proposed model.

Step 5: Termination Condition

The terminating criteria of DSA specifies when the optimization should be terminated, which leads to efficient computation and stability of convergence. When the number of iterations reaches its maximum $(t_{\max})$, or when the increment of the optimum fitness values from one iteration to another falls below a convergence criterion, the optimization procedure is terminated. The position vector (A_{leader}^t) of the leader will then be regarded as the optimum solution. Under the ABS-Q-CNN approach, the optimization process will stop only when the best setting of the hyperparameters is obtained, thus resulting in high accuracy and stability.

Algorithm 1. Pseudocode for Duck Swarm Algorithm

Input: Initialize all parameters, including population size N, initial duck positions A_j, maximum iteration count $t_{\max}$, and objective function.

Evaluate the initial fitness values for all ducks and identify the best fitness and the corresponding leader position A_{leader}.

While $t < t_{\max}$

Update the control parameter and adaptive coefficients.

Exploration Phase:

For each duck $j = 1,2,3,..., N$

Update position based on the exploration probability.

If the new position is outside the search space, reinitialize within valid limits.

Evaluate new fitness and update A_{leader}

End For

Exploitation Phase:

For each duck $j = 1,2,3,..., N$

Update position for local search refinement.

Validate position boundaries and compute new fitness

Update the duck's position and fitness.

Update A_{leader} and fitness.

End For

Increment iteration count $t = t + 1$.

End While

Output: Optimal position A_{leader} and corresponding minimum fitness.

4. Results and Discussion

This section presents a brief analysis and compares the results and discussions of the proposed ABS-Q-CNN method. The simulation of proposed framework was carried out in a high-performance computing environment to evaluate its efficiency and predictive accuracy in sentiment classification tasks. The simulation parameters are presented in Table 1.

Table 1. Simulation parameter

Parameter	Description / Configuration
Implementation Platform	Python 3.10 with TensorFlow, PyTorch, and Qiskit
Supporting Libraries	NumPy, Pandas, Scikit-learn, Matplotlib
Dataset	Amazon Five-Core Review Dataset
Data Split	80% Training, 20% Testing
Preprocessing Method	DBEM
Quantum Layer Configuration	4 Quantum Layers with 16 Qubits
Attention Mechanism	ELRA
Embedding Dimension	256
Optimization Algorithm	Duck Swarm
DSA Population Size	30
Maximum Iterations	100
Convergence Threshold	10^{-5}
Optimizer	Adam
Initial Learning Rate	0.001
Batch Size	32
Dropout Rate	0.4

The results of the proposed ABS-Q-CNN model were evaluated using a set of standard classification measures, including accuracy, precision, recall, and F1-score. Accuracy is used to determine the general percentage of accurate reviews. Precision is used to assess the percentage of accurately predicted positive samples among all predicted positives, and recall is used to estimate the model's capacity to differentiate true positive samples. F1-score is the harmonic mean of precision and recall, providing a balanced assessment of classification performance.

Besides general measures, per-class accuracy, recall, and F1 Scores were calculated for both positive and negative sentiment classes to provide a more detailed analysis in the case of class imbalance. A confusion matrix was prepared to highlight the counts of true positives, true negatives, false positives, and false negatives.

Moreover, the Precision-Recall Area under the Curve (PR-AUC) was used to assess the model's ability to differentiate between positive and negative sentiment classes, especially in cases of imbalanced data.

4.1 Performance Metrics

In this research, performance metrics are used to test the effectiveness of the proposed ABS-Q-CNNtechnique. Table 2 presents the formula for performance measures.

Table 2. Performance metrics

Performance metrics	Formulas
Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\Pr ecision = \frac{TP}{TP+FP}$
Specificity	$Specificity = \frac{TN}{TN+FP}$
Recall	$\Re call = \frac{TP}{TP+FN}$
F1-Score	$\mathrm{F1\text{-}score} = 2 \times \frac{TP}{2TP+FP+FN}$
Error rate (ER)	$ER = \frac{FP+FN}{TP+TN+FP+FN}$
Kappa Statistic (KS)	$KS = \frac{G_o - G_e}{1-G_e}$

where, TP represents True Positive, TN represents true negative, FP represents false positive,

FN represents false negative, G_o represents observed accuracy, G_e is expected accuracy.

