DOI: 10.53469/jtpes.2024.04(02).06

Enhancing E-commerce Recommendations: Unveiling Insights from Customer Reviews with BERTFusionDNN

Zhiming Zhao[1], Ning Zhang[2], Jize Xiong[3], Mingyang Feng[4], Chufeng Jiang[5], Xiaosong Wang[6]

[1] Computer Science, East China University of Science and Technology, Shanghai, China
[2] Computer Science, University of Birmingham, Dubai, United Arab Emirates
[3,4] Computer Information Technology, Northern Arizona University, Flagstaff, USA
[5] Computer Science, The University of Texas at Austin, Fremont, USA
[6] Computer Network Technology, Xuzhou University of Technology, Xuzhou, China
[1] zhiming817@gmail.com, [2] nxz243@alumni.bham.ac.uk, [3] jasonxiong824@gmail.com, [4] zgjsntfmy@gmail.com,
[5] chufeng.jiang@utexas.edu, [6] wang138125@gmail.com

Abstract: ***In the domain of e-commerce, customer reviews wield significant influence over business strategies. Despite the existence of various recommendation methodologies like collaborative filtering and deep learning, they often encounter difficulties in accurately analyzing sentiment and semantics within customer feedback. Addressing these challenges head-on, this paper introduces BERTFusionDNN, a novel framework merging BERT for extracting textual features and a Deep Neural Network for integrating numerical features. We assess the efficacy of our approach using a Women Clothing E-Commerce dataset, benchmarking it against established techniques. Our method adeptly extracts valuable insights from customer reviews, fortifying e-commerce recommendation systems by surmounting barriers associated with deciphering both textual nuances and numerical intricacies. Through this endeavor, we pave the way for more robust and effective strategies in leveraging customer feedback to optimize e-commerce experiences and drive business success.***

Keywords: E-commerce; Recommendation System; BERTFusionDNN.

1. INTRODUCTION

In the domain of e-commerce, scrutinizing customer reviews holds immense significance for discerning consumer preferences and informing business strategies. Our focus lies in dissecting a dataset from Women Clothing E-Commerce, primarily comprising customer feedback. This dataset boasts nine complementary features, providing a fertile ground for in-depth exploration of textual data from various angles. It's essential to highlight that, owing to the proprietary nature of the dataset, any mentions of the company within the reviews have been anonymized and substituted with the term "retailer".

Various methodologies in e-commerce recommendation systems have been explored, including collaborative filtering, social network analysis, and deep learning techniques. Studies focus on personalized recommendations, diverse applications, hybrid methods, comparative insights, and comprehensive analyses of customer-generated data for decision-making [1-5]. Recent studies emphasize timely, accurate, personalized recommendations with scalable algorithms [6-9]. Studies proposed a utility-based framework, investigated share recommendation strategies, enhanced sequential recommendations, and introduced a convolutional neural network-based framework [10-13]. However, these approaches often struggle with sentiment analysis, aspect extraction, and semantic understanding in customer review data. Such scenarios are not atypical, and specific types of tools have been engineered for the purpose of data visualization [14]. Some researchers also mentioned the difficulty to tackle with the issues of syntax and semantic [15-17]. Forecasting and attention mechanism methods have been proposed to address these issues, but they lack the ability to generalize [18-20].

To address these challenges, we propose a novel approach named BERTFusionDNN, which leverages BERT (Bidirectional Encoder Representations from Transformers) [21] for text feature extraction and a Deep Neural Network (DNN) [22] for cross-referencing numerical features. BERT, a state-of-the-art language representation model, excels in capturing semantic meaning and contextual information from textual data, thus providing a robust foundation for our analysis. A multitude of research endeavors utilize this model as a foundational benchmark for comparative analysis [23-25] and finding it difficult to manipulate the big data in the recommendation system [26], and other domain specific areas such as quantum programs [27], cybercrime [28], and online threat [29]. Complementing BERT with a DNN allows us to effectively integrate numerical features, enhancing the comprehensiveness and accuracy of our model. In this paper, we present our methodology in detail, outlining the steps involved in preprocessing the dataset, extracting features using BERT, and integrating numerical features through a DNN architecture. We then evaluate the performance of our approach against existing methods on relevant metrics, demonstrating its effectiveness in uncovering insights from customer review data in the context of e-commerce. Through our work, we aim to contribute to the advancement of e-commerce recommendation systems, offering a robust and scalable solution to leverage the wealth of information contained within customer reviews.

