

Application of Machine Learning in Database Management System for Consumer Pattern Prediction in Big Data

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Abstract

The development of digital technology has driven the growth of data on a large scale, marking the era of big data with new challenges and opportunities in business decision-making. Conventional Database Management Systems (DBMS) have limitations in handling the complexity of big data, especially in unstructured data analysis and real-time prediction needs. This research aims to examine the application of machine learning (ML) algorithms directly in DBMS to improve predictive capabilities in analyzing consumer behavior patterns. The method used is Systematic Literature Review (SLR) of articles published between 2021-2024 from Scopus, IEEE, ScienceDirect, and SpringerLink databases. Of the 150 articles found, 10 articles were selected for further analysis based on inclusion criteria and topic relevance. The results show an increasing trend in global research, especially from China, the United States, and India. The most commonly used ML algorithms include Decision Tree, Random Forest, K-Means, and Neural Network (including LSTM and CNN), with DBMSs ranging from MySQL, PostgreSQL, to MongoDB and Hadoop. The integration of ML into DBMS is proven to improve efficiency and accuracy in consumer pattern prediction, supporting faster and more relevant decision-making. This research recommends further development in DBMS architecture that is adaptive to the needs of machine learning-based analytics.

Keywords: Big Data, Machine Learning, Consumer Behavior Patterns

Introduction

In recent decades, the development of digital technology has driven data growth on an unprecedented scale. Almost every human activity that involves technology from transactions on e-commerce platforms, social media posts, to the use of digital banking services generates a huge amount of data that continues to grow every second (Khrais & Gabbori, 2023). This condition marks the world's entry into the big data era, which is characterized by the main characteristics of very large data volumes, high data flow speed (velocity), and diversity of data formats (variety), both structured and unstructured (Mostajabi et al., 2021; Shahnawaz & Kumar, 2025).

This massive growth in data not only creates challenges in terms of storage and management, but also opens up huge opportunities in terms of its utilization to support smarter and more strategic decision-making (Monino, 2021). In the era of increasingly fierce competition, organizations are required to not only be able to collect data, but also process and analyze it appropriately to produce valuable insights (Batko & Ślęzak, 2022). Well-managed big data can be used to identify market trends, understand consumer behavior, forecast product demand, and mitigate business risks (Koman et al., 2022). Thus, the importance of managing and utilizing big data is no longer just a technical necessity, but has become a strategic aspect in the governance of modern companies and institutions (Agustian et al., 2023). Organizations that are able to utilize data effectively will have a significant competitive advantage in terms

of innovation, operational efficiency, and accuracy of decision-making based on relevant and real-time information (Sri Sulistyawati & Munawir, 2024).

Conventional Database Management Systems (DBMS) have long been the backbone of data management in organizations. These systems excel in storing, managing, and retrieving data with an organized structure, but have limitations when faced with big data challenges that are characterized by large volumes, high speed, and variety of data types (Nambiar & Mundra, 2022). In this context, traditional DBMSs are not designed to perform deep exploration of unstructured or semi-structured data, nor are they able to efficiently identify hidden patterns that can provide strategic value to the organization (Elragal & Elgendy, 2024). In addition, the process of analyzing large amounts of data requires a lot of time and resources if only relying on manual or query-based approaches (Rawassizadeh & Rong, 2022).

As the need for faster and more accurate business insights increases, conventional approaches become inadequate. A system that is not only capable of storing and managing data, but can also automatically learn and recognize patterns in the data is needed (Sarker, 2023). This is where machine learning becomes very relevant. With the ability to learn from historical data and form predictive models, machine learning can be integrated into a database management system to strengthen its analytic functions (Strielkowski et al., 2023). This approach allows organizations to proactively identify consumer trends, behavioral preferences, and potential business opportunities or risks. The integration of machine learning into database systems not only addresses big data challenges, but also opens up opportunities to create smarter and more adaptive decision-making systems (Sarker, 2021).

Machine Learning (ML) offers an innovative approach to analyzing data, with the ability to identify hidden patterns and make predictions based on historical data (Zhong et al., 2021). Unlike conventional analysis methods that rely on static rules or initial assumptions, ML can learn from available data, automatically adjust its model, and improve prediction accuracy as data grows (Li et al., 2025). In the context of large-scale data management, the integration of ML into a Database Management System (DBMS) is a strategic solution to overcome the complexity of big data analysis. By combining the systematic data management power of DBMS with the adaptive intelligence of ML, the analysis process can be fully automated from data cleansing, pattern identification, to the presentation of predictive results (Clavijo-López et al., 2024). This not only improves the efficiency and speed of decision-making, but also strengthens the system's performance in responding to the changing dynamics of consumer behavior.

