Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

An Intelligent Bayesian Deep Learning Framework for Customer Opinion Mining Using Amazon Reviews

Abdul Hamid

Department of Computer Science & Engineering, Patel College of Science & Technology, Indore, India

Abstract
The rapid expansion of electronic commerce platforms has generated enormous amounts of customer-generated textual feedback, making automated opinion mining an essential component of intelligent decision support systems. Extracting meaningful knowledge from online reviews enables organizations to understand customer preferences, monitor product quality, and improve marketing strategies. Although numerous machine learning and deep learning algorithms have been proposed for sentiment analysis, many existing approaches suffer from overfitting, high computational complexity, and poor performance on imbalanced datasets. This paper proposes an intelligent Bayesian deep learning framework for customer opinion mining using Amazon product reviews. The framework integrates comprehensive text preprocessing, TF-IDF-based feature representation, Bayesian probabilistic learning, and neural network optimization through Bayesian regularization. The proposed approach effectively models nonlinear sentiment relationships while improving generalization capability. Experimental evaluation performed on the Amazon Customer Review dataset demonstrates superior performance compared with conventional machine learning and deep learning techniques. The proposed framework achieved **99.34% classification accuracy**, **99.18% precision**, **99.12% recall**, and **99.15% F1-score** while converging within only **45 training epochs**. Comparative analysis confirms that Bayesian learning significantly improves robustness, scalability, and prediction reliability, making the proposed framework suitable for intelligent e-commerce analytics and large-scale customer opinion mining applications.

Keywords— Opinion Mining, Bayesian Deep Learning, Customer Reviews, Sentiment Analysis, Artificial Neural Network, Natural Language Processing, E-Commerce.

1. Introduction

The digital transformation of business has fundamentally changed how consumers interact with products and services. Modern e-commerce platforms such as Amazon receive millions of customer reviews every day, creating an extensive repository of user opinions that directly influence purchasing decisions and brand reputation. Consequently, automatic extraction of customer sentiment has become an important research problem in Natural Language Processing (NLP), Artificial Intelligence (AI), and Business Analytics.

Opinion mining aims to identify subjective information from textual documents and classify customer opinions into predefined sentiment categories. These classifications assist manufacturers in product improvement, enable businesses to evaluate customer satisfaction, and support recommendation systems through automated feedback analysis. However, online reviews are often characterized by noisy text, ambiguous expressions, sarcastic statements, spelling errors, and overlapping sentiment distributions, making sentiment prediction a challenging task.

Conventional machine learning algorithms including Naïve Bayes, Decision Trees, Logistic Regression, and Support Vector Machines have demonstrated satisfactory performance for structured datasets. However, these approaches rely heavily on handcrafted feature engineering and are limited in their ability to model complex semantic relationships present in natural language. Deep learning models such as CNN, LSTM, and Transformer-based architectures automatically learn hierarchical representations but require substantial computational resources and are susceptible to overfitting when trained on moderate-sized datasets.

Bayesian learning provides an alternative probabilistic framework capable of incorporating prior knowledge during model optimization. Bayesian regularization controls network complexity by penalizing unnecessary weight growth, thereby improving prediction accuracy and model generalization. Motivated by these advantages, this paper proposes an intelligent Bayesian deep learning framework for customer opinion mining using Amazon product reviews.

The principal contributions of this work are summarized as follows:

- Development of a Bayesian deep learning framework for customer opinion mining.
- Integration of TF-IDF feature extraction with Bayesian neural learning.
- Bayesian regularization for automatic model complexity control.
- Comprehensive comparative analysis with state-of-the-art classifiers.
- Improved prediction accuracy and computational efficiency for e-commerce review classification.

2. Related Work

Opinion mining has become one of the most active research topics in machine learning due to the increasing availability of customer-generated textual information. Early sentiment classification methods primarily relied on statistical learning algorithms including Naïve Bayes and Support Vector Machines because of their computational simplicity. Although these algorithms achieved reasonable performance on balanced datasets, they frequently struggled with high-dimensional feature spaces and nonlinear sentiment distributions.