2. RELATED WORK

In the realm of e-commerce recommendation systems, extensive research has been conducted to enhance user satisfaction and optimize business outcomes. Here, we present a synthesis of key contributions in this dynamic field. Sarwar et al. [1] conducted a comprehensive analysis of recommendation algorithms, highlighting the paramount importance of personalized recommendations in e-commerce settings. Schafer et al. [2] further expanded on this foundation by exploring various applications of recommendation systems in e-commerce. Addressing the challenge of diverse user preferences, Li et al. [3] proposed a hybrid collaborative filtering method tailored for multiple-interests and multiple-content recommendation. Huang et al. [4] subsequently contributed valuable insights through a comparative study of recommendation algorithms, shedding light on their respective strengths and limitations.

Emphasizing the significance of timely recommendations, [7] innovatively applied social network analysis to develop a novel C2C e-commerce recommender system. Acknowledging the importance of personalized recommendations, Zhang et al. [8] delved into tailored recommendation algorithms for e-commerce platforms. Gosh et al. [9] explored the scalability aspect by investigating the application of alternating least squares (ALS) on Apache Spark for large-scale e-commerce platforms.

Proposing a framework based on weighted expected utility, Ji et al. [11] further examined share recommendation strategies within the context of social e-commerce platforms. Innovative approaches such as semantic-enhanced models for sequential product recommendations by Nasir and Ezeife [12] and convolutional neural network-based frameworks for product recommendation by Latha and Rao [13] further contribute to the evolution of e-commerce recommendation systems, reflecting a continuous effort to meet evolving user demands and business objectives.

BERT, which stands for Bidirectional Encoder Representations from Transformers, is a deep learning language model designed to improve the efficiency of natural language processing tasks. This model surpasses various techniques in diverse domains, including cybercrime [30], transportation [31], resource allocation [32], and three-dimensional imagery [33]. Unlike recent language representation models, BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. This allows BERT to consider context by analyzing the relationships between words in a sentence bidirectionally. BERT is widely used in AI for language processing pre-training. For example, it can be used to discern context for better results in search queries. BERT outperforms many other architectures in a variety of token-level and sentence-level NLP tasks. BERT is a revolutionary model in the field of NLP and has been fine-tuned for use in a variety of fields, including biology, data science, underground economics [34] and medicine [35, 36].

3. ALGORITHM AND MODEL

3.1 BERTFusionDNN Model

As shown in Figure 1, the BERTFusionDNN model introduced in this study enhances e-commerce recommendation systems by leveraging textual and numerical features extracted from customer reviews. BERT, a cutting-edge language representation model, captures semantic meaning and contextual information from text, facilitating accurate sentiment and semantic analysis. Additionally, the model integrates a Deep Neural Network (DNN) for processing numerical features such as customer ratings and age. By combining both types of features, BERTFusionDNN comprehensively understands customer preferences and sentiments expressed in reviews, thereby improving the accuracy and relevance of product recommendations. This innovative approach underscores the fusion of natural language processing and deep learning techniques in e-commerce recommendation systems.

