https://doi.org/10.7840/kics.2024.49.9.1274

Enhancing Service Excellence: Blockchain-AI TF-IDF Recommendations

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ABSTRACT

Recommendation systems, ubiquitous across diverse sectors such as e-commerce, streaming services, and social media, play a pivotal role in tailoring user experiences. However, their application remains underexplored in sectors like dealerships and vehicles, where personalized suggestions can significantly enhance customer engagement and decision-making. Despite their widespread use, limited attention has been directed towards optimizing recommendation systems for the unique dynamics of the dealership and vehicle sectors, presenting an untapped potential for improvement and innovation. Utilizing software, artificial intelligence, and algorithms, our system addresses user complaints by seamlessly integrating AI algorithms and blockchain technology for enhanced security. Leveraging the Term Frequency-Inverse Document Frequency of Records (TF-IDF) vectorization for precision, the system demonstrates remarkable accuracy (99.8%) through cosine similarity (CS) and K-Nearest Neighbors evaluation. Propelled by advanced AI algorithms, it outperforms other blockchain-based recommendation systems, showcasing its potential in dealership and vehicle-related contexts.

Key Words : Algorithm, Artificial Intelligence, Blockchain, Cosine Similarity, Data, KNN, Recommendation system, Software, TD-IDF

Ⅰ. Introduction

In the expansive landscape of recommendation systems, widely employed in domains like energy preservation, e-commerce, healthcare, and social media, challenges posed by intricate datasets are met with innovative solutions, particularly within the realm of artificial intelligence. Techniques such as collaborative filtering, matrix factorization, and content-based systems have been devised to elevate recommendation precision. Collaborative filtering utilizes user behavior data to identify similarities, matrix factorization dissects complex data, and content-based systems align item attributes with user profiles, collectively contributing to more accurate recommendations[1].

Within this vast applicability, recommendation systems encounter challenges across domains, from energy preservation to social media. These applications necessitate the examination and extraction of substantial volumes of diverse user data, encompassing demographics, preferences, social interactions, and more. The datasets integral to crafting precise recommender systems often contain sensitive information. Unfortunately, the prevailing emphasis on achieving model accuracy has led to an oversight regarding security and the preservation of user privacy within recommender systems[2].

Efforts to address security and privacy concerns

※ This research was supported by Kumoh National Institute of Technology (2022-2023).
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논문번호 : 202403-045-0-SE, Received February 29, 2024; Revised April 11, 2024; Accepted May 16, 2024

within recommender systems have been made, with various risk reduction techniques employed. However, none have comprehensively succeeded in ensuring both cryptographic security and the robust protection of users' private information. This highlights a persistent gap in existing methodologies, where the imperative to enhance system accuracy has inadvertently led to an underestimation of the paramount importance of addressing security and privacy concerns[3].

In the ongoing evolution of recommender systems, striking an optimal balance between precision and user data protection remains a central challenge. This challenge is highlighted by the sensitive nature of the datasets involved, necessitating a nuanced approach to ensure that improvements in recommendation system accuracy align with robust user security and privacy measures. As the field progresses, there is an increasing recognition of the necessity to close the gap between achieving model accuracy and safeguarding user information, making the pursuit of a harmonious balance a key priority in the evolution of recommendation systems, driven by software, artificial intelligence, and algorithms[4].

Using blockchain technology appears to be a viable way to close the gap and improve security and privacy preservation in recommender systems. This tactical decision is supported by blockchain's inherent security and privacy features as well as its resilience, adaptability, fault tolerance, and trust qualities[5]. This endeavor was spurred by the goal of creating a recommendation system that is based on content and specifically designed to recommend servicing operations to dealership customers based on operation codes. Enhancing the security and openness of the recommendation system data through the incorporation of blockchain technology was the overall goal. The primary goal is:

- To address these complaints and establish connections with operation codes, which results in reducing the inconsistencies present within the dataset.
- To enhance security and transparency in data management, which is a crucial step that involves storing the information directly from the recommendation system on the blockchain, utilizing advanced artificial intelligence algorithms.
- To comprehensively evaluate both the recommendation system, driven by artificial intelligence algorithms and the smart contract within the blockchain, an in-depth analysis is undertaken to gauge their effectiveness and impact.

The rest of the paper is organized as Section Ⅲ for system design and experimental setup, Section Ⅳ for result discussion and system evaluation, and Section Ⅴ to conclude the study.