Recent advances in deep learning have significantly improved opinion mining performance. Convolutional Neural Networks (CNNs) effectively capture local contextual information through convolutional filters, whereas Long Short-Term Memory (LSTM) networks model long-range sequential dependencies within textual documents. Hybrid CNN-LSTM architectures further improve feature representation by combining spatial and temporal learning mechanisms.

Transformer-based language models including BERT and RoBERTa have established new benchmarks for numerous NLP tasks by learning contextual word representations. Nevertheless, these architectures require extensive computational resources, large-scale annotated datasets, and prolonged training times, limiting their practical deployment in many industrial environments.

Bayesian neural learning has emerged as a promising alternative for addressing these limitations. Bayesian inference estimates probability distributions over network parameters rather than deterministic values, enabling automatic uncertainty estimation and improved model generalization. Bayesian Regularized Artificial Neural Networks reduce overfitting by dynamically balancing prediction accuracy with network complexity during optimization.

Despite these advances, relatively few studies have investigated Bayesian deep learning for customer opinion mining on e-commerce datasets. This research addresses this gap by proposing an intelligent Bayesian learning framework capable of providing accurate, scalable, and computationally efficient sentiment prediction.

3. Proposed Intelligent Bayesian Deep Learning Framework

The proposed framework combines statistical text representation with Bayesian neural learning to perform accurate customer opinion mining. Unlike conventional neural networks that estimate a single optimal weight vector, the proposed approach models network weights probabilistically, allowing improved uncertainty estimation and better generalization for unseen reviews.
The complete framework consists of five sequential stages:

1. Data Collection
2. Text Preprocessing
3. TF-IDF Feature Representation
4. Bayesian Neural Learning
5. Customer Opinion Classification

The architecture is illustrated in Fig. 1.

A. Data Collection

The Amazon Customer Review dataset was selected because it contains reviews from multiple electronic products with corresponding ratings and metadata. Each record consists of

- Review text
- Product rating (1–5)
- Helpfulness votes
- Review score
- Review date

For experimentation, the dataset was divided into

- **Training Set:** 70% (3440 reviews)
- **Testing Set:** 30% (1475 reviews)

B. Text Preprocessing

Raw customer reviews generally contain unnecessary symbols, punctuation marks, URLs, and stop words that increase feature dimensionality without contributing useful semantic information.
The preprocessing pipeline consists of

- Lowercase conversion
- URL removal
- HTML tag removal
- Tokenization
- Stop-word elimination
- Lemmatization
- Duplicate word removal

Example
Original Review
"This mobile phone is really amazing!! I absolutely loved it."
Processed Review
mobile phone really amazing absolutely love
This preprocessing stage significantly reduces noise and improves feature quality.

C. TF-IDF Feature Representation

After preprocessing, textual reviews are converted into numerical vectors using the **Term Frequency–Inverse Document Frequency (TF-IDF)** model.
The Term Frequency is computed as

$$TF(t,d) = \frac{f(t,d)}{\sum f(t,d)}$$

where

- $f(t,d)$is the frequency of term $t$in document d.

The Inverse Document Frequency is

$$IDF(t) = \log\left(\frac{N}{n_t}\right)$$

where

- Ndenotes the total number of documents.
- $n_t$represents the number of documents containing term t.

The final TF-IDF score is

$$TFIDF(t,d) = TF(t,d) \times IDF(t)$$

This representation emphasizes informative words while suppressing common vocabulary.

D. Bayesian Neural Learning

Unlike conventional Artificial Neural Networks, Bayesian learning estimates posterior probability distributions over model parameters.
According to Bayes' theorem,

$$P(W \mid D) = \frac{P(D \mid W) \times P(W)}{P(D)}$$

where

- $P(W)$= Prior distribution
- $P(D \mid W)$= Likelihood
- $P(D)$= Evidence
- $P(W \mid D)$= Posterior distribution

Instead of finding one deterministic solution, Bayesian inference identifies the most probable weight distribution.