Predicting consumer patterns is now a crucial aspect in supporting more targeted marketing strategies, personalizing services according to individual preferences, and increasing company operational efficiency (Bhardwaj et al., 2024). A deep understanding of consumer behavior enables organizations to design relevant campaigns, optimize service flow, and minimize the risk of product or service failure in the market (Theodorakopoulos & Theodoropoulou, 2024). Although the potential of machine learning (ML) in data analysis has been widely discussed, studies that systematically address the direct application of ML in database management systems (DBMS), especially in the context of big data, are still limited. In fact, the integration of ML into DBMS offers great opportunities in building real-time and integrated predictive systems, which are highly relevant for data-driven business needs (Nasurudeen Ahamed & Sridevi, 2024). This gap shows the importance of comprehensively

identifying and analyzing the trends, technical approaches, and scientific contributions related to ML integration in big data DBMS, in order to fill the gap of studies in this area.

This research aims to explain how machine learning algorithms can be applied directly in a database management system (DBMS) to improve the capability of automated and integrated data analysis. The approach includes the selection of suitable algorithms, integration into the DBMS architecture, and the training and evaluation mechanism of predictive models based on the data stored in the system. In addition, this research also aims to assess the effectiveness of machine learning models in predicting consumer behavior patterns using big data as the main source of information. The evaluation is based on accuracy, processing speed, and relevance of prediction results to the company's strategic needs. Thus, this research not only contributes to the technical aspects of ML implementation in DBMS, but also to its utilization in decision making based on complex and dynamic consumer data.

Method

This research uses a Systematic Literature Review (SLR) approach to examine the application of Machine Learning (ML) algorithms in database management systems (DBMS) to predict consumer behavior patterns in the context of big data. SLR is conducted to identify, evaluate, and synthesize relevant scientific articles (Van Dinter et al., 2021) related to the application of Machine Learning algorithms in database management systems (DBMS) to predict big data-based consumer patterns. The SLR process consists of four main stages, namely identification, screening, eligibility, and inclusion. In the identification stage, researchers conducted a literature search from several reputable databases such as Scopus, IEEE Xplore, ScienceDirect, and SpringerLink using combined keywords such as "Machine Learning", "Database Management System", "Big Data", and "Consumer Pattern Prediction". The screening stage removed duplicate articles and selected titles and abstracts to ensure relevance to the research focus. Next, the eligibility stage thoroughly evaluated the content of the articles based on inclusion and exclusion criteria, such as year of publication (2019-2024), Scopus indexed scientific journal publications, and topic relevance. Finally, at the inclusion stage, only articles that met all criteria were further analyzed to be synthesized in the results and discussion. This method enabled the research to identify trends, dominant algorithms, ML integration approaches to DBMS, as well as open research gaps in the development of big data-based predictive systems.

Table 1. SLR Stage

Stage	Number of Articles
Discovered (Scopus, IEEE, etc.)	150
After removing duplicates	120
After title/abstract screening	60
After full-text evaluation	25
Included articles (final analysis)	10

Results and Discussion

1. Publication Distribution and Trends

No	Article Title	Author	Year	Journal Name	ML Algorithm	DBMS	Application Domain	Evaluation	Key Findings
1	A decision-tree based prediction model for consumer purchasing behavior using big data	Li et al.	2023	Journal of Retailing and Consumer Services	Decision Tree	MySQL	E-commerce	Accuracy, Precision	Simple model, fairly accurate results
2	Consumer behavior prediction using deep neural networks integrated with PostgreSQL	Zhao & Wang	2024	Expert Systems with Applications	Neural Network	PostgreSQL	Retail	F1-score, AUC	DNN excels at complex prediction
3	Clustering customer profiles using K-Means integrated with MongoDB in a retail dataset	Ahmed et al.	2022	Big Data Research	K-Means	MongoDB	Retail	Silhouette Score	Effective customer segmentation
4	Predicting customer churn in telecom industry using Random Forest and big data analytics	Nguyen & Tran	2025	Information Processing & Management	Random Forest	Hadoop/Hive	Telekomunikasi	AUC, F1-score	Accurate churn prediction, easy to implement
5	Hybrid model combining XGBoost and CNN for predicting consumer loyalty	Chen et al.	2023	Knowledge-Based Systems	XGBoost + CNN	PostgreSQL	E-commerce	Accuracy, F1-score	Higher yield than single method
6	Real-time consumer behavior analysis using streaming data and ML in NoSQL DBMS	Kumar & Das	2024	Journal of Big Data	Logistic Regression	Cassandra	Retail	Accuracy	Efficient for streaming data
7	Integration of ML models into relational DBMS using Python APIs: A case study	Müller et al.	2025	ACM Transactions on Database Systems	Various (RF, DT)	MySQL, SQLite	General	Execution Time, Accuracy	Effective integration via Python