In our model, the BERT embedding for a contextual feature, denoted as, is obtained by passing the input text through a pre-trained BERT model. This process ensures that the embeddings accurately represent the semantic meaning and contextual nuances of the input text, enabling our model to effectively leverage BERT's capabilities for text feature extraction.

$$E_{BERT} = BERT(x) \tag{1}$$

In addition to BERT, the BERTFusionDNN model also integrates a Deep Neural Network (DNN) for the integration of numerical features, denoted as E_{DNN}. This DNN component is responsible for processing and analyzing numerical data associated with each review, such as customer ratings, age, and positive feedback count.

$$E_{DNN} = DNN(x) \tag{2}$$

To construct a comprehensive representation of our feature set, we concatenate the embeddings derived from both BERT and the DNN.

$$E_{concat} = Concatenate(E_{BERT}, E_{DNN}) \tag{3}$$

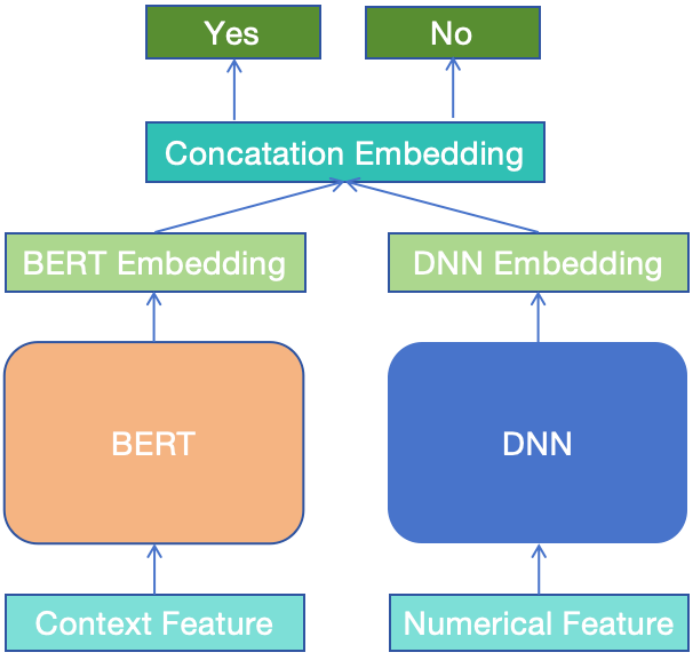

Figure 1: BERTFusionDNN Model

The concatenated embedding is then passed through a binary classification layer, which includes fully connected layers and a softmax activation function. This output layer generates probabilities for each class (Yes, No).

$$P(recommendation = c|E_{concat}) = Softmax\big(FC(E_{concat})\big) \tag{4}$$

Where c represents one of the classes (Yes, No).

3.2 Prospects of Large Language Models (LLM)

The integration of Large Language Models (LLMs), exemplified by GPT [37], GPT-2 [38], and GPT-3 [39], holds significant promise for advancing e-commerce recommendation systems [40]. With their extensive pre-trained knowledge and contextual understanding of language, LLMs play a pivotal role in enhancing natural language understanding and processing capabilities. By harnessing the power of LLMs, e-commerce recommendation systems can effectively analyze customer reviews to extract valuable insights and sentiments. This enables a deeper comprehension of the nuances and subtleties present in customer feedback, ultimately leading to improved accuracy in product recommendations.

4. EXPERIMENTS

4.1 Datasets

This Women Clothing E-Commerce dataset comprises 23,486 customer reviews, providing a rich source of information for understanding product experiences. With ten feature variables, including Clothing ID, Age, Title, Review Text, Rating, Recommended IND, Positive Feedback Count, Division Name, Department Name, and Class Name, the dataset offers a comprehensive view of customer sentiments and preferences. Ratings range from 1 to 5, indicating satisfaction levels, while the Recommended IND variable denotes product recommendations. Categorical variables such as Division Name, Department Name, and Class Name offer additional context about the reviewed products. This anonymized dataset ensures confidentiality while enabling in-depth analysis of customer feedback. It serves as a valuable resource for enhancing e-commerce recommendation systems by uncovering insights from customer reviews and informing business strategies. The dataset will be split into training, validation, and test sets in a ratio of 7:1:2, respectively, to ensure robust model training, validation, and evaluation processes.