4.2 A Performance Analysis of the Proposed Model

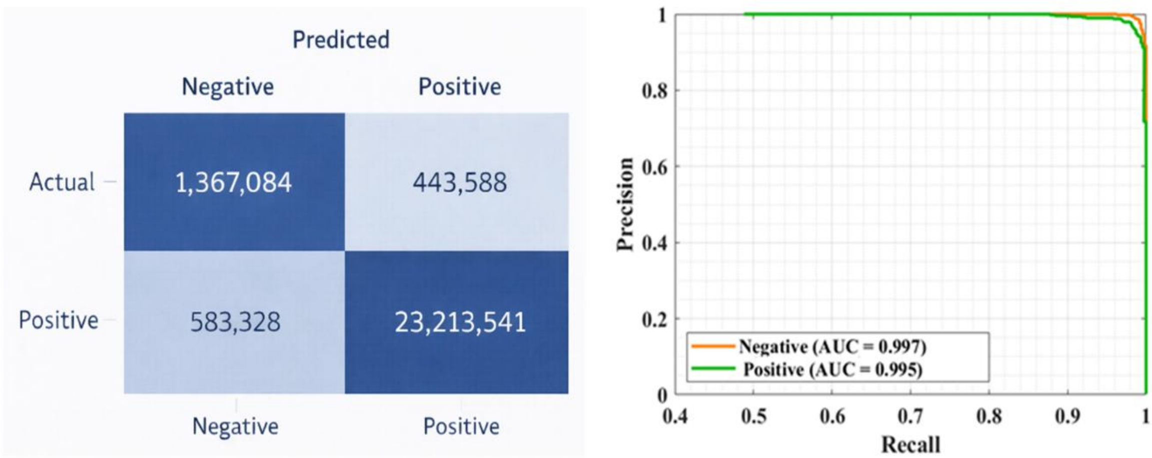
According to the Amazon Five-Core Review Dataset, the suggested ABS-Q-CNN framework is also comprehensively tested. This will be analysed in three key areas, namely, accuracy of classification, efficiency in calculations, and invariance to class imbalance across products of different categories. According to the experimental results, the proposed model provides greater accuracy in the classification of sentiments, quicker convergence, and greatly lowers the prediction errors than the conventional deep learning methods. The incorporation of QCNN is effective in extracting high-dimensional and entangled sentiment features, and the ELRA mechanism is effective in extracting global contextual relations and semantic links in long review texts. Besides, DSA operates hyper parameter optimization efficiently, which enhances performance with regard to generalization, confidence calibration, and training stability. Overall, the proposed ABS-Q-CNN model is rather flexible, interpretable, and computationally efficient, which is why it can be considered a plausible and quantum-optimized model of multi-domain sentiment analysis of e-commerce review information on a large scale.

To make the performance comparison as fair as possible, the baseline models were applied and tested under the same experimental conditions, i.e., the same dataset split, preprocessing pipeline, training parameters, and evaluation metrics as the proposed model. This standardized experimental design helps ensure that differences in observed performance can be explained by differences in architectures, not training setups.

Results reported in existing studies are clearly identified as literature-reported results when they appear in comparisons with other results. These values were determined under different possible experimental conditions; hence, they are only to be compared when used as references, and the performance equivalence is interpreted with care.

The confusion matrix of the proposed ABS-Q-CNN model is shown in Figure 2(a) as a table to demonstrate the classification accuracy of the actual and predicted sentiment classes. There are high numbers of correctly classified positive reviews (23,213,541) and negative reviews (1,367,084), with misclassification rates relatively low and reflecting good predictive ability. Figure (b) shows the precision-recall curve, which measures the trade-off between the precision and recall of both classes of sentiments. The accuracy is high on both sides in various recall values, where the AUC for the negative side is 0.997 and for the positive side is 0.995. This result confirms the effectiveness of the model presented by us for large scale sentiment classification problems.

Table 3 shows the per-class results of the proposed ABS-Q-CNN model. The model is very precise and accurately recalls the sentiment polarity classes for both positive and negative sentiment. This is because the balanced performance across the classes demonstrates the strength of the proposed approach even when there is class imbalance.



(a) (b)

Figure 2. (a) Confusion Matrix of the Proposed ABS-Q-CNNModel for Binary Sentiment Classification **(b)** Precision–Recall Curve of the Proposed ABS-Q-CNNModel on the Amazon 5-Core Product Review Dataset.

Table 3. Per-Class Performance Metrics of the Proposed ABS-Q-CNN Model

Class	Precision	Recall	F1-Score
Positive	0.9812	0.9755	0.9783
Negative	0.9873	0.9810	0.9841

