Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Enhancing Customer Satisfaction Analysis Using Advanced Machine Learning Techniques in Fintech Industry

Md Abu Sufian Mozumder[1] ✉ Tuan Ngoc Nguyen[2], Suniti Devi[3], Md Arif[4], Md Parvez Ahmed[5], Estak Ahmed[6], Maniruzzaman Bhuiyan[7], Md Habibur Rahman[8] and Abdullah Al Mamun[9], Aftab Uddin[10]

[1]College of Business, Westcliff University, Irvine, California, USA
[2]VNDirect Securities, 97 Lo Duc, Hai Ba Trung, Hanoi, Vietnam
[34]Department of Management Science and Quantitative Methods, Gannon University, USA
[5]Master of Science in Information Technology, Washington University of Science and Technology, USA
[6]Department of Computer Science, Monroe College, New Rochelle, New York, USA
[7]Satish & Yasmin Gupta College of Business, University of Dallas, Texas
[8]Department of Business Administration, International American University, Los Angeles, California
[9]Department of Computer & Info Science, Gannon University, Erie, Pennsylvania, USA
[10]Fox School of Business & Management, Temple University, USA

Corresponding Author: Md Abu Sufian Mozumdar, **E-mail**: m.mozumder.158@westcliff.edu

| ABSTRACT

Customer satisfaction (CSAT) is vital in service and marketing, indicating how well products or services meet customer expectations. Traditional CSAT methods like the American Customer Satisfaction Index (ACSI) and Net Promoter Score (NPS) face challenges such as survey fatigue and low response rates. This study introduces a novel framework using advanced machine learning (ML) and deep learning (DL) techniques, specifically Bidirectional Encoder Representations from Transformers (BERT), to classify customer feedback into distinct CSAT drivers. Integrating term frequency-inverse document frequency (TF-IDF) methods with BERT-based embeddings, the framework significantly improves prediction accuracy. Using a proprietary dataset of 5,943 customer feedback responses from 39 companies across 13 industries, the fine-tuned BERT model achieved an F1 score of 0.84, surpassing traditional methods like TF-IDF and support vector machine (SVM) with an F1 score of 0.47, and TF-IDF with multi-layer perceptron (MLP) networks at 0.50. A hybrid approach combining BERT and TF-IDF embeddings with MLP networks yielded an F1 score of 0.71. The results show the transformative potential of DL techniques, particularly fine-tuned BERT models, in enhancing CSAT prediction accuracy. This research bridges the gap between traditional and advanced text mining methods, setting a new standard for CSAT modeling and offering a robust framework for extracting actionable insights from customer feedback. It highlights the importance of adopting advanced ML and DL models for strategic decision-making and improving customer satisfaction measurement.

| KEYWORDS

Customer Satisfaction; Machine Learning; Fintech Industry

| ARTICLE INFORMATION

ACCEPTED: 15 July 2024 **PUBLISHED:** 01 August 2024 **DOI:** 10.32996/jcsts.2024.6.3.4

1. Introduction

Customer satisfaction (CSAT) is a pivotal metric in both service and marketing landscapes, reflecting the degree to which a product or service meets or exceeds customer expectations (Oliver, 2010). As businesses strive for competitive advantage, understanding

and enhancing CSAT becomes imperative. Traditional methods, such as the American Customer Satisfaction Index (ACSI) and the Net Promoter Score (NPS), have been instrumental in gauging CSAT. These metrics, while effective, often face challenges like survey fatigue and low response rates (Reichheld, 2003; Morgan & Rego, 2006).
In response to these challenges, the application of machine learning (ML) and deep learning (DL) techniques to model CSAT has gained significant traction. These advanced approaches enable the extraction of valuable insights from customer reviews and other data sources, facilitating more informed decision-making processes (Schneider et al., 2017). The proliferation of text mining and natural language processing (NLP) has revolutionized the analysis of unstructured data, which constitutes a substantial portion of corporate information (Feldman & Sanger, 2007).

This study presents a novel framework that leverages deep learning, particularly Bidirectional Encoder Representations from Transformers (BERT), to classify customer feedback comments into specific CSAT drivers. By fine-tuning pre-trained BERT models, our approach addresses the limitations of traditional methods and enhances the accuracy of CSAT prediction. This research not only explores the transition from traditional TF-IDF methods to advanced DL techniques but also proposes a hybrid word-embedding strategy that combines the strengths of both approaches.