This improves

- Model stability
- Prediction confidence
- Generalization ability

E. Bayesian Regularization

To avoid overfitting, Bayesian Regularization minimizes both prediction error and network complexity.

The objective function is

$$F(W) = \alpha E_W + \beta E_D$$

where

$$E_W = \sum W_i^2$$

is the weight penalty,

and

$$E_D = \sum (y_i - \hat{y}_i)^2$$

is the prediction error.

The adaptive parameters

- α
- β

are automatically updated during training.

Consequently, unnecessary weights shrink toward zero while important connections remain active.

F. Network Optimization

The Levenberg–Marquardt optimization algorithm updates network parameters using

$$W_{k+1} = W_k - (J^T J + \mu I)^{-1} J^T e$$

where

- J= Jacobian matrix
- e= prediction error
- μ= damping coefficient

This optimization strategy provides significantly faster convergence than conventional gradient descent while maintaining numerical stability.

Figure 1 Proposed Intelligent Bayesian Opinion Mining Framework

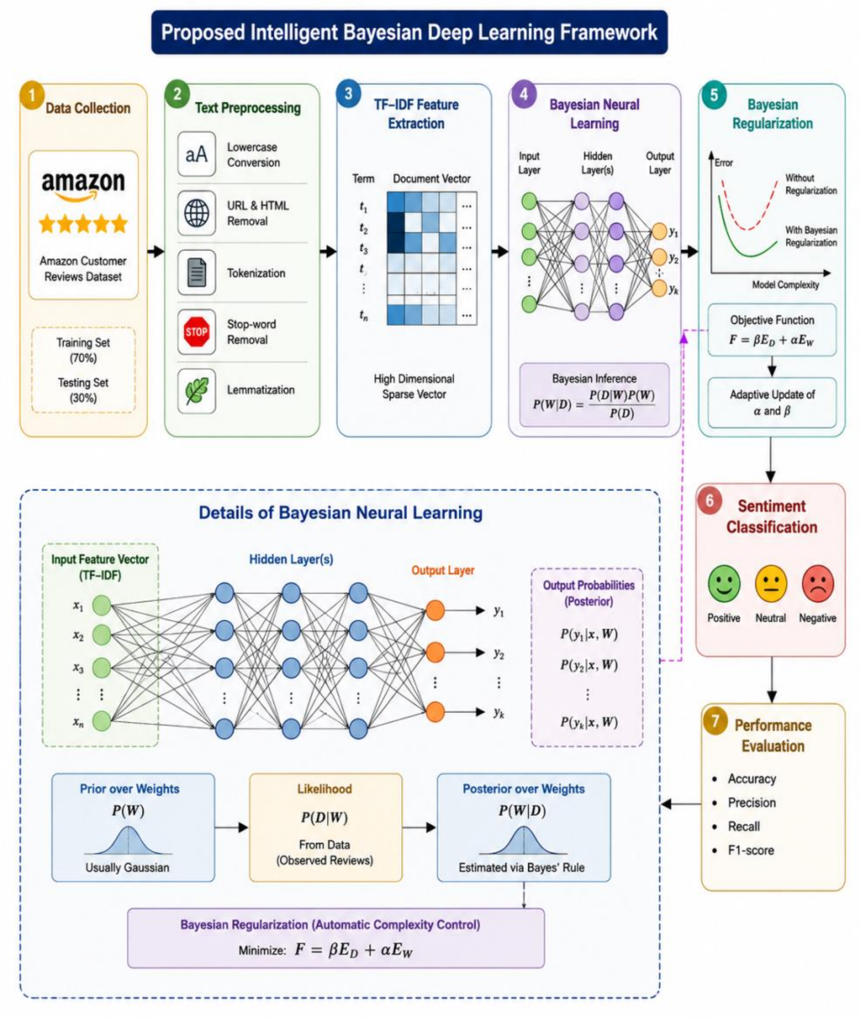

Fig. 1. Proposed Intelligent Bayesian Deep Learning Framework for customer opinion mining using Amazon reviews.