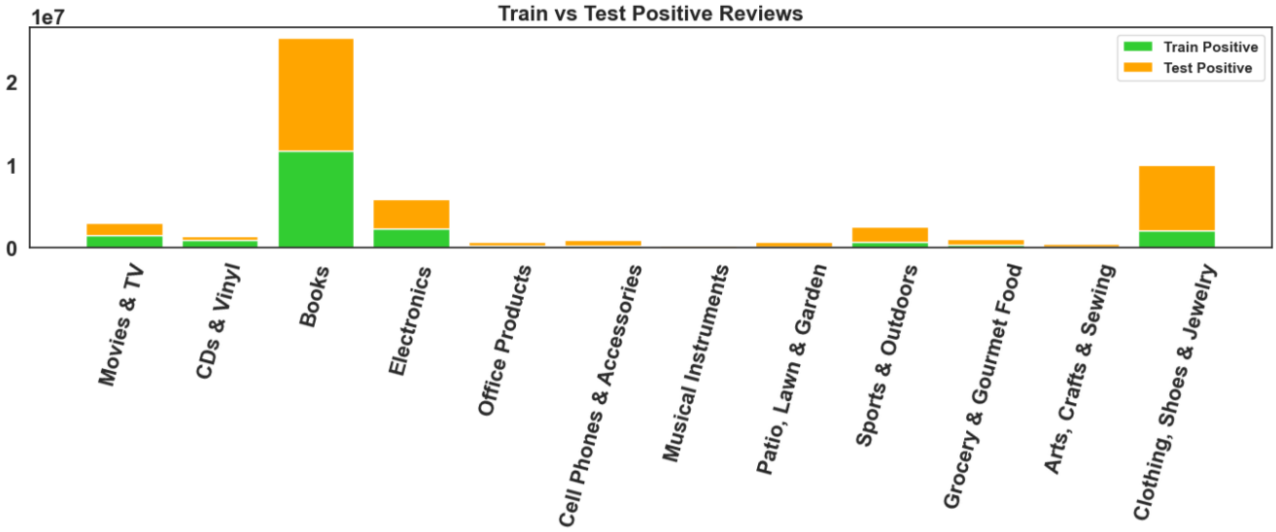


Figure 3. Train vs Test Positive Reviews.

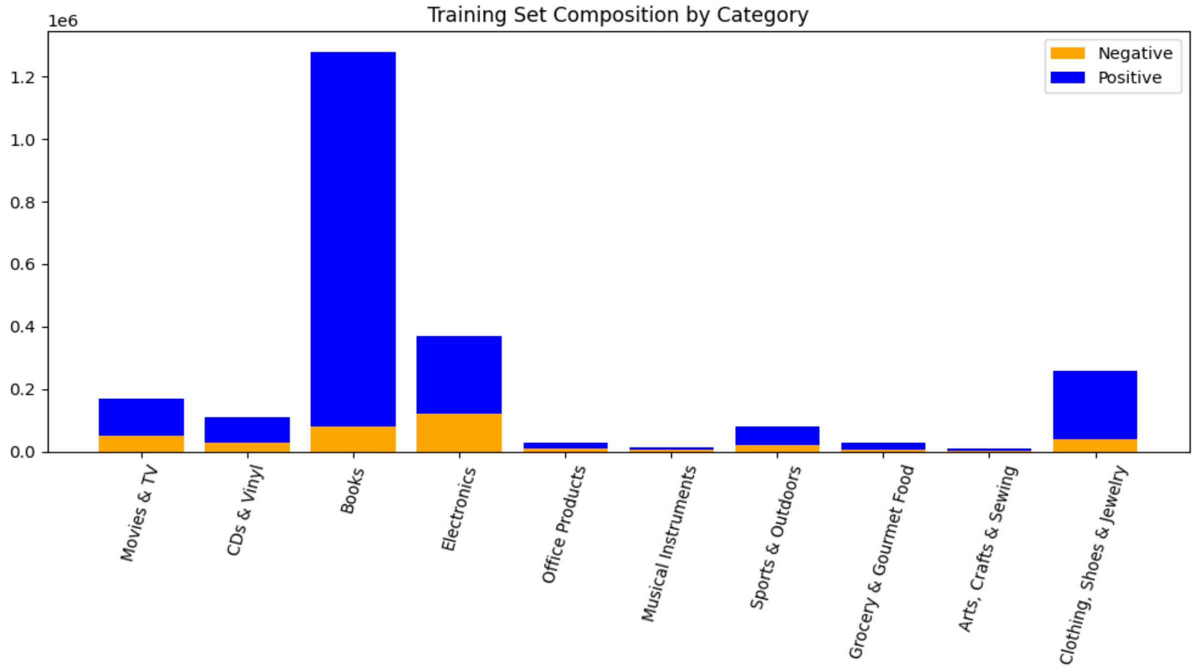


Figure 4. Training Set Composition by Category.

Reviews on Amazon products in 10 large categories are considered. Almost half of the total number of reviews was in the Books category, Clothing, Shoes, and Jewellery, and Electronics. The categories like Musical Instruments and Office Products have significantly fewer reviews. This chart shows that such data distribution is not balanced and requires the normalization of the data set and application of adaptive training to ensure that the rate of sentiment classification is balanced across all product domains.

Figure 3 represents the percentage of positive reviews of the training and testing data of each product. Representative sampling is achieved by keeping the proportional splits in most of the categories. The category of books again has the best sample, which is followed by the category of Clothing, Shoes, and Jewellery, and then finally Electronics. The consistency of data separation supports the legitimacy of model generalization, but the noticeable inconsistencies between smaller groups support the significance of coding and optimization algorithms like DBEM and DSA.