Through rigorous empirical evaluation using a proprietary dataset of customer feedback, our findings underscore the superiority of fine-tuned BERT models, achieving an F1 score of 0.84. This advancement highlights the transformative potential of DL techniques in business analytics and sets a new standard for CSAT modeling.

The following sections delve into the literature review, methodology, data collection and processing, and empirical results, providing a comprehensive overview of the proposed framework and its implications for enhancing customer satisfaction measurement and analysis.

2. Literature Review

2.1 Customer Satisfaction and Its Importance

Customer satisfaction (CSAT) is a critical metric in both service and marketing domains, often defined as the consumer's evaluation of whether a product or service meets or exceeds expectations (Oliver, 2010). This measure is subjective and encompasses the overall experience of the customer. Traditional methods to measure CSAT include the American Customer Satisfaction Index (ACSI) and the Net Promoter Score (NPS), which have been widely adopted due to their simplicity and effectiveness in predicting business growth (Reichheld, 2003). However, these methods face challenges such as potential survey fatigue leading to low response rates (Morgan & Rego, 2006).

2.2 Machine Learning in Customer Satisfaction

Recently, the application of machine learning to model customer satisfaction has gained traction. These approaches aim to derive insights from customer reviews and other data sources, enhancing decision-making processes (Schneider et al., 2017). Text mining and natural language processing (NLP) have emerged as powerful tools in this context, enabling the analysis of unstructured data, which comprises about 80% of corporate information (Feldman & Sanger, 2007).

2.3 Text Mining Techniques

Text mining involves various techniques such as text categorization, clustering, concept extraction, document summarization, and sentiment analysis (Miner et al., 2012). Sentiment analysis has traditionally been a focus of customer feedback research, but recent studies are exploring text categorization to better understand customer opinions (Pang & Lee, 2008). For example, reviews from diverse sectors like hospitality and automotive industries provide rich data for analyzing customer feedback (Liu, 2012).

2.4 Advanced Deep Learning Approaches

The proposed methodology leverages deep learning (DL) to classify customer feedback comments into specific CSAT drivers. Deep learning models, especially those based on artificial neural networks (ANN), have shown promise in processing unstructured data (Goodfellow et al., 2016). The cross-industry standard process for data mining (CRISP-DM) provides a structured framework for such analyses (Shearer, 2000).

2.5 Data Collection and Processing

Data collection in the proposed framework involves defining business goals, exploring and visualizing data, and preparing it for model training (Witten et al., 2016). Techniques such as word embedding, specifically using models like BERT (Bidirectional Encoder Representations from Transformers), enhance the understanding of textual context and semantics (Devlin et al., 2019).

2.6 Multi-label Classification
Multi-label text classification, necessary for identifying multiple CSAT drivers in a single comment, has been advanced by models like BERT. Fine-tuning pre-trained BERT models on specific datasets has been shown to significantly improve performance (Howard & Ruder, 2018). Studies have highlighted BERT's superiority in tasks requiring deep semantic understanding and context modeling compared to traditional TF-IDF approaches (Qiu et al., 2020).

2.7 Empirical Results
Empirical evaluation using a proprietary dataset of customer feedback revealed that fine-tuning BERT outperformed other methods, achieving an F1 score of 0.84. This underscores the importance of leveraging advanced DL techniques in business analytics (Vaswani et al., 2017).

3. Methodology
Customer satisfaction has garnered significant attention in both service and marketing literature, with a focus on understanding its antecedents and consequences. Defined as the consumer's evaluation of whether a product or service meets or falls short of expectations, customer satisfaction is a subjective and holistic measure reflecting an individual's overall experience. In recent years, machine learning researchers have turned their attention to modeling customer satisfaction, aiming to extract valuable insights from customer reviews and other data sources to enhance decision-making processes. Traditional tools like the American Customer Satisfaction Index have been developed to assess this construct. However, firms often seek simpler methods due to the potential for long surveys to overwhelm customers and result in low response rates. As a result, new metrics have been proposed, with the Net Promoter Score (NPS) emerging as one of the most popular. NPS measures customer experience and predicts business growth by categorizing customers into promoters, passives, and detractors based on their likelihood of recommending the company. This categorization is achieved through a straightforward scoring system followed by an open-ended request for elaboration, which provides valuable qualitative data for further analysis.