4.2 Evaluation Metrics

Precision, Recall, and F1-score are the measures used in the named entity recognition. P (Positive) represents positive samples in all the samples. N (Negative) represents negative samples in all the samples. TP (True Positives) is the number of positive samples predicted as positive. FN (False Negatives) is the number of positive samples predicted as negative. FP (False Positives) is the number of negative samples predicted as positive. TN (True Negatives) is the number of negative samples predicted as negative. Precision is the proportion of true positive samples in all the samples that are predicted to be positive, which is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Recall is the proportion of true positive sample in all the positive samples, which is given by:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

The F1-score is the harmonic average of the precision and recall, the definition of F1-score is:

$$F1 = \frac{2 * Precison * Recall}{Precision + Recall} \tag{7}$$

4.3 Results

As shown in Table 1, here are the results obtained from different models evaluated in the study:

Table 1: Model Results

Model	*Precision*	*Recall*	*F1-Score*
RNN+DNN	97.90%	90.41%	94.00%
LSTM+DNN	89.87%	99.53%	94.45%
GRU+DNN	89.16%	99.00%	93.82%
BERTFusionDNN	96.46%	94.86%	95.65%

The results demonstrate the superior performance of the BERTFusionDNN model when compared to alternative models, including RNN+DNN [41], LSTM+DNN [42], and GRU+DNN [43], particularly in terms of F1-Score. Notably, the BERTFusionDNN model achieves exceptionally high F1-Score, highlighting its efficacy in accurately classifying data and significantly improving the overall performance of e-commerce recommendation systems.

5. CONCLUSION

In this study, we introduced BERTFusionDNN, a novel approach aimed at enhancing e-commerce recommendations by analyzing customer reviews. Leveraging BERT for text feature extraction and a Deep Neural Network for numerical feature integration, our model effectively extracts valuable insights from the Women Clothing E-Commerce dataset. Through rigorous evaluation and comparison with existing techniques, we demonstrated the superiority of our approach in addressing challenges related to sentiment analysis and semantic understanding in customer reviews. By partitioning the dataset into training, validation, and test sets, we ensured robust model training, validation, and evaluation processes.

Our work contributes significantly to the advancement of e-commerce recommendation systems by providing a scalable and accurate solution for leveraging customer feedback. Moving forward, future research directions may explore the application of BERTFusionDNN in other domains and datasets such as multi-core computer [44], geographic information system [45], blockchain [46], as well as the integration of additional features to further enhance recommendation accuracy and relevance. Ultimately, our study underscores the importance of leveraging advanced machine learning techniques to unlock valuable insights from customer reviews and improve e-commerce experiences in an increasingly competitive market landscape.