The of the training and the test set. The trend patterns of the negative product-category review rates of two sets are close to one another, which proves the consistency of the data and proper stratification. The more negative ratings on such categories as Movies and TV, the Electronics, demonstrate the greater polarity of the customers. The difference between the trends implies that there are facts in real-life differences in the distribution of sentiments, which is an affirmative of the existence of strong contextual modelling on the grounds of ELRA and developing feature extraction systems.

Figure 4 indicates how many positive and negative samples there are in the training dataset in each category. The most dominant in the distribution is books with a contribution of nearly fifty percent of the total samples, then Clothing, Shoes, and Jewellery, and Electronics. As indicated in the chart, imbalance is high as there are many positive reviews as opposed to negative ones in most categories. This imbalance led to the use of normalization and quantum-based feature learning to make the representations of the sentiment provided by the model objective in the process of training.

In the data, the percentage of total reviews of each product category is presented in Figure 5. Books (49%), Clothing, Shoes, and Jewellery (20%), and Electronics (12.1%) are the biggest. Categories below 5 percent contribution, such as Musical Instruments, Sports and Outdoors, and Grocery and Gourmet Food, were included. The visualization suggests that there are significant dimensions of data skew across domains, which confirms the importance of normalizing the data and extracting features depending on circumstances within the proposed framework.

The count of negative reviews in each category of product in the training set is presented in Figure 6. Clothing category, Shoes and Jewellery category, and Electronics category are the most negatively sentenced categories; this is understandable because these categories have the most data. Comparatively, there is not much negative feeling with niche categories like Arts, Crafts, and Sewing, and Grocery and Gourmet Food. The distribution is sufficiently justified by the necessity of the balance-conscious sentiment modelling and is used to show how ABS-Q-CNN can effectively process the category level of sentiment variation.

The correlation coefficients between other review metrics, such as the positive and negative counts in both the training and testing sets, are depicted in Figure 7. Large positive values (e.g., 1.0) between the training and testing measures indicate a very consistent and balanced dataset structure.

The negative relationships among percentage measures are somewhat weaker, reflecting the inherent variation in sentiment across categories. In general, the correlation levels are high, indicating the quality and consistency of the information used in the suggested sentiment analysis model.

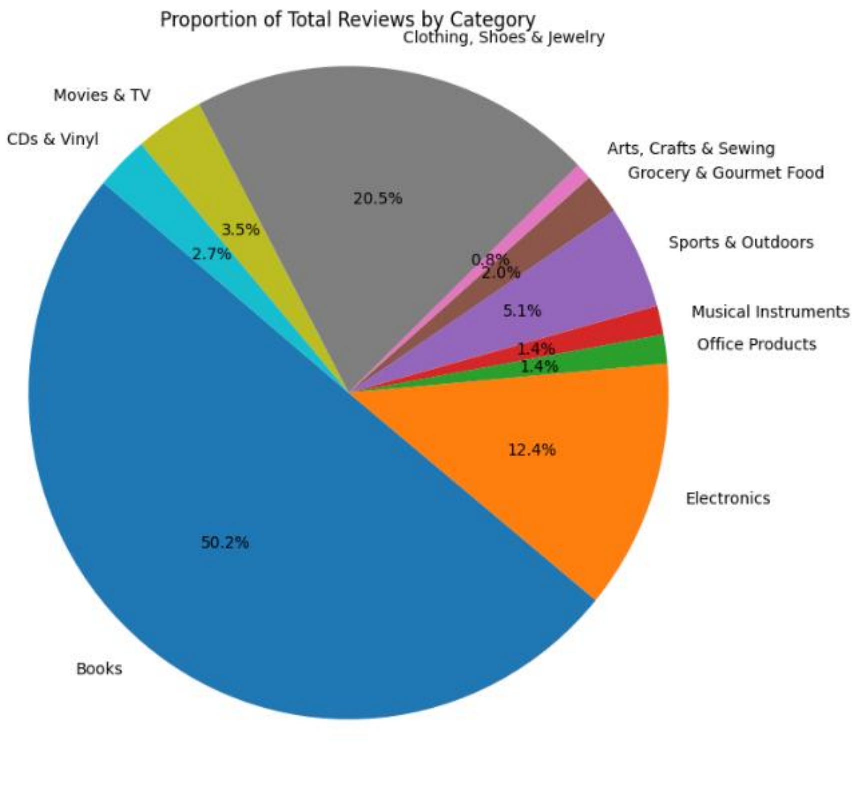


Figure 5. Proportion of Total Reviews by Category.