Ⅱ. Literature Review

Content-based recommender systems find diverse applications, with information retrieval being a prominent use case. The initial phase involves manual term assignment, employing a chosen method to align these terms with the data in the client's profile. Subsequently, a learning algorithm is selected to implement these strategies and deliver relevant results[6]. As illustrated in Fig 1, a content-based recommendation system typically analyzes user preferences by examining similar content to what the user has previously engaged with, aiming to provide tailored recommendations based on identified patterns and preferences.

In information retrieval and content-based filtering

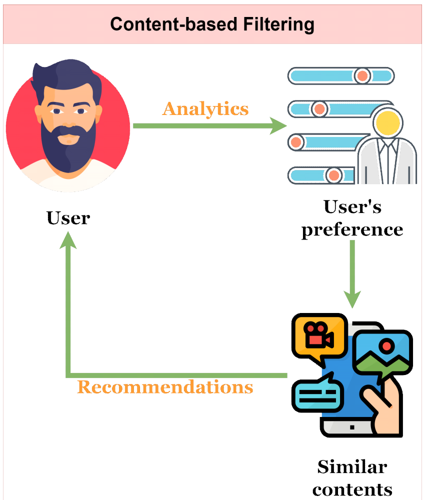


Fig. 1. Content-based Filtering Flow Diagram.

(CBF) frameworks like content-based recommenders, the principles of Term Frequency (TF) and Inverse Document Frequency (IDF) are pivotal in gauging the relative significance of documents, news stories, images, etc.

In natural language processing and information retrieval, TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical metric used to evaluate the importance of terms inside documents in relation to a corpus. The Inverse Document Frequency component assesses the phrase's rarity or commonality throughout the entire corpus, whereas the phrase Frequency component determines how frequently a term appears within a document. TF-IDF generates a weighted score for each term in a text by multiplying these two values together, which takes into account the phrase's originality within the corpus as well as its frequency in the document. This method makes it easier to find terms that are most representative of the content of a document by giving priority to phrases that are common inside a document but uncommon throughout the corpus[7].

Within recommender systems, CBF is a widely adopted technique, leaning on item descriptions and user preference profiles. This utilization of TF and IDF is integral to boosting the accuracy of recommendations and ensuring user satisfaction in the realm of software-driven, artificial intelligence-enhanced algorithms[8].

Diverse machine learning techniques have been employed in CBF, encompassing decision trees, K-means, neural networks, and naïve Bayes[9]. In the case of a naïve Bayes classifier, the fundamental idea involves assessing the desirability of an item by examining its attribute information. CBF is typically classified into three main categories: pure CBF, semantic analysis, and network analysis. Pure CBF is a recommendation system methodology that solely depends on an item's intrinsic qualities to produce user recommendations. This approach looks past user input and collaborative data, evaluating an item's inherent qualities and matching them to a user's preferences based on past interactions or expressly expressed preferences. In a pure CBF movie recommendation system, for example, recommendations would only be based on the content features (genres, stars, directors) of movies the user has already favored in the past, disregarding other users' preferences. Pure CBF is useful for utilizing item features, but it might not be the best at diversifying recommendations or helping people find new things[10].

Typically, there are two primary models for assessing user similarity: vector similarity (VS) and the Pearson correlation coefficient (PCC)[11]. While both PCC and VS are straightforward, they share a limitation-they consider only the items that are corated. This limitation can result in a scenario where two users appear highly similar solely because they have a few co-rated items and coincidentally rank these items similarly. To address this, [12]. proposed introducing a correlation significance weighting factor, aiming to diminish the influence of similarity weights derived from a small number of corated items.

Furthermore, in addition to the methods mentioned above, [13] also put forth similarity measures utilizing graph theory. Moreover, **Luo2008** proposed a collaborative filtering framework that incorporates both local user similarity and global user similarity. While these studies significantly enhance the accuracy of memory-based algorithms by refining similarity measures, limited attention has been given to the prediction score models, which we believe hold greater significance than similarity measures in the context of software-driven recommendation systems.

Semantic analysis in content-based recommendation systems involves the extraction and interpretation of the meaning and context within content items. Unlike traditional approaches that rely on explicit features, semantic analysis employs techniques such as Natural Language Processing for textual content or computer vision for images and videos to understand the underlying concepts and relationships [14]. By delving into the implicit meaning of content, semantic analysis aims to enhance the recommendation system's understanding, providing more nuanced and contextually relevant suggestions based on the user's preferences.