REFERENCES

[1] Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2000, October). Analysis of recommendation algorithms for e-commerce. In Proceedings of the 2nd ACM Conference on Electronic Commerce (pp. 158-167).
[2] Schafer, J. B., Konstan, J. A., & Riedl, J. (2001). E-commerce recommendation applications. Data mining and knowledge discovery, 5, 115-153.
[3] Li, Y., Lu, L., & Xuefeng, L. (2005). A hybrid collaborative filtering method for multiple-interests and multiple-content recommendation in E-Commerce. Expert systems with applications, 28(1), 67-77.
[4] Huang, Z., Zeng, D., & Chen, H. (2007). A comparative study of recommendation algorithms in e-commerce applications. IEEE Intelligent Systems, 22(5), 68-78.
[5] Zhang, L., Howard, S., Montpool, T., Moore, J., Mahajan, K., & Miranskyy, A. (2023). Automated data validation: An industrial experience report. Journal of Systems and Software, 197, 111573.
[6] Chen, J., Zhang, X., Wu, Y., Ghosh, S., Natarajan, P., Chang, S. F., & Allebach, J. (2022). One-stage object referring with gaze estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 5021-5030).
[7] Bahabadi, M. D., Golpayegani, A. H., & Esmaeili, L. (2014). A novel C2C e-commerce recommender system based on link prediction: applying social network analysis. arXiv preprint arXiv:1407.8365.
[8] Zhang, Z., Xu, G., & Zhang, P. (2016). Research on E-commerce platform-based personalized recommendation algorithm. Applied computational intelligence and soft computing, 2016.
[9] Gosh, S., Nahar, N., Wahab, M. A., Biswas, M., Hossain, M. S., & Andersson, K. (2020, December). Recommendation system for e-commerce using alternating least squares (ALS) on apache spark. In International Conference on Intelligent Computing & Optimization (pp. 880-893). Cham: Springer International Publishing.
[10] Chen, J., Lin, Q., & Allebach, J. P. (2020). Deep learning for printed mottle defect grading. Electronic Imaging, 2020(8), 184-1.
[11] Ji, H., Zhu, J., Wang, X., Shi, C., Wang, B., Tan, X., ... & He, S. (2021, May). Who you would like to share with? A study of share recommendation in social e-commerce. In Proceedings of the AAAI conference on artificial intelligence (Vol. 35, No. 1, pp. 232-239).
[12] Nasir, M., & Ezeife, C. I. (2023). Semantic enhanced Markov model for sequential E-commerce product recommendation. International Journal of Data Science and Analytics, 15(1), 67-91.
[13] Latha, Y. M., & Rao, B. S. (2023). Product recommendation using enhanced convolutional neural network for e-commerce platform. Cluster Computing, 1-15.
[14] Sun, Z., Dhital, A., Areejitkasem, N., Pradhan, N., & Banic, A. (2014, August). Effects on performance of analytical tools for visually demanding tasks through direct and indirect touch interaction in an immersive visualization. In 2014 International Conference on Virtual Reality and Visualization (pp. 186-193). IEEE.
[15] Su, J., Nair, S., & Popokh, L. (2023, February). EdgeGym: A Reinforcement Learning Environment for Constraint-Aware NFV Resource Allocation. In 2023 IEEE 2nd International Conference on AI in Cybersecurity (ICAIC) (pp. 1-7). IEEE.
[16] Jin, X., Manandhar, S., Kafle, K., Lin, Z., & Nadkarni, A. (2022, November). Understanding iot security from a market-scale perspective. In Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security (pp. 1615-1629).