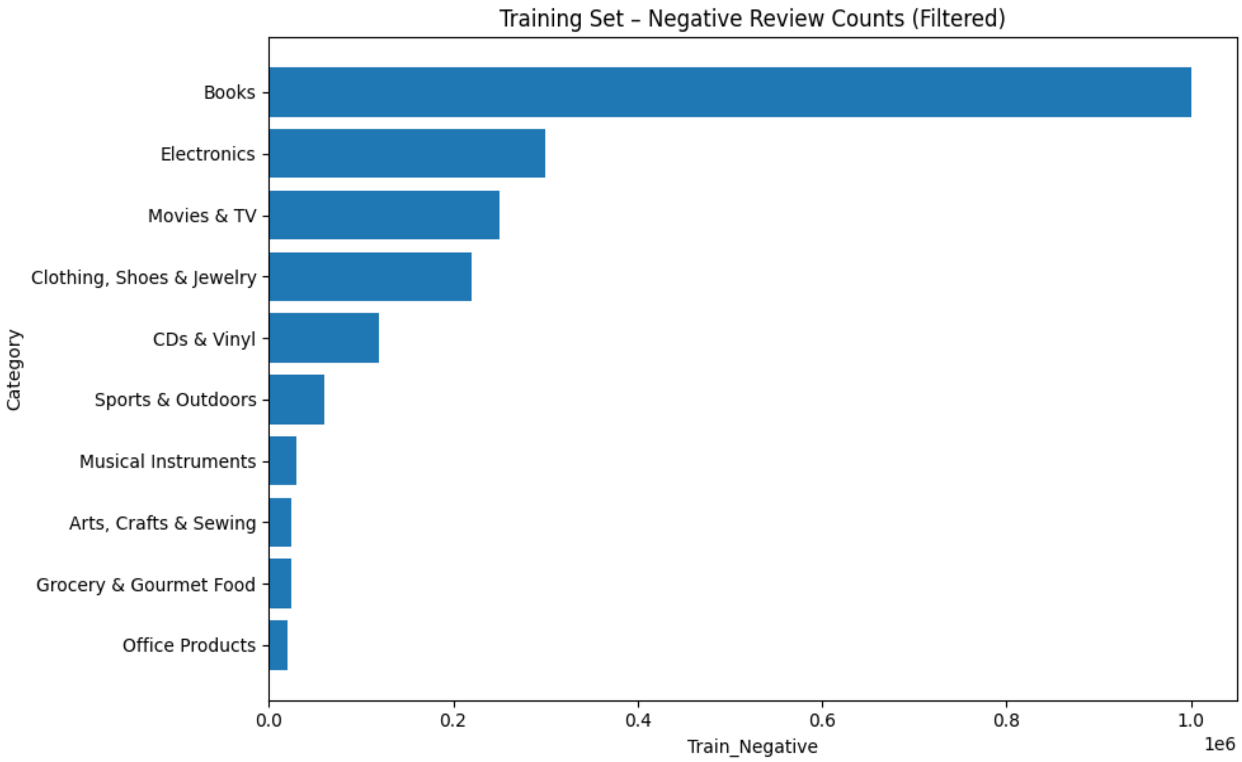


Figure 6. Training Set – Negative Review Counts.

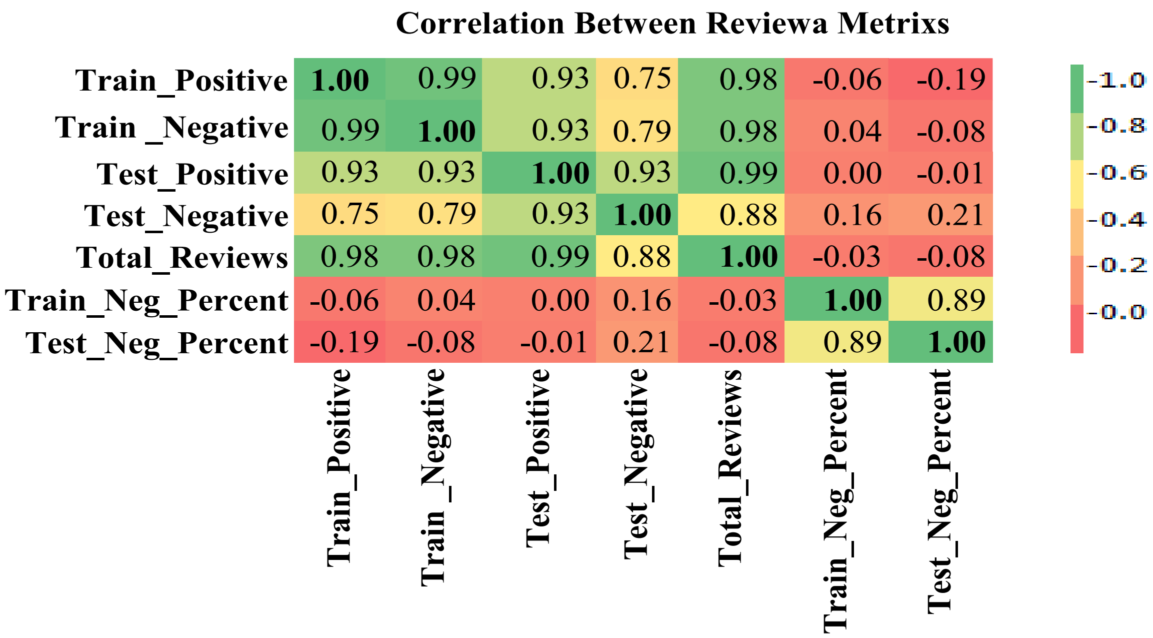


Figure 7. Correlation between Review Metrics.