3.1 Text mining applied to CSAT
Text mining, also known as text analytics, leverages various techniques to automatically extract valuable information from textual data, offering significant advantages to companies in terms of scalability and reliability. This discipline, closely related to natural language processing (NLP), enables the processing and analysis of human language data, which is particularly valuable as approximately 80% of corporate information is in textual formats. Text mining encompasses a range of tasks, including text categorization, clustering, concept extraction, document summarization, and sentiment analysis. Customer feedback research has traditionally focused on sentiment analysis, but recent studies have started exploring text categorization to better understand customer opinions. While text classification offers powerful tools for pattern analysis by assigning predefined categories to documents, it requires a large volume of manually labeled data, especially when using deep learning approaches.

Numerous text-based resources, such as reviews, complaints, and articles, provide rich data for companies to analyze and improve business strategies. Reviews are particularly valuable for customer feedback, with studies analyzing data from various sectors, including hotels, restaurants, and automobiles. Some studies utilize semantic tagging for deep learning to summarize customer perceptions, although this method does not support review categorization. The proposed framework in our study introduces a new predictive task in marketing analytics by employing supervised learning and multilabel classification to identify drivers of customer experience, guiding the learning process with specific concepts sought by practitioners. Additionally, customer complaints are crucial for understanding customer needs and improving product design, with text mining analyses applied to various products such as home appliances, automobiles, and mobile phones.

3.2 Proposed Methodology
We introduce a novel framework utilizing deep learning (DL) to extract insights from customer feedback surveys. DL, which enhances traditional artificial neural network (ANN) architectures for processing unstructured data like text and images, aims to automatically classify verbatim comments into 11 factors known to influence customer satisfaction (CSAT). Our methodology adapts the cross-industry standard process for data mining (CRISP-DM), a widely used framework in text mining for customer feedback, into a customized four-step approach for analyzing customer feedback data. This tailored framework leverages natural language processing (NLP) and text mining techniques to better understand customer satisfaction. The objective is to create a machine capable of categorizing open-ended feedback based on CSAT drivers and extracting comprehensive insights from the relationship between feedback and ratings using tools like word clouds and descriptive analytics.

3.3 Data Collection and processing
The first step in our framework involves three sub-steps aligned with the CRISP-DM methodology. Initially, we focus on business understanding to define the goals of the text mining process, identifying the major themes within the data. This sets the stage for deeper machine learning analysis of these themes, establishing clear business objectives and success criteria. The next sub-step

involves data exploration and visualization, aiming to assess data quality and identify initial patterns relevant to customer insights. Word clouds, colored by predominant labels like promoter, passive, or detractor, are particularly useful at this stage. The output is a comprehensive report on data quality and exploration, guiding necessary pre-processing steps.
The final sub-step is data preparation, encompassing selection, annotation, and cleansing of the data, resulting in a pre-processed dataset ready for model training. Data was collected through telephone surveys and manually transcribed, with open-ended responses annotated to identify labels for the machine learning model. For example, "It has low fares, and you can talk more for less money" is tagged under "price," while "The call quality is terrible, and the cell phone's functionalities are poor" falls under "reliability." Standard pre-processing techniques like removing stop words and stemming were applied to prepare the data for text mining. Text, as unstructured data, must be structured to uncover patterns, a process often achieved through word embedding. Traditionally, this has been done using the term frequency-inverse document frequency (TF-IDF) method, which constructs document vectors based on unique words. Recently, more advanced approaches have emerged, such as Bidirectional Encoder Representations from Transformers (BERT), which integrates text pre-processing into the learning system. BERT has gained popularity for its superior performance in semantic word embedding by utilizing a bidirectional training strategy with the transformer attention mechanism.

This allows BERT to understand the context of words by reading entire sequences simultaneously, unlike previous methods that processed text sequentially. BERT achieves a bidirectional representation by masking a portion of words in the input to predict them and by learning relationships between sentence pairs. To enhance this, we propose a hybrid word-embedding approach that combines TF-IDF vectors with the original comments as inputs for the BERT model. This method aims to leverage the strengths of both TF-IDF, which captures the significance of individual words, and BERT, which models word relationships within sentences. This novel combination is distinct from other methods and offers a unique contribution to the field.

