Economic Sciences
https://economic-sciences.com
ES (2024) 20(2), 455-464 | ISSN:1505-4683

Machine Learning for Business Analytics: Enhancing Forecasting Accuracy

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Abstract

Business intelligence (BI) has shifted significantly as a result of the rapid advancement of digital technology, opening up new opportunities for strategic insights and data-driven decision-making. This study explores the relationship between these two fields, concentrating on how information management systems and artificial intelligence (AI) may work together to improve financial predictions' precision, dependability, and scalability. A key component of successful predictive modelling is data warehousing, which unifies enormous volumes of historical and current financial data from several sources into a single repository. With the use of this aggregated data, AI-powered prediction models—which include deep learning architectures, machine learning algorithms, and other sophisticated statistical methods—can provide accurate and useful forecasts and nuanced insights. With a thorough assessment of 152 publications from 1969 to 2023, this study methodically analyses and compares cutting-edge supply chain (SC) forecast techniques and technologies throughout a certain time period. In order to forecast the effects on the human workforce, inventory, and SC as a whole, a novel framework that incorporates Big Data Analytics into SC Management (problem identity, data sources, and exploratory analysis of information, machine-learning model training, hyperparameter adjustment, performance evaluation, and optimisation) has been proposed. First, the need of gathering data in accordance with the SC strategy and the methods for doing so have been covered.

Keywords: *- Artificial Intelligence (AI), Workforce, Inventory, Deep Learning Architectures, Big Data Analytics, Data Analysis, Supply Chain (SC), Optimization, Accuracy, Reliability, Financial Forecasts.*

I. INTRODUCTION

In current age of rapid technology development, business intelligence is essential to the company's decision-making process on its future initiatives. By extending the support of based on reality systems, business intelligence (BI) is defined as the ideas, methods, and techniques that positively influence business decisions [1]. Raw and disjointed data are transformed into meaningful, fully useful data by the architecture and technology. This insightful information facilitates the development of new plans, superior operational performance, tactical insights, or sound decision-making for the company's future [1, 2].

organisation Intelligence (BI) is poised to become a key component of almost every kind of organisation in the near future. For analytics and sound decision-making, business intelligence (BI) is essential for all types of enterprises across all industries [1, 2]. In addition to increasing business organisations' efficacy and efficiency, it also lowers expenses and losses. In addition to increasing revenue, it aids in consumer retention and attraction [2, 3] and offers several other noteworthy advantages. Business intelligence (BI) forecasts the market's future tendencies. One technique and method for implementing a business intelligence (BI) idea utilising demand forecasting for a specific firm is machine learning.

Prior to the broad use of heuristic and fundamental statistical techniques, forecasting sales was often a crude procedure ingrained in managers' and owners' common sense and intuition [1, 3]. Without any official methodological backing, decisions were mostly relied on subjective observations and crude extrapolations of historical sales success [3, 4]. This unofficial strategy was mostly subjective and unstructured, mainly depending on personal judgement and local market expertise.

These antiquated techniques were insufficient as companies grew and marketplaces became more dynamic. As a result, heuristic techniques were created and widely used, offering a more methodical but still mostly intuitive approach to predicting. Heuristics, which drew on past data patterns and accumulated business experience, were a little more methodical and contained rules of thumb [3, 5]. The first steps towards improved scientific techniques in forecasting were taken by the emergence of fundamental statistical techniques that used basic mathematical models to estimate future sales based on previous data [3, 5].

But the dynamics of the profession have changed significantly in the current period due to a paradigm shift towards complex computational and data-driven techniques. As markets got more complicated and data became more accessible, the shortcomings of heuristic and basic statistical approaches became evident. The requirement for more precise forecasting, which is essential for effective inventory control, financial preparation [5, 6], and strategic decision making, was the driving force for this change. Forecasting errors may result in significant monetary losses, lost opportunities, and inefficient operations. In order to improve prediction accuracy, companies are therefore increasingly using cutting-edge approaches, such as contemporary statistical models and techniques for machine learning [6].

This change is being largely facilitated by the confluence of Big Data, Artificial Intelligence (AI), and the Internet of Things (IoT), which allows companies to use data to improve operational effectiveness and gain a competitive edge. The analysis of big data is crucial to corporate intelligence because it allows for the study of massive datasets to reveal hidden trends, correlations, and patterns [7, 8]. By offering complex algorithms for applications like machine learning, natural language processing, and predictive analytics, Artificial Intelligence (AI) technologies greatly enhance the capacity to analyse data [8, 9]. These AI-powered techniques help to automate intricate data analysis processes and provide insights that may guide important business choices. Real-time data from linked devices and sensors is provided by IoT integration, which enhances the business intelligence environments [8, 9].

The constant quest for efficiency and flexibility in the ever-changing field of the Supply Chain Management (SCM) [9, 10] has fuelled a steady advancement in forecasting techniques and technology. In order to identify and assess the state-of-the-art in Supply Chain (SC) projections, this paper does a methodical investigation. In the end, it suggests a unique framework that incorporates the power of Big Data Analytics (BDA) into SCM [9, 10]. The need for advanced forecasting techniques has been highlighted by the growing intricacy and interdependence of global SCs. The way we view and improve SC forecasting is changing as a result of the re-evaluation of traditional methods in the aftermath of technology breakthroughs.

BDA integration is a game-changer, offering improved predictive power and a comprehensive framework that includes problem identification, data sourcing, exploratory analysis of information, training Machine Learning (ML) models, hyperparameter tuning, performance assessment, and optimisation [9, 11]. Over the last several years, the SC has developed enough to find new approaches and strategies for resolving SCM issues. Based on its administration, communication, and control, the SC may create its configuration.

One such shift is brought about by the emergence of big data (BD) [12]. Through a variety of tools, resources, and applications, BD may be used to enhance decision-making reprocesses and change business models, much like other domains. As a result, BD and SC usages are linked to support one another. Even if SCM principles are already well-rounded, they may still be enhanced. Recent studies on increasing efficiency via teamwork, RFID use, and intelligent products are a few instances of innovations that have improved SCM procedures. Newer technology are also making it possible to find creative solutions to SC issues. One example of a disruptive invention is BDA [12]. Even though BD has already been around for a while, methods for understanding it are relatively recent, and these systems haven't been fully incorporated into other fields of study. One of the main issues that need attention is the lack of data utilisation and pertinent procedures in SC [14].

The research examines a range of AI methods, including unsupervised learning strategies like clustering and reducing dimensionality as well as supervised learning strategies like regression classification and analysis algorithms [12, 14].

These techniques are assessed according to how well they can handle and decipher the large datasets that are usually kept in data warehouses [14]. Particular focus is placed on how these large datasets may be used to train and verify AI models in order to increase predicting accuracy and reduce mistakes [13, 14]. The study also looks at how scalable AI-enhanced forecasting models are, highlighting their ability to manage rising data quantities and rising processing needs. The difficulties and solutions of the integration process are examined