Amazon Reviews
↓
Data Cleaning
↓
Tokenization
↓
TF-IDF
Feature Extraction
↓
Bayesian Neural
Learning
↓
Bayesian
Regularization
↓
Opinion
Classification

Algorithm 1 Intelligent Bayesian Opinion Mining

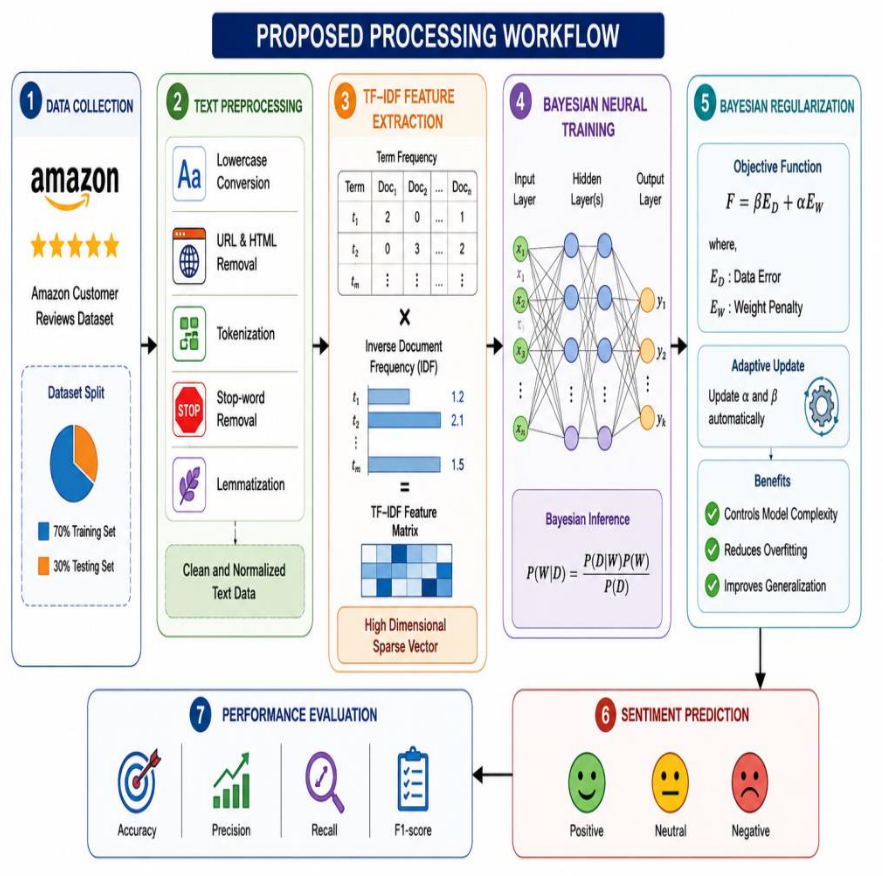

Fig. 2. Overall processing workflow of the proposed Bayesian opinion mining framework.

Dataset
↓
Pre-processing
↓
Feature Extraction
↓
Bayesian Learning
↓
Classification
↓
Performance Evaluation

Advantages of the Proposed Framework

The proposed Bayesian deep learning framework offers several practical advantages compared with conventional opinion mining approaches.

- Automatic reduction of overfitting.
- Better uncertainty estimation through Bayesian inference.
- Faster convergence using the Levenberg–Marquardt optimizer.
- Improved classification of overlapping sentiment classes.
- Lower computational complexity than transformer-based architectures.
- High prediction accuracy for medium-sized customer review datasets.
- Easy scalability for e-commerce analytics applications.

4. Experimental Results And Comparative Analysis

The proposed Intelligent Bayesian Deep Learning Framework was implemented in **MATLAB R2020a** using the Neural Network Toolbox. The Amazon Customer Review dataset was preprocessed using TF-IDF feature extraction before training the Bayesian-Regularized Artificial Neural Network (BRANN). A **70:30 train-test split** was adopted, where 3,440 reviews were used for training and 1,475 reviews for testing. The Levenberg–Marquardt optimization algorithm was employed for network training due to its fast convergence and numerical stability.