However, despite the advancements in CBF techniques, including those utilizing decision trees, K-means, neural networks, and naïve Bayes, none of the mentioned studies, have placed a primary focus on the security of the dataset or its safe storage. While these approaches excel in assessing intrinsic qualities and enhancing recommendation precision, the critical aspect of safeguarding user data and ensuring its secure storage has been relatively overlooked. This highlights a notable gap in the existing research, emphasizing the need for future studies to not only advance recommendation system methodologies but also prioritize the security and privacy aspects of the datasets they rely on. Addressing these concerns is crucial for building user trust and promoting the responsible and ethical deployment of recommendation systems in various domains.

Ⅲ. Proposed System

The process flow of the proposed system, which combines a recommendation system and blockchain in a novel way and is specifically intended to handle customer complaints in the context of car dealerships, is explained in Fig 2. Users attempt to connect to the blockchain network by using a smart contract during the system initiation process. The system's main goal is to provide users with operation services that are customized to their individual complaints while also protecting and authenticating any relevant information within the blockchain network. The main purpose of the operational flow is to maximize gas cost efficiency outside of the blockchain network. In particular, the software uses TF-IDF vectorization in the early phases of the recommendation system's processing of user data by artificial intelligence algorithms, which transform textual data into numerical representations. In line with the overriding objective of guaranteeing security and verification, the system is divided into two parts: a thorough dataset preparation phase and output data storage in the blockchain. These diligent procedures highlight the mutually beneficial connections between blockchain technology, artificial intelligence algorithms, and reliable engineered recommendations designed specifically for vehicle dealerships.

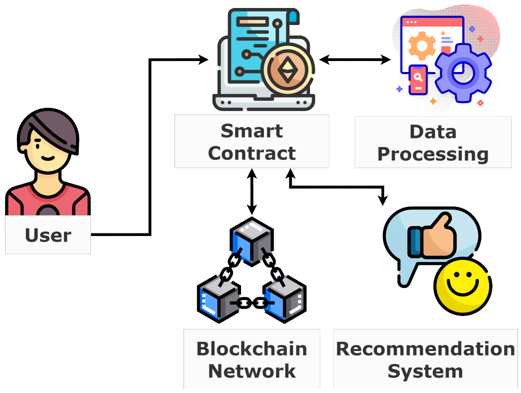


Fig. 2. Proposed System Diagram

3.1 Data Filtering and Processing

Derived from the "Meta Monkey" repository[15], the initial dataset-a broad compilation encompassing various aspects of vehicle maintenance, sales, and ownership with 156 rows and 200 columns-underwent meticulous preprocessing to tailor it for our recommendation system. Specifically, two pivotal columns, labor complaints, and operation codes, were extracted using Python's Pandas library, focusing on relevant data for system optimization. This extraction was followed by deduplication and data cleansing, employing Pandas functions such as **drop_duplicates()** to remove redundant entries, and **fillna()** or **dropna()** for handling missing values, ensuring a coherent dataset devoid of nulls. Regular expressions facilitated the standardization of operation codes and labor complaints, achieving uniformity across these critical variables. These steps refined the dataset to a structured format containing 90 unique labor complaints and 42 distinct operation codes, significantly enhancing the recommendation system's accuracy and efficiency by leveraging clean, relevant data for analysis.

Fig. 3 illustrates the dataset preparation process within the context of artificial intelligence framework-based recommendation systems, where the use of cosine similarity (CS) and CBF has been instrumental in predicting outcomes and delivering personalized service recommendations to users.

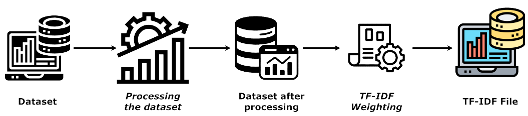


Fig. 3. Visualization of the Dataset Preparation Processing

Using the features offered by the NumPy and Pandas libraries, this approach was implemented in Python. This system stands out in particular for its remarkable capacity to handle conflicting data with ease. Its primary function is to identify vehicle-related complaints submitted by users and then link those complaints to certain operation codes. Because of this customized methodology, the software can offer correct recommendations, highlighting its major focus on precisely identifying the operation code that corresponds to the user's complaint.