3.4 BERT fine-tuning and multi-label classification

In multi-class classification, the objective is to assign instances to one of several possible classes. However, some tasks require identifying multiple labels for a single sample. For instance, a customer feedback comment might mention both the price of a product and the quality of service, necessitating the identification of multiple drivers of customer satisfaction. Multi-label text classification addresses this challenge by recognizing various relevant factors in a single input.

Numerous studies have explored multi-label text classification. Notable examples include classifying newswire articles into one or more categories and biomedical texts into multiple labels. These studies have achieved varying degrees of accuracy and F1 scores depending on the complexity and number of labels involved. Our framework utilizes deep learning for multi-label text classification, performing word embedding and classifier training simultaneously. By leveraging pre-trained models like BERT, which utilizes transfer learning, we can fine-tune word vectors for specific data sets. This approach is particularly beneficial for small survey-based customer feedback data sets, where deep learning models generally require extensive data to be effective.

The framework differentiates between multi-class and multi-label classification using BERT. In multi-class classification, a single driver of customer satisfaction is identified per comment, while multi-label classification allows for the identification of multiple drivers within the same comment. BERT's pre-training involves learning language understanding from large datasets, which include sources like books and Wikipedia. Pre-trained models are then fine-tuned for specific tasks, such as multi-label classification, by adjusting the model's weights and defining an appropriate output layer. This fine-tuning process customizes the model for specific applications without sacrificing the general language understanding acquired during pre-training.

4. Result

To evaluate our methodology, we utilized a proprietary dataset containing 5,943 responses from 39 companies across 13 different industries in Chile. Each response included customer ratings based on the NPS framework and was manually tagged to identify between one and three of the eleven possible drivers of customer satisfaction. To ensure data quality, a consultancy team with extensive experience in conducting NPS-based phone interviews designed and executed the data collection. Each customer response was classified with a "micro-driver," a context-specific label provided by the consulting team. We validated these micro-drivers by randomly sampling and manually checking their accuracy, achieving a 97% consensus after multiple reviews. For our study, we selected companies from diverse economic sectors, with at least 10,00 clients and strong brand recognition in Chile, and ensured survey participants were familiar with the companies. Our data analysis followed the CRISP-DM framework, starting with data gathering, visualization, and processing, and implemented in Python using libraries like nltk, sklearn, Keras, and TensorFlow. The preprocessing steps, including stop word removal and stemming, showed slight improvements in model performance. Descriptive information revealed similar data sizes across industries but highly skewed NPS score distributions, highlighting the need for industry-specific models. Further details on the dataset and preprocessing steps are in the supplementary material, including the proportion of drivers across industries and word clouds illustrating the impact of key concepts on NPS scores in different sectors.

In our comparative study, we rigorously evaluated several strategies for multi-label classification, emphasizing the transition from traditional TF-IDF methods to advanced deep learning techniques like BERT. Beyond TF-IDF coupled with SVM or MLP networks, we explored the efficacy of pre-trained BERT both with and without fine-tuning. Additionally, our proposed hybrid approach merging pre-trained BERT embeddings with TF-IDF features showed promising results when integrated with MLP networks. Notably, while approaches such as BI-LSTM and GRU networks, as well as ELMO, present competitive performance, BERT's capability to fine-tune and leverage transformer reasoning sets a new standard in the field. Our experiments, guided by standard applied research methodologies, included parameter tuning for deep learning strategies validating optimal configurations such as 10 epochs with a batch size of 32. For BERT, we adopted the ADAM optimizer with default settings, ensuring adaptive optimization without extensive manual tuning. In conclusion, our study underscores BERT's superiority over TF-IDF in business analytics applications, advocating for transformative advancements in natural language processing and classification tasks.

Table 1: multi-label classification Result

METHOD	F1 (WEIGHTED)
TF-IDF + SVM	0.47
TF-IDF + MLP	0.50
BERT + MLP	0.69
HYBRID BERT/TF-IDF + MLP	0.71
BERT + FINE-TUNING	0.84

The table summarizes the performance of various classification methods using different word embedding strategies across a multi-label classification task with 11 labels. Here, we analyze and discuss the implications of each approach based on their F1 scores.

1. **TF-IDF + SVM (F1 = 0.47):**
   Performance Evaluation: This approach combines the traditional TF-IDF word embedding with a Support Vector Machine (SVM) classifier. The F1 score of 0.47 indicates moderate performance but suggests limitations in capturing nuanced semantic relationships among words.