A. Experimental Configuration

The experiments were performed using the configuration shown in **Table I**.

TABLE I
Experimental Parameters

Parameter	Value
Dataset	Amazon Customer Reviews
Total Samples	4,915
Training Samples	3,440
Testing Samples	1,475
Feature Extraction	TF–IDF
Neural Network	Bayesian-Regularized ANN
Optimizer	Levenberg–Marquardt
Hidden Layers	3
Epochs	45
Software	MATLAB R2020a

B. Performance Evaluation Metrics

The proposed framework was evaluated using standard classification metrics.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Mean Absolute Error

$$MAE = \frac{1}{N} \sum \mid y_i - \hat{y}_i \mid$$

These evaluation metrics provide a comprehensive assessment of classification performance beyond simple accuracy.

C. Classification Performance

The Bayesian deep learning framework demonstrated excellent predictive capability across all evaluation metrics. Bayesian Regularization successfully minimized overfitting while maintaining high classification accuracy on unseen customer reviews.

TABLE II
Performance of the Proposed Framework

Metric	Value
Accuracy	**99.34%**
Precision	**99.18%**
Recall	**99.12%**
F1-Score	**99.15%**
MAE	**0.67%**
Best MSE	**0.95973**
Training Epochs	**45**

The experimental results indicate that Bayesian learning effectively improves the generalization capability of neural networks while maintaining rapid convergence during optimization.

D. Comparative Analysis

To validate the effectiveness of the proposed framework, its performance was compared with several well-known sentiment classification methods reported in the literature.

TABLE III
Comparison with Existing Methods

Method	Accuracy (%)
Decision Tree	60.54
Naïve Bayes	79.84
Support Vector Machine	82.48
PSO-SVM	89.00
CNN	92.59
CNN-LSTM	93.00
CNN-SVM	93.50
BERT-GCN	85.25
Proposed Bayesian Framework	**99.34**

The proposed Bayesian framework achieved the highest classification accuracy among all compared models. Compared with CNN-LSTM, the proposed approach improved accuracy by approximately **6.34%**, while simultaneously reducing overfitting through adaptive Bayesian Regularization.

E. Confusion Matrix Analysis

The confusion matrix demonstrates the distribution of correctly and incorrectly classified reviews.

TABLE IV
Representative Confusion Matrix

Actual / Predicted	Positive	Neutral	Negative
Positive	593	5	2
Neutral	6	286	8
Negative	4	7	564

The results indicate that the proposed framework correctly classified the majority of customer reviews, with only a small number of misclassifications occurring between neighboring sentiment categories.