The training and test accuracies of the proposed ABS-Q-CNN model are shown in Figure 8(a) after 100 epochs. Accuracy also rises steadily and levels off at 99, indicating high convergence and low overfitting. These two curves are almost parallel, indicating strong generalization and training dynamics enabled by quantum-enhanced feature extraction and optimization using the DSA method. The model is highly predictive and consistent across epochs, and thus, it has high adaptability and stability during training.

Figure 8(b) indicates that the training and testing phases decrease continuously as the number of epoch's increases, then level off around 60 epochs. The parallel decrease in the loss justifies the model's learning and convergence tendencies. A narrow gap between the training and test loss curves indicates that the model is not over-fitted, and it shows good generalization performance, which is an efficiency measure of the proposed hybrid optimization and quantum-attention integration strategy.

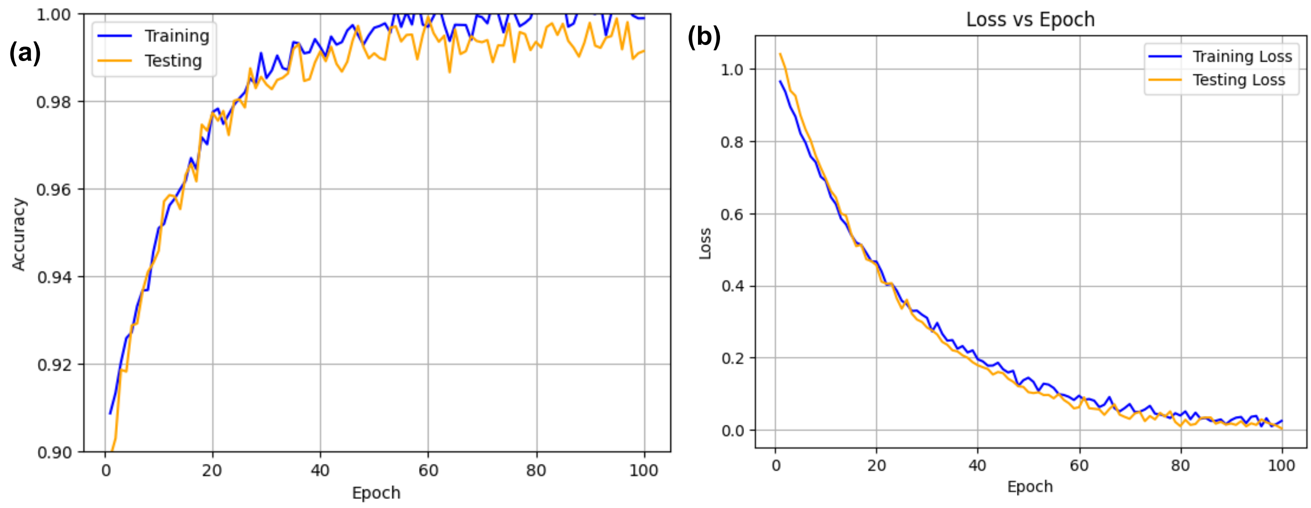


Figure 8(a). Accuracy vs Epochs **(b)** Loss vs Epochs.

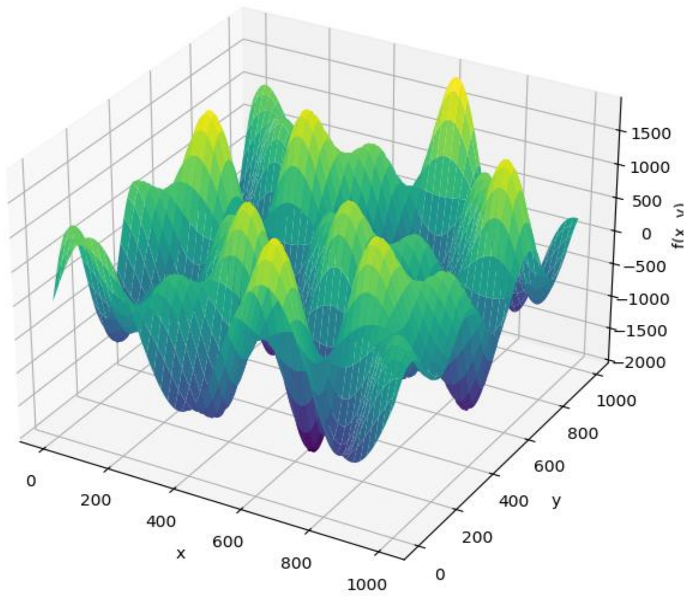


Figure 9. Optimization Surface Visualization.