To further enhance the adaptability and precision of our dealership recommendation system, we expanded our dataset with the inclusion of two pivotal columns: *Operation_Codes_num* and *Labor_complaint_num*. These columns are specifically designed to encapsulate the vectorized forms of operation codes and labor complaints, achieved through the application of Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. This vectorization process underpins the transformation of textual data into a structured numeric format, facilitating advanced analysis.

The essence of this transformation process is captured as follows:

Each dataset sample is transfigured into a numeric vector situated within a multidimensional vector space. Within this space, each dimension is aligned with a unique term from the dataset, and the corresponding value in each dimension (v_i) is indicative of the TF-IDF score for that term, computed as:

$$v_i = tf(t,d) \times idf(t,D) \qquad (1)$$

Here, $tf(t, d)$ signifies the term frequency of term t in document d, whereas $idf(t, D)$ represents the inverse document frequency of term t across the complete set of documents D.

These vectorized representations are instrumental in evaluating sample similarities, accomplished via the implementation of CS, which is defined by the equation:

$$CosineSimilarity(\mathbf{Lc}, \mathbf{Ro}) = \frac{\mathbf{Lc} \cdot \mathbf{Ro}}{\|\mathbf{Lc}\| \|\mathbf{Ro}\|} \qquad (2)$$

In this context, **Lc** and **Ro** denote the vectorized representations of labor complaints and operation codes within the TF-IDF multidimensional space, respectively.

3.2 Blockchain Implementation

The smart contract, developed with Solidity on the Ethereum network, is a fundamental component of our blockchain-based recommendation system, with its primary objective being to securely store essential data used by the system on the blockchain network, ensuring safety and security (as illustrated in Fig. 4).

The contract incorporates a user registration feature, allowing users to register and emit a corresponding "NewUserRegistered" event. Registered users are granted access to submit complaints through the "submitComplaint" function, exclusively accessible to registered users via the "onlyRegisteredUser" modifier. This contract efficiently tracks and securely stores user complaints on the blockchain, emitting a "NewUserComplaint" event with each submission. Users can retrieve specific complaint details using the "getComplaintDetails" function. Administered by an administrator, the contract employs the "onlyOwner" modifier to restrict specific functions to the owner. This blockchain-integrated system aims to offer a secure and transparent platform for managing automotive user complaints and service recommendations.

The proposed system securely stores recom-

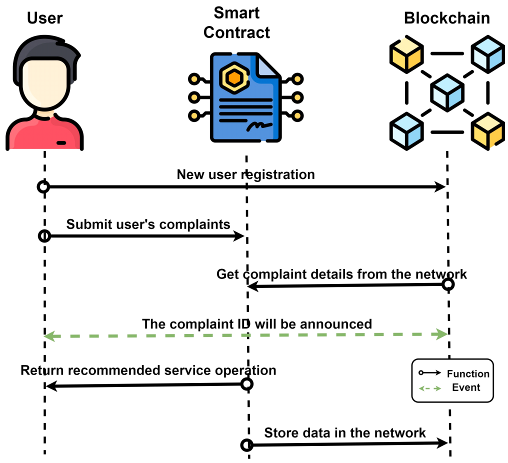


Fig. 4. Sequence Diagram Showing the Flow of the Proposed Solution

mendation system data in a decentralized manner through smart contracts on the Georli test network, powered by Ethereum and implemented using Remix IDE. The smart contracts were developed using the Solidity programming language. For testing purposes, Truffle was employed on an MSI Computer running the Windows 10 Operating system, equipped with an Intel(R) Core(TM) i5-8500 CPU @ 3.00GHz, 6 Core(s), NVIDIA GeForce GT 1030 GPU CUDA: 0 (Tesla K80, 11441.1875MB), and 36GB RAM. The validation of the proposed system is conducted based on gas cost metrics.

Ⅳ. Result Discussion

The insights unveiled in Fig. 6 provide a comprehensive visual representation of the outcomes stemming from the computation of CS between test samples and their corresponding K-nearest neighbors. This graph stands as a vivid summary, encapsulating the essence of our analytical endeavors.

The table distinctly reveals a high degree of similarity between test samples and their K-nearest neighbors (KNN), with values approaching 1.0. This

demonstrates the effectiveness and precision of our methodology across various KNN model configurations (KNN 0-4), which differ in the number of neighbors considered, distance metrics used, and neighbor weighting. Despite these variations, the CS values consistently remain high, affirming the robustness of our approach in identifying close matches. The consistently elevated similarity values indicate that our methodology is effective regardless of parameter adjustments, such as the number of neighbors, distance calculations, or neighbor weighting. This high similarity is a result of the meticulous application of the K-nearest neighbors algorithm, ensuring accurate and relevant recommendations.