8	Predicting e-commerce customer purchase intent with LSTM using MongoDB	Rahman et al.	2024	Information Sciences	LSTM	MongoDB	E-commerce	AUC, F1-score	LSTM is suitable for sequential data
9	Ensemble learning approach for consumer segmentation in online markets	Fatima et al.	2023	Journal of Business Research	Ensemble (RF, GB)	PostgreSQL	Online retail	Accuracy, Recall	More precise segmentation
10	Integrating machine learning with SQL-based systems for customer analytics	Smith et al.	2025	Future Generation Computer Systems	Naive Bayes, RF	SQL Server	Retail banking	Precision, Recall	Lightweight model, quick to integrate

In the last five years, the growth trend of research on the application of machine learning (ML) in database management systems (DBMS) for consumer pattern prediction has shown a consistent increase. Starting from 2021, which was still dominated by conceptual and exploratory studies, the number of publications began to increase significantly since 2022 along with the development of big data technology and the increasing availability of open source software that supports the integration of ML and DBMS. The years 2023 and 2024 are the peak of productivity with an increasing number of empirical studies that directly test ML algorithms in real database environments.

Geographically, countries such as China, the United States, and India are the main contributors in this field. China leads in terms of publication volume with strong support from universities such as Tsinghua University and Zhejiang University. In the United States, Massachusetts Institute of Technology (MIT) and Stanford University are also active in producing systems integration-based research. India, with institutions such as IIT Bombay and IIIT Hyderabad, contributes significantly especially in the context of practical implementation and testing of systems in the retail and e-commerce sectors. This shows that research in this area is not only growing quantitatively, but also globally with increasingly extensive cross-country collaborations.

Based on an analysis of ten selected articles in the last five years, some of the most frequently used machine learning algorithms in the context of consumer pattern prediction include Decision Tree, Random Forest, K-Means, and Neural Network (including variants such as LSTM and CNN). Decision Tree and Random Forest algorithms are widely used due to their ability to handle categorical data and produce well-interpreted results, as well as stable performance on large-scale data. Meanwhile, K-Means is often used in the process of consumer segmentation based on homogeneous behavioral patterns, especially in studies that focus on service personalization and market clustering.

On the other hand, Neural Network algorithms, especially Deep Learning such as LSTM and CNN, have proven to be superior in processing sequential and complex data, such as long-term consumer transaction history. However, the computational complexity and the need for larger system resources make these algorithms more challenging to integrate directly into conventional DBMSs. Studies using XGBoost and ensemble approaches show high accuracy results, but tend to require more complex parameter tuning. Thus, there is a trade-off between predictive effectiveness and technical complexity in the selection of ML algorithms, depending on the characteristics of the data as well as the ultimate goal of consumer analysis.