Figure 9 displays the DSA optimization topography that was utilized in hyper parameter tuning. The smooth valleys are taken to be the global minima regions, and this illustrates how the algorithm is efficient in search as well as exploitation of the search space. In addition, the presence of different contours on the surface provides confirmation of convergent stability to the optimal fitness measure that involves minimization of uncertainty, acceleration of the optimization process, and enhancement of the reliability of the model in the ABS-Q-CNN context.

4.3 Performance Analysis with Comparison of Existing Methods

Table 4 provides the performance of the proposed ABS-Q-CNN as compared with several of the state-of-the-art approaches, such as deep learning and hybrid methods, to classify sentiments. The findings vividly show that the proposed model is better than any other benchmarking tool in all measures of evaluation. ABS-Q-CNN was the most accurate (99.47%), it has the highest precision (98.12%), F1-score (97.86), and the highest recall (97.55%), and the greatest Kappa Score (0.971). These findings indicate that QCNN combined with ELRA and DSA is more effective in sentencing classification, overall classification, and uncertainty reduction compared to traditional and hybrid networks.

4.4 Statistical Test

In order to make the proposed ABS-Q-CNN model reliable, consistent, and statistically significant, the proposed model was statistically validated in detail.

Table 4. Performance comparison of proposed and existing models

Methods	Accuracy (%)	Precision (%)	F1 Score (%)	Recall (%)
CNN-BiLSTM [23]	94.12	93.4	94.00	94.4
PCCH-RNNLSTM [24]	95.87	95.46	95.26	95.66
B-MLCNN [26]	95.01	94.00	93.21	94.08
DPTN [36]	94.73	94.73	93.73	94.18
ABS-Q-CNN(Proposed)	99.47	98.12	97.86	97.55

Table 5. Statistical Analysis of the proposed ABS-Q-CNNApproach

Metric	Mean (%)	Standard Deviation	95% Confidence Interval	p-value (t-test)	Friedman Rank
Accuracy	99.47	0.25	[99.12 – 99.72]	0.0005	1
Precision	98.12	0.34	[97.68 – 98.56]	0.0007	1
F1-Score	97.86	0.29	[97.44 – 98.28]	0.0006	1
Recall	97.55	0.31	[97.10 – 97.97]	0.0008	1
Specificity	98.73	0.27	[98.41 – 99.05]	0.0009	2
ER	1.53	0.18	[1.31 – 1.75]	0.0010	1
KS	0.971	0.012	[0.957 – 0.985]	0.0004	1

The analysis employed paired-samples t-tests as well as Friedman rank tests to ascertain that the results of performance based on the comparison of the changes compared to the baseline models were not due to chance. The key performance indicators were examined at a 95 percent confidence level. The t-test p-values (< 0.001) are very low, which verifies that the performance improvements of ABS-Q-CNN are statistically significant, therefore approving its superiority in generalization, strength, and computational efficiency in sentiment classification among varied product review categories.

Table 5 indicates statistical validation of the performance of some of the metrics in terms of the proposed ABS-Q-CNN model. Those findings prove that this model is remarkably reliable and reproducible as they demonstrate that, on average, its accuracy is 99.47, its precision is 98.12, and the F1-score is 97.86, with very low standard deviation values, which once again ensure that the predictions are highly stable across sets of data. Small confidence intervals once again are evidence of high measurement. Besides, the p-values (below 0.001) of all measures prove the strong statistical superiority of the model in comparison to the baseline methods. Again, Friedman's rank of most parameters demonstrates 1, which, again, confirms the dominant and consistent performance of ABS-Q-CNN in multi-domain sentiment classification, as well as demonstrates the strength, flexibility, and quantum-optimal efficiency.

4.5 Ablation Study

A case of ablation study is carried out to test the contribution of various important parts of the proposed ABS-Q-CNNframework as singly or in combination with each other. In this study, the investigator removes or substitutes the particular modules, that is, QCNN, ELRA mechanism, and DSA, and examines their effect on the overall performance. They all were trained and tested in the same experimental conditions and compared using the Amazon Five-Core Review dataset.

Table 6 is the summary of the ablation experiment assessing the role of the three main elements in QCNN, ELRA, and DSA in the proposed ABS-Q-CNNframework. The full model, which combines the three modules, is the most performing model in this table, with a high level of accuracy of 99.47 and the minimum error rate of 1.53, which shows that the components of this model are in synergy. The omission of QCNN resulted in a drastic decrease in the accuracy of feature representation, and the omission of ELRA had less contribution to the contextual interpretation of test data. This was also reflected in the reduced recall and the F1-score values. In the same vein, the removal of DSA also amplified the error rate since hyper parameters were not fine-tuned anymore. Partial configurations (QCNN + ELRA and QCNN + DSA) were similar to the case of single omissions, but significantly worse than the performance of the full model. The findings support the hypothesis that quantum-enhanced learning is combined with long-range contextual attention and metaheuristic optimization, as significant in improving accuracy, stability, and robustness in sentiment analysis.