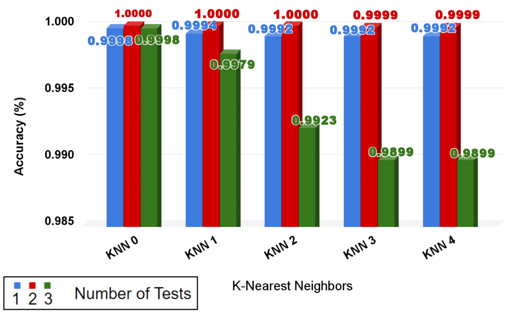
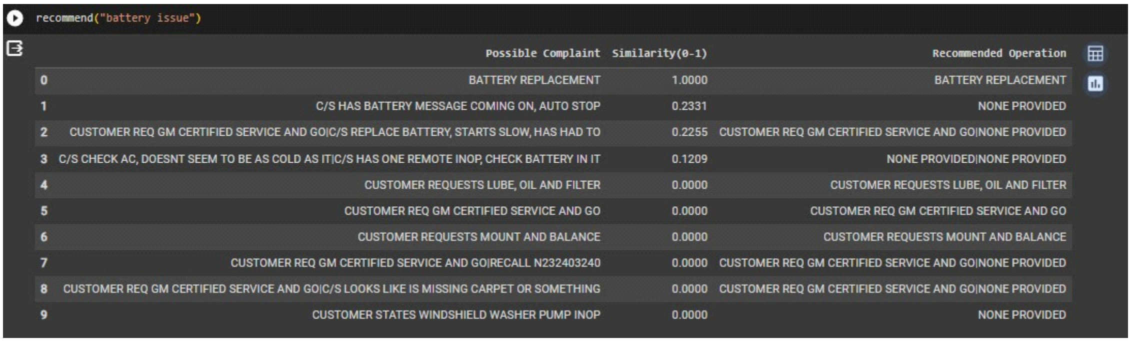


Fig. 6. Cosine Similarity Comparison of Test Samples with Their K-Nearest Neighbors

Moreover, Fig 5 serves as an illustrative example, portraying a scenario wherein a user inputs a keyword pertaining to their vehicle-related complaint. In response, the recommendation system adeptly generates a personalized suggestion, recommending a suitable operation to address the reported issue. This visual representation offers valuable insights into the user-centric functionality of our approach, highlighting its robustness and reliability. Utilizing CS values, the model recommends several operations to the user based on his input, which is going to be translated into possible complaints that might align with his input. This aspect is particularly crucial in the context of our research findings, as it significantly contributes to the overall success and efficacy of our work. The ability of the recommendation system to tailor sugges-



```
recommend("battery issue")
```

<table>
<tr><th></th><th>Possible Complaint</th><th>Similarity(0-1)</th><th>Recommended Operation</th></tr>
<tr><td>0</td><td>BATTERY REPLACEMENT</td><td>1.0000</td><td>BATTERY REPLACEMENT</td></tr>
<tr><td>1</td><td>C/S HAS BATTERY MESSAGE COMING ON, AUTO STOP</td><td>0.2331</td><td>NONE PROVIDED</td></tr>
<tr><td>2</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO|C/S REPLACE BATTERY, STARTS SLOW, HAS HAD TO</td><td>0.2255</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO|NONE PROVIDED</td></tr>
<tr><td>3</td><td>C/S CHECK AC, DOESNT SEEM TO BE AS COLD AS IT|C/S HAS ONE REMOTE INOP, CHECK BATTERY IN IT</td><td>0.1209</td><td>NONE PROVIDED|NONE PROVIDED</td></tr>
<tr><td>4</td><td>CUSTOMER REQUESTS LUBE, OIL AND FILTER</td><td>0.0000</td><td>CUSTOMER REQUESTS LUBE, OIL AND FILTER</td></tr>
<tr><td>5</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO</td><td>0.0000</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO</td></tr>
<tr><td>6</td><td>CUSTOMER REQUESTS MOUNT AND BALANCE</td><td>0.0000</td><td>CUSTOMER REQUESTS MOUNT AND BALANCE</td></tr>
<tr><td>7</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO|RECALL N232403240</td><td>0.0000</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO|NONE PROVIDED</td></tr>
<tr><td>8</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO|C/S LOOKS LIKE IS MISSING CARPET OR SOMETHING</td><td>0.0000</td><td>CUSTOMER REQ GM CERTIFIED SERVICE AND GO|NONE PROVIDED</td></tr>
<tr><td>9</td><td>CUSTOMER STATES WINDSHIELD WASHER PUMP INOP</td><td>0.0000</td><td>NONE PROVIDED</td></tr>
</table>