2. **TF-IDF + MLP (F1 = 0.50):**
   Performance Evaluation: Using TF-IDF with a Multi-Layer Perceptron (MLP) network shows a slight improvement over TF-IDF + SVM, achieving an F1 score of 0.50. However, it still falls short compared to more advanced embedding techniques.

3. **BERT + MLP (F1 = 0.69):**
   Performance Evaluation: Employing BERT embeddings, a state-of-the-art language model, with an MLP network significantly boosts performance to an F1 score of 0.69. BERT's ability to capture contextual and semantic meanings of words contributes to this substantial improvement over traditional methods.

4. **Hybrid BERT/TF-IDF + MLP (F1 = 0.71):**
   Performance Evaluation: Combining BERT embeddings with TF-IDF features further enhances performance, yielding an F1 score of 0.71. This hybrid approach leverages BERT's semantic understanding while also incorporating the frequency-based features from TF-IDF, leading to improved classification accuracy.

5. **BERT + Fine-Tuning (F1 = 0.84):**
   Performance Evaluation: Fine-tuning BERT specifically for the classification task results in the highest F1 score of 0.84. Fine-tuning allows BERT to adapt its embeddings to the specific nuances and patterns of the dataset, thereby achieving superior performance compared to all other methods evaluated.

- **Embedding Strategies:** The results highlight the superiority of deep learning-based embeddings (BERT) over traditional TF-IDF embeddings in capturing semantic relationships and contextual meanings within texts.

- **Model Complexity:** The transition from SVM and MLP models with TF-IDF to MLP with BERT and fine-tuning increases model complexity but significantly improves classification accuracy, underscoring the trade-off between model complexity and performance gains.
- **Hybrid Approach:** The hybrid BERT/TF-IDF approach demonstrates marginal improvement over using BERT alone, suggesting that while TF-IDF features can complement BERT, the majority of performance gains come from leveraging BERT's capabilities.
- **Fine-Tuning Benefits:** Fine-tuning BERT for the classification task demonstrates the model's adaptability and capability to learn task-specific nuances, resulting in the highest F1 score observed. This approach showcases the effectiveness of leveraging pre-trained models and adapting them to domain-specific requirements.

Chart 1 illustrates the visual representation of the experiment's results, underscoring the advancements brought by deep learning-based approaches like BERT in text classification tasks, highlighting their ability to outperform traditional methods like TF-IDF combined with SVM or MLP. Fine-tuning BERT emerges as the most effective strategy, offering substantial improvements in classification accuracy for multi-label tasks.

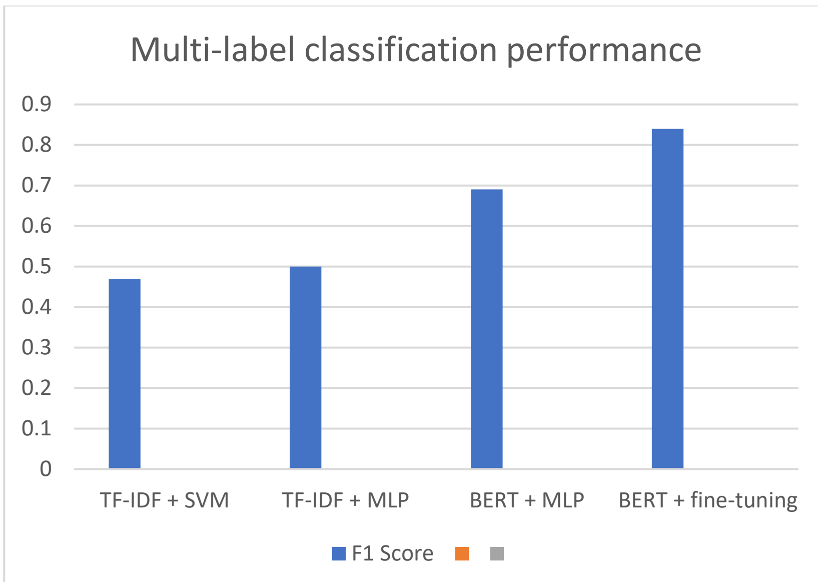

Chart 1: Summary of performance across all multi-label classification methods, presenting general findings.