[17] Xiong, J., Feng, M., Wang, X., Jiang, C., Zhang, N., & Zhao, Z. (2024). Decoding sentiments: Enhancing covid-19 tweet analysis through bert-rcnn fusion. Journal of Theory and Practice of Engineering Science, 4(01), 86-93.
[18] Liu, S., Wu, K., Jiang, C., Huang, B., & Ma, D. (2023). Financial time-series forecasting: Towards synergizing performance and interpretability within a hybrid machine learning approach. arXiv preprint arXiv:2401.00534.
[19] Wang, X., Xiao, T., Tan, J., Ouyang, D., & Shao, J. (2020). MRMRP: multi-source review-based model for rating prediction. In Database Systems for Advanced Applications: 25th International Conference, DASFAA 2020, Jeju, South Korea, September 24–27, 2020, Proceedings, Part II 25 (pp. 20-35). Springer International Publishing.
[20] Liu, T., Xu, C., Qiao, Y., Jiang, C., & Chen, W. (2024). News recommendation with attention mechanism. arXiv preprint arXiv:2402.07422.
[21] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.
[22] Cheng, H. T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., ... & Shah, H. (2016, September). Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems (pp. 7-10).
[23] Xiao, T., Zeng, L., Shi, X., Zhu, X., & Wu, G. (2022, September). Dual-Graph Learning Convolutional Networks for Interpretable Alzheimer's Disease Diagnosis. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 406-415). Cham: Springer Nature Switzerland.
[24] Popokh, L., Su, J., Nair, S., & Olinick, E. (2021, September). IllumiCore: Optimization Modeling and Implementation for Efficient VNF Placement. In 2021 International Conference on Software, Telecommunications and Computer Networks (SoftCOM) (pp. 1-7). IEEE.
[25] Liao, J., Kot, A., Guha, T., & Sanchez, V. (2020, October). Attention selective network for face synthesis and pose-invariant face recognition. In 2020 IEEE International Conference on Image Processing (ICIP) (pp. 748-752). IEEE.
[26] Sun, Z., Zhang, H., Liu, Z., Xu, C., & Wang, L. (2016, June). Migrating GIS big data computing from Hadoop to Spark: an exemplary study Using Twitter. In 2016 IEEE 9th International Conference on Cloud Computing (CLOUD) (pp. 351-358). IEEE.
[27] Zhang, L., Radnejad, M., & Miranskyy, A. (2023). Identifying Flakiness in Quantum Programs. arXiv preprint arXiv:2302.03256.
[28] Sun, Z. (2022). In the Light and in the Shadows: Human-Centered Analysis in Cybercrime. Arizona State University.
[29] Zhang, P., Sun, Z., Kyung, S., Behrens, H. W., Basque, Z. L., Cho, H., ... & Doupé, A. (2022, November). I'm SPARTACUS, No, I'm SPARTACUS: Proactively Protecting Users from Phishing by Intentionally Triggering Cloaking Behavior. In Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security (pp. 3165-3179).
[30] Sun, Z., Oest, A., Zhang, P., Rubio-Medrano, C., Bao, T., Wang, R., ... & Zhang, Y. (2021). Having Your Cake and Eating It: An Analysis of {Concession-Abuse-as-a-Service}. In 30th USENIX Security Symposium (USENIX Security 21) (pp. 4169-4186).
[31] Liu, T., Xu, C., Qiao, Y., Jiang, C., & Yu, J. (2024). Particle Filter SLAM for Vehicle Localization. arXiv preprint arXiv:2402.07429.
[32] Su, J., Nair, S., & Popokh, L. (2022, November). Optimal Resource Allocation in SDN/NFV-Enabled Networks via Deep Reinforcement Learning. In 2022 IEEE Ninth International Conference on Communications and Networking (ComNet) (pp. 1-7). IEEE.
[33] Hu, J., Wang, N., Yang, B., Chen, G., Guo, X., & Wang, B. (2023). S3DS: Self-supervised Learning of 3D Skeletons from Single View Images. Proceedings of the 31st ACM International Conference on Multimedia, 6948–6958.
[34] Sun, Z., Rubio-Medrano, C. E., Zhao, Z., Bao, T., Doupé, A., & Ahn, G. J. (2019, March). Understanding and predicting private interactions in underground forums. In Proceedings of the Ninth ACM Conference on Data and Application Security and Privacy (pp. 303-314).
[35] Liu, Y., Yang, H., & Wu, C. (2023). Unveiling Patterns: A Study on Semi-Supervised Classification of Strip Surface Defects. IEEE Access, 11, 119933-119946.
[36] Liao, J., Sanchez, V., & Guha, T. (2022, October). Self-Supervised Frontalization and Rotation Gan with Random Swap for Pose-Invariant Face Recognition. In 2022 IEEE International Conference on Image Processing (ICIP) (pp. 911-915). IEEE.
[37] Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.

[38] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI blog, 1(8), 9.
[39] Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. Advances in neural information processing systems, 33, 1877-1901.
[40] Su, J., Jiang, C., Jin, X., Qiao, Y., Xiao, T., Ma, H., ... & Lin, J. (2024). Large Language Models for Forecasting and Anomaly Detection: A Systematic Literature Review. arXiv preprint arXiv:2402.10350.
[41] Jordan, M. I. (1997). Serial order: A parallel distributed processing approach. In Advances in psychology (Vol. 121, pp. 471-495). North-Holland.
[42] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.
[43] Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.
[44] Zhang, H., Sun, Z., Liu, Z., Xu, C., & Wang, L. (2015, June). Dart: A geographic information system on hadoop. In 2015 IEEE 8th International Conference on Cloud Computing (pp. 90-97). IEEE.
[45] Zhang, L., & Down, D. G. (2019). APEM—Approximate Performance Evaluation for Multi-Core Computers. Journal of Circuits, Systems and Computers, 28(01), 1950004.
[46] Pourmajidi, W., Zhang, L., Steinbacher, J., Erwin, T., & Miranskyy, A. (2021). Immutable log storage as a service on private and public blockchains. IEEE Transactions on Services Computing.