Fig. 5. Recommendation System in Action

tions based on user-provided keywords showcases the practical and user-friendly nature of our approach, affirming its applicability in addressing real-world concerns within the automotive domain.

Additionally, Table1 provides a concise overview of the gas costs associated with various functions within the smart contract. Gas costs, representing the computational effort required to execute each function on the Ethereum blockchain, are crucial metrics for evaluating efficiency and cost-effectiveness. Impressively, the gas costs for essential functions like 'registerUser' and 'submitComplaint' are relatively low at 51,655 and 164,023, respectively. Notably, functions such as 'complaintCount', 'getComplaint-Details', 'owner', 'userComplaints', and 'users' incur zero gas costs, indicating their minimal impact on the overall computational expenses. This emphasizes the cost-efficiency of the smart contract, making it an economical and practical solution for implementing blockchain-enabled recommendation systems.

Lastly, we conducted a comparative analysis of various blockchain-based recommendation system (RS) models, utilizing the available results at our disposal. Table 2 provides insights into the characteristics and performance outcomes of the frameworks considered in the comparison, encompassing publication year, implemented approach, computational time, and recommendation accuracy. Primarily, it's evident that all the approaches documented in the table have been proposed recently, aligning with the contemporary trend within the RS community to integrate blockchain into recommendation systems. As for computational time, there's notable variation among frameworks, influenced by factors such as the deployed blockchain platform, cryptographic algorithms, targeted applications, the nature of RS developed, and the user base. In terms of recommendation accuracy, all frameworks performed admirably, with results exceeding 80%. Notably, [17] demonstrated the highest accuracy at 97.5%, while Abbas et al. [18] achieved a slightly lower accuracy of 80.5%. Meanwhile, our proposed model, employing KNN and CS, achieved the highest accuracy among the compared works. This success could be attributed to the utilization of a smaller dataset and the application of TF-IDF vectorization, contributing to the model's optimal performance.

Table 1. Gas Cost Metrics for Blockchain-Enabled Recommendation System Functions

Function	Gas
registerUser	51,655
submitComplaint	164,023
complaintCount	0
getComplaintDetails	0
owner	0
userComplaints	0
users	0

Ⅴ. Conclusion

Recommendation systems have become increasingly vital in the automotive industry, where tailoring solutions to individual user needs is paramount. Our innovative software-driven approach, linking user complaints to specific operating codes, has resulted in a recommendation system that excels in accurately determining codes based on user input, significantly elevating its effectiveness. The strategic incorporation of blockchain technology has further fortified the system's security and transparency, marking a note-worthy convergence of artificial intelligence, algorithms, and systems. The successful fusion of TF-IDF trans-

Table 2. Comparative Performance Analysis of Current Blockchain-Based Recommendation System Frameworks

Work	Year	Approach	Accuracy(%)
[16]	2019	A RS utilizing smart contracts on a distributed ledger platform	90.6
[17]	2019	Blockchain-powered smart contracts for decentralized knowledge graphs in RS	83.3
[18]	2020	Blockchain and ML-driven RS for the pharmaceutical industry.	80.5
[19]	2021	Combine LSTM-based deep learning with blockchain for a trustworthy RS	97.5
Our Work	2024	TF-IDF vectorization combined with a blockchain-powered RS	99.8

formation, CS, and blockchain lays a robust foundation for the system's integrity and precision. Notably, our evaluation revealed satisfactory KNN results, underscoring the system's efficacy and remarkably low gas usage, enhancing its efficiency. Looking ahead, our future work involves integrating InterPlanetary File System (IPFS) into the system to lower the consumption of gas while storing the data in the blockchain network directly, as well as the development of a decentralized application (DApp) aimed at enabling direct customer interaction with the system. This initiative aims to foster a more seamless and user-friendly experience in the realm of automotive service recommendations, ensuring enhanced accessibility and usability for our users.

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