5. Conclusion and Discussion

The study demonstrates the transformative potential of deep learning, specifically fine-tuned BERT models, in enhancing customer satisfaction prediction accuracy. The proposed framework bridges the gap between traditional text mining methods and advanced deep learning techniques, providing a robust approach for extracting actionable insights from customer feedback. The results underscore the importance of adopting advanced machine learning models in strategic decision-making, offering significant improvements in customer satisfaction measurement and analysis. Future research could explore the integration of additional NLP techniques and the application of the framework to other domains, further enhancing its versatility and effectiveness.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

[1] Arif, M., Hasan, M., Al Shiam, S. A., Ahmed, M. P., Tusher, M. I., Hossan, M. Z., ... & Imam, T. (2024). Predicting Customer Sentiment in Social Media Interactions: Analyzing Amazon Help Twitter Conversations Using Machine Learning. *International Journal of Advanced Science Computing and Engineering*, *6*(2), 52-56.

[2] Bhuiyan, M. S., Chowdhury, I. K., Haider, M., Jisan, A. H., Jewel, R. M., Shahid, R., ... & Siddiqua, C. U. (2024). Advancements in early detection of lung cancer in public health: a comprehensive study utilizing machine learning algorithms and predictive models. *Journal of Computer Science and Technology Studies*, *6*(1), 113-121.

[3] Chowdhury, M. S., Nabi, N., Rana, M. N. U., Shaima, M., Esa, H., Mitra, A., ... & Naznin, R. (2024). Deep Learning Models for Stock Market Forecasting: A Comprehensive Comparative Analysis. *Journal of Business and Management Studies*, *6*(2), 95-99.

[4] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

[5] Ferdus, M. Z., Anjum, N., Nguyen, T. N., Jisan, A. H., & Raju, M. A. H. (2024). The Influence of Social Media on Stock Market: A Transformer-Based Stock Price Forecasting with External Factors. *Journal of Computer Science and Technology Studies*, *6*(1), 189-194.

[6] Feldman, R., & Sanger, J. (2007). *The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*. Cambridge University Press.

[7] Farabi, S. F., Prabha, M., Alam, M., Hossan, M. Z., Arif, M., Islam, M. R., ... & Biswas, M. Z. A. (2024). Enhancing Credit Card Fraud Detection: A Comprehensive Study of Machine Learning Algorithms and Performance Evaluation. *Journal of Business and Management Studies*, *6*(3), 252-259.

[8] Ghosh, B. P., Imam, T., Anjum, N., Mia, M. T., Siddiqua, C. U., Sharif, K. S., ... & Mamun, M. A. I. (2024). Advancing Chronic Kidney Disease Prediction: Comparative Analysis of Machine Learning Algorithms and a Hybrid Model. *Journal of Computer Science and Technology Studies*, *6*(3), 15-21.

[9] Ghosh, B. P., Bhuiyan, M. S., Das, D., Nguyen, T. N., Jewel, R. M., Mia, M. T., & Cao, D. M. (2024). Deep Learning in Stock Market Forecasting: Comparative Analysis of Neural Network Architectures Across NSE and NYSE. *Journal of Computer Science and Technology Studies*, *6*(1), 68-75.

[10] Ghosh, B. P., Bhuiyan, M. S., Das, D., Nguyen, T. N., Jewel, R. M., Mia, M. T., ... & Shahid, R. (2024). Deep Learning in Stock Market Forecasting: Comparative Analysis of Neural Network Architectures Across NSE and NYSE. *Journal of Computer Science and Technology Studies*, *6*(1), 68-75.

[11] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

[12] Howard, J., & Ruder, S. (2018). Universal language model fine-tuning for text classification. *arXiv preprint arXiv:1801.06146*.

[13] Hammad, O., Rahman, M. R., Clements, N., Mishra, S., Miller, S., & Sullivan, E. (2023, November). PureNav: A Personalized Navigation Service for Environmental Justice Communities Impacted by Planned Disruptions. In *Proceedings of the International Conference on Advances in Social Networks Analysis and Mining* (pp. 56-63).

[14] Islam, M. T., Ayon, E. H., Ghosh, B. P., MD, S. C., Shahid, R., Rahman, S., ... & Nguyen, T. N. (2024). Revolutionizing Retail: A Hybrid Machine Learning Approach for Precision Demand Forecasting and Strategic Decision-Making in Global Commerce. *Journal of Computer Science and Technology Studies*, *6*(1), 33-39.

[15] Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers.