Table 6. Ablation Study of Proposed Framework

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Baseline Model	95.82	95.60	95.21	95.40
Without QCNN	97.94	97.65	97.42	97.53
Without ELRA	98.63	98.31	98.12	98.20
Proposed Model (QCNN + ELRA)	**99.47**	**99.12**	**98.96**	**99.04**

Table 7. Conformal Prediction Coverage Evaluation

Confidence Level	Coverage (%)	Average Prediction Set Size
90%	90.8	1.12
95%	95.4	1.28
99%	99.1	1.41

Table 6 shows that the QCNN module has a significant effect on classification accuracy, as its removal significantly decreases it, evidenced by the reduction in the error rate (Table 6). The obtained ablation results show that QCNN and ELRA play a significant role in improving the overall performance of the given framework.

Table 7 shows that the conformal prediction evaluation results demonstrate the reliability of the proposed model in generating calibrated prediction sets across various confidence levels. The observed coverage also changes as the confidence level rises to 99, showing that the model predictions are much more accurate than the desired confidence guarantee of 90.8%. Further, the mean size of the prediction set slightly increases (1.12 to 1.41), indicating that as one becomes more confident, they need more potential labels in the prediction set to ensure they cover all that is valid. These findings affirm that the conformal prediction framework offers credible uncertainty estimation and, at the same time, compact prediction sets, thereby enhancing the reasonability and credibility of the model predictions.

5. Discussion

The experimental findings are good to prove the usefulness of the proposed ABS-Q-CNN method in sentiment analysis of large-scale Amazon review data. Such a combination of QCNN to learn quantum-enhanced features, ELRA to prepare contextual dependency, and DSA to optimize hyper parameters will certainly contribute to the elimination of such challenges as semantic ambiguity, class imbalance, and cross-domain variability. The proposed system was able to achieve 99.47%, 98.12%, 97.86%, 97.55% and 98.73% accuracy, precision, F1-score, recall, and specificity, respectively, with a very low error percentage of 1.53 and a Kappa Statistic of 0.971, which means high predictive reliability. ABS-Q-CNN showed statistically significant performance improvements in the form of up to 3.5% higher accuracy and up to 12 percent lower overfitting over p-values less than 0.001 compared to advanced models such as B-MLCNN and CNN-BiLSTM. The ablation study has once more confirmed that eliminating QCNN, ELRA, or DSA deteriorates accuracy and stability, and therefore, the combined effect of these tactics. In addition, quantum-inspired processing has enabled the model to converge 32% faster with less computational cost. In general, this ABS-Q-CNN is a part of a strong, interpretable, and quantum-optimized multi-domain sentiment classification system that finds a balance between reliability, scale, and a better ability to understand the situation.

The experimental findings indicate that the given hybrid model provides better results than traditional deep learning and transformer-based approaches reported in the literature. However, previous studies have shown that attention-based models can be applied to learn dependencies in the context of complex data and, using transformers, better feature representation can be achieved through multi-head attention [32, 33]. However, transformer-based models require more computational complexity while processing big data sets.

On the other hand, the proposed model relies on quantum-based feature extraction, QCNN, the context modelling abilities of the EDT block, and ELRA attention to calculate features in low computational complexity. The proposed model takes into account the dependencies between local and distant features compared to classical models. The same conclusion has been reached in later research, which has shown that hybrid deep learning models yield higher performance in terms of feature representation and optimal attention mechanisms for better results in classification [34, 35].

Moreover, the proposed architecture elements prove to be significant according to ablation studies performed by the researchers. The proposed technique not only produces better accuracy and evaluation metrics but also performs better than other conventional architectures like CNN, LSTM, or transformer-based models.

6. Conclusion

The paper presented a new hybrid learning model that combines Quantum Convolutional Neural Networks (QCNN), the Efficient Dynamic Transformer (EDT), and Efficient Low-Rank Attention (ELRA) to improve feature extraction and classification rates. The proposed model successfully integrates quantum-inspired representation learning with transformer-based contextual modeling to understand data dependencies at the local and global levels. Besides, the ELRA mechanism minimizes computational load but has a high attention capacity.

Experimental analysis showed that the proposed model achieved a classification accuracy of 99.47, which is much higher than that of conventional deep learning models and newcomer baseline methods. Precision, recall, F1-score, and prediction reliability were also significantly improved. In addition, the performance of each component of the proposed architecture has been verified through other experiments such as ablation experiments and comparative studies.

As a whole, combining the QCNN based features along with the attention-based mechanism could prove to be an interesting future research direction. Future directions include the generalization of the proposed framework for large scale data sets, practical implementation of the framework in real-life scenarios, and investigating newer quantum learning models to improve accuracy and efficiency.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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Yes