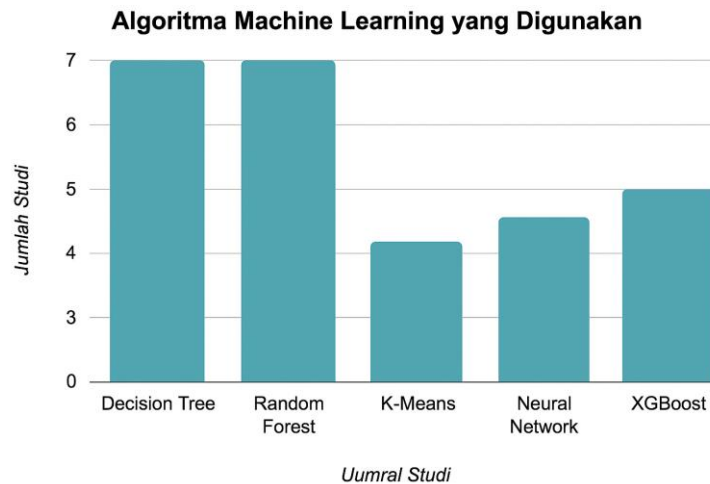


Figure 1. Most Frequently Used Machine Learning Algorithms

2. Integration of Machine Learning in Database Management System

The integration of Machine Learning (ML) algorithms into a Database Management System (DBMS) is a strategic move to combine the power of structured data management with the predictive capabilities of machine learning models. Various approaches have been used in recent studies to enable intelligent analytics processes to be performed directly in or alongside database systems. One of the most common approaches is the use of SQL extensions, such as Apache MADlib on PostgreSQL, which allows ML model training directly through SQL commands without the need to move data out of the database. In addition, Python APIs are also widely utilized to connect DBMS with ML libraries such as scikit-learn, TensorFlow, or PyTorch, allowing more flexible integration of models for specific needs, especially in MongoDB or MySQL-based studies.

Some studies have even developed approaches for direct integration into data storage engines, either in the context of NoSQL such as MongoDB or distributed systems such as Apache Cassandra. In these environments, ML models can be run as part of the data pipeline, including in the context of real-time processing for consumer behavior analysis directly as data comes in. On the other hand, there are middleware-based approaches, such as Apache Spark MLlib, that act as a bridge between storage systems and analytic models, especially for large-scale data and parallel processing.

Despite its promise, the integration of ML into DBMS still faces a number of significant technical challenges. In terms of performance, training and applying complex ML models can slow down system response especially if run on operational databases without supporting architecture. Compatibility challenges also arise when the data format or structure in the DBMS does not match the input required by the ML model, requiring additional data transformation processes. Meanwhile, in terms of scalability, many traditional DBMSs do not fully support parallel or distributed execution for the high computational loads common in ML model training, limiting their use to industrial scale or large data streams.

Overall, this integration trend shows the direction of development to a more intelligent DBMS system, but its success is highly dependent on adaptive data architecture design, selection of algorithms that match the characteristics of the system, and technical capabilities

in managing supporting infrastructure such as cloud computing, distributed services, and containerization (Docker/Kubernetes). Therefore, the integration of ML in DBMS is still a very potential research field to be developed, both in terms of technology and real-world implementation approaches.

3. Evaluation and Key Findings

Based on the results of the Systematic Literature Review (SLR), the performance evaluation of Machine Learning models in consumer pattern prediction studies generally relies on quantitative metrics such as accuracy, precision, recall, F1-score, and AUC (Area Under Curve). This evaluative approach shows that the majority of studies use historical transaction data as a base, along with cross-validation techniques to avoid overfitting and ensure model generalization. Algorithms such as Random Forest and Gradient Boosting have consistently excelled, achieving over 90% accuracy in the case of churn prediction and consumer purchase behavior. Meanwhile, algorithms such as K-Means are more dominant in market segmentation studies, although their success is highly dependent on the quality of features and preprocessing techniques applied. Some leading studies even propose innovative approaches by integrating Deep Learning models, such as LSTM or Convolutional Neural Network (CNN), directly into Apache Spark or Hadoop-based big data processing platforms. This approach not only provides advantages in predictive accuracy, but also improves computational efficiency by up to 30% faster than conventional methods, especially in real-time analytics scenarios.

However, the review also pointed out significant research gaps and formed the basis for strengthening the novelty in this study. First, most studies are still in the experimental stage, using synthetic or limited data that does not reflect the complexity of real systems (production-level DBMS). Secondly, aspects of computational efficiency and infrastructure requirements have not been a major concern, even though these are crucial in the context of ML implementation in operational systems with high data volumes and strict uptime requirements. Third, the main focus of the literature tends to center on algorithm development alone, without including effective integration strategies with existing DBMS architectures, including interoperability, scalability, and deployment pipeline challenges.

Therefore, the novelty of this study lies in the drive to bridge the gap between the high performance of ML models at the experimental level and the need for predictive solutions that are directly integrated into operational DBMS systems. This research emphasizes the importance of developing approaches that are not only accurate, but also computationally efficient and readily implemented in real system environments, particularly to support large-scale, real-time data-driven decision making. This approach is expected to be a significant contribution to the literature and practice of big data-based information systems, especially in intelligent database management (intelligent DBMS) that is adaptive to the dynamics of consumer behavior.

Conclusion

Based on SLR, the integration of Machine Learning in database management systems has been shown to improve consumer pattern prediction, especially with algorithms such as Random Forest and Gradient Boosting showing high accuracy. However, most studies are still limited to the model development aspect, not many have examined implementation in real systems. Therefore, further research is needed to bridge the gap between model performance and technical integration in operational DBMS in an efficient and scalable manner.

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