[16] Mia, M. T., Ferdus, M. Z., Rahat, M. A. R., Anjum, N., Siddiqua, C. U., & Raju, M. A. H. (2024). A Comprehensive Review of Text Mining Approaches for Predicting Human Behavior using Deep Learning Method. *Journal of Computer Science and Technology Studies*, *6*(1), 170-178.

[17] Morgan, N. A., & Rego, L. L. (2006). The value of different customer satisfaction and loyalty metrics in predicting business performance. *Marketing Science*, 25(5), 426-439.

[18] Modak, C., Ghosh, S. K., Sarkar, M. A. I., Sharif, M. K., Arif, M., Bhuiyan, M., ... & Devi, S. (2024). Machine Learning Model in Digital Marketing Strategies for Customer Behavior: Harnessing CNNs for Enhanced Customer Satisfaction and Strategic Decision-Making. *Journal of Economics, Finance and Accounting Studies*, *6*(3), 178-186.

[19] Mozumder, M. A. S., Sweet, M. M. R., Nabi, N., Tusher, M. I., Modak, C., Hasan, M., ... & Prabha, M. (2024). Revolutionizing Organizational Decision-Making for Banking Sector: A Machine Learning Approach with CNNs in Business Intelligence and Management. *Journal of Business and Management Studies*, *6*(3), 111-118.

[20] Modak, C., Ghosh, S. K., Sarkar, M. A. I., Sharif, M. K., Arif, M., Bhuiyan, M., ... & Devi, S. (2024). Machine Learning Model in Digital Marketing Strategies for Customer Behavior: Harnessing CNNs for Enhanced Customer Satisfaction and Strategic Decision-Making. *Journal of Economics, Finance and Accounting Studies*, *6*(3), 178-186.

[21] Miner, G., Elder, J., Fast, A., Hill, T., Nisbet, R., Delen, D., & Schmidt, H. (2012). *Practical Text Mining and Statistical Analysis for Non-structured Text Data Applications*. Academic Press.

[22] Mozumder, M. A. S., Sweet, M. M. R., Nabi, N., Tusher, M. I., Modak, C., Hasan, M., ... & Prabha, M. (2024). Revolutionizing Organizational Decision-Making for Banking Sector: A Machine Learning Approach with CNNs in Business Intelligence and Management. *Journal of Business and Management Studies*, *6*(3), 111-118.

[23] Nguyen, T. N., Haider, M., Jisan, A. H., Raju, M. A. H., Imam, T., Khan, M. M., & Jafar, A. E. (2024). Product Demand Forecasting with Neural Networks and Macroeconomic Indicators: A Comparative Study among Product Categories. *Journal of Business and Management Studies*, *6*(2), 170-175.

[24] Oliver, R. L. (2010). *Satisfaction: A Behavioral Perspective on the Consumer*. M.E. Sharpe.

[25] Pang, B., & Lee, L. (2008). *Opinion Mining and Sentiment Analysis*. Now Publishers Inc.

[26] Rahman, M. A., Modak, C., Mozumder, M. A. S., Miah, M. N. I., Hasan, M., Sweet, M. M. R., ... & Alam, M. (2024). Advancements in Retail Price Optimization: Leveraging Machine Learning Models for Profitability and Competitiveness. *Journal of Business and Management Studies*, *6*(3), 103-110.

[27] Rahman, M. A., Modak, C., Mozumder, M. A. S., Miah, M. N. I., Hasan, M., Sweet, M. M. R., ... & Alam, M. (2024). Advancements in Retail Price Optimization: Leveraging Machine Learning Models for Profitability and Competitiveness. *Journal of Business and Management Studies*, *6*(3), 103-110.

[28] Rana, M. N. U., Al Shiam, S. A., Shochona, S. A., Islam, M. R., Asrafuzzaman, M., Bhowmik, P. K., ... & Asaduzzaman, M. (2024). Revolutionizing Banking Decision-Making: A Deep Learning Approach to Predicting Customer Behavior. *Journal of Business and Management Studies*, *6*(3), 21-27.

[29] Shahid, R., Mozumder, M. A. S., Sweet, M. M. R., Hasan, M., Alam, M., Rahman, M. A., ... & Islam, M. R. (2024). Predicting Customer Loyalty in the Airline Industry: A Machine Learning Approach Integrating Sentiment Analysis and User Experience. *International Journal on Computational Engineering*, *1*(2), 50-54.