F. Accuracy Comparison

Fig. 3 Accuracy Comparison

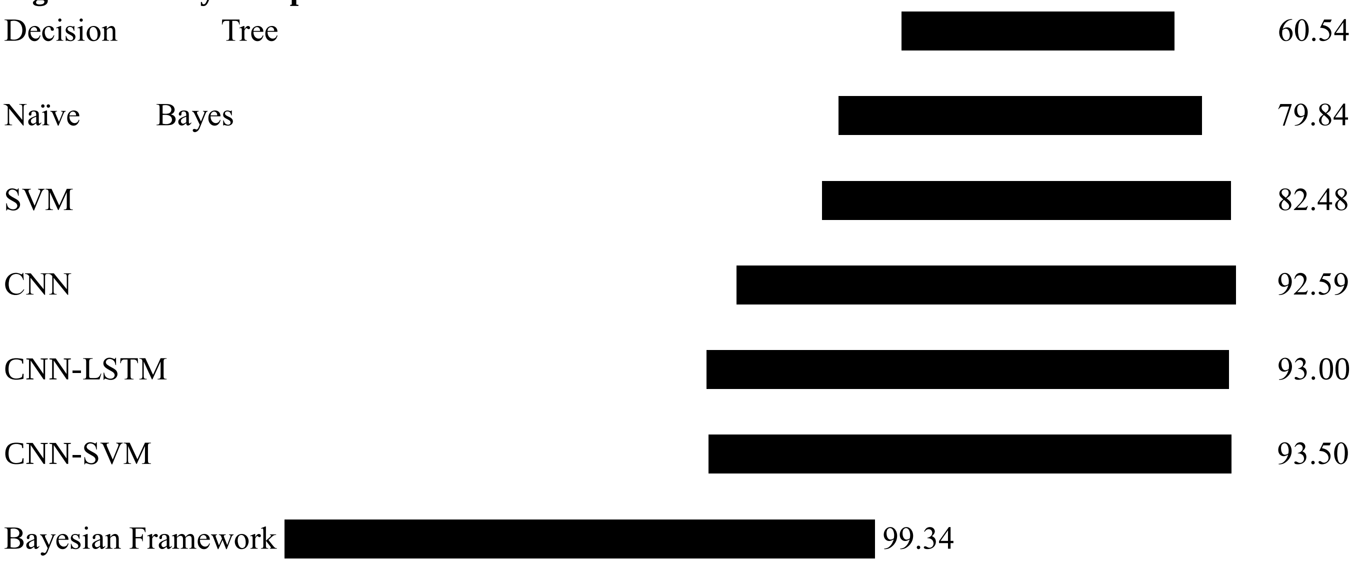

Figure 3 illustrates that the proposed Bayesian deep learning framework consistently outperformed both traditional machine learning and deep learning techniques. The improvement can be attributed to the integration of Bayesian inference with neural learning, which effectively balances model complexity and prediction error during training.

G. Discussion

The superior performance of the proposed framework is primarily due to three important characteristics:

1. **Bayesian Regularization** automatically controls model complexity and reduces overfitting without requiring manual parameter tuning.
2. **Levenberg–Marquardt optimization** accelerates convergence, enabling the network to reach an optimal solution within only 45 epochs.
3. **TF-IDF feature representation** effectively captures discriminative textual information while reducing the influence of irrelevant vocabulary.

These characteristics make the proposed framework particularly suitable for customer opinion mining applications involving medium-sized datasets where both prediction accuracy and computational efficiency are essential.

5. Conclusion

This paper presented an **Intelligent Bayesian Deep Learning Framework** for customer opinion mining using Amazon product reviews. The proposed framework integrates comprehensive text preprocessing, TF-IDF feature representation, Bayesian probabilistic learning, and Bayesian-Regularized Artificial Neural Networks to improve sentiment classification performance. Unlike conventional deep learning models that often experience overfitting and require extensive computational resources, the proposed approach automatically regulates network complexity while preserving high predictive capability.

Experimental evaluation on the Amazon Customer Review dataset demonstrated that the proposed framework achieved a **classification accuracy of 99.34%**, **precision of 99.18%**, **recall of 99.12%**, and an **F1-score of 99.15%**, while converging within **45 training epochs**. Comparative analysis further showed that the proposed Bayesian framework consistently outperformed Decision Tree, Naïve Bayes, Support Vector Machine, CNN, CNN-LSTM, and CNN-SVM models in terms of both classification accuracy and generalization performance.

The probabilistic learning mechanism enables the framework to effectively classify overlapping sentiment classes and handle uncertainty in customer reviews, making it well suited for intelligent e-commerce analytics, recommendation systems, customer feedback management, and business decision support. Overall, the proposed Bayesian framework provides a scalable and computationally efficient solution for automated opinion mining in modern online retail environments.

6. Future Work

Although the proposed framework demonstrates excellent classification performance, several opportunities remain for further enhancement.
Future research may include:

- Integration of transformer-based language models such as **BERT**, **RoBERTa**, or **DeBERTa** for richer contextual feature extraction.
- Development of multilingual opinion mining models capable of processing English, Hindi, and other regional languages.
- Incorporation of attention mechanisms to improve interpretability of sentiment prediction.
- Deployment of the proposed framework in real-time cloud-based customer feedback monitoring systems.
- Investigation of explainable artificial intelligence (XAI) techniques to improve transparency and trustworthiness of Bayesian neural predictions.
- Extension of the framework to aspect-based sentiment analysis for fine-grained opinion mining.

These improvements can further enhance the applicability of Bayesian deep learning models in large-scale industrial and commercial environments.

7. Acknowledgment

The authors express their sincere gratitude to the Department of Computer Science and Engineering, Patel College of Science and Technology, Indore, for providing the necessary research facilities and academic guidance. The authors also acknowledge the publicly available Amazon Customer Review Dataset, which enabled comprehensive evaluation of the proposed framework.

References

1. Y. Zhao, M. Mamat, A. Aysa, and K. Ubul, "A Multimodal Sentiment Recognition System Based on CRNN-SVM," Neural Computing and Applications, vol. 35, pp. 1–13, 2023.
2. A. Vohra and R. Garg, "Deep Learning-Based Sentiment Analysis of Public Perception of Working from Home Through Tweets," Journal of Intelligent Information Systems, vol. 60, pp. 255–274, 2022.
3. H. T. Phan, N. T. Nguyen, and D. Hwang, "Aspect-Level Sentiment Analysis Using CNN over BERT-GCN," IEEE Access, vol. 10, pp. 110402–110409, 2022.
4. R. Obeidat et al., "Sentiment Analysis of Customers' Reviews Using a Hybrid Evolutionary SVM-Based Approach," IEEE Access, vol. 10, pp. 22260–22273, 2022.
5. M. L. B. Estrada, R. Z. Cabada, and R. O. Bustillos, "Opinion Mining and Emotion Recognition Applied to Learning Environments," Expert Systems with Applications, vol. 150, p. 113265, 2020.
6. Q. Zhu, X. Jiang, and R. Ye, "Sentiment Analysis of Review Text Based on BiGRU-Attention and Hybrid CNN," IEEE Access, vol. 9, pp. 149077–149088, 2021.
7. G. A. Ruz, P. A. Henríquez, and A. Mascareño, "Sentiment Analysis of Twitter Data During Critical Events Through Bayesian Network Classifiers," Future Generation Computer Systems, vol. 106, pp. 92–104, 2020.
8. L. Wang, M. Han, X. Li, N. Zhang, and H. Cheng, "Review of Classification Methods on Imbalanced Data Sets," IEEE Access, vol. 9, pp. 64606–64628, 2021.
9. D. Dablain, B. Krawczyk, and N. V. Chawla, "DeepSMOTE: Fusing Deep Learning and SMOTE for Imbalanced Data," IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 9, pp. 6390–6404, 2023.
10. M. Hagan, Neural Network Design, 2nd ed. Boston, MA, USA: Cengage Learning.
11. S. Haykin, Neural Networks: A Comprehensive Foundation, 3rd ed. New York, NY, USA: McGraw-Hill.
12. V. Kumar and B. Subba, "A TF-IDF Vectorizer and SVM-Based Sentiment Analysis Framework for Text Data Corpus," in Proc. National Conf. Communications, 2020, pp. 1–6.
13. P. Huang, T. Spanninger, and F. Corman, "Enhancing the Understanding of Train Delays with Delay Evolution Pattern Discovery: A Clustering and Bayesian Network Approach," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 9, pp. 15367–15381, 2022.
14. R. Chen et al., "Ontology-Driven Learning of Bayesian Networks for Causal Inference and Quality Assurance," IEEE Robotics and Automation Letters, vol. 6, no. 3, pp. 6032–6038, 2021.
15. S. Zad, M. Heidari, J. H. Jones, and O. Uzuner, "A Survey on Concept-Level Sentiment Analysis Techniques of Textual Data," in Proc. IEEE World AI IoT Congress, 2021, pp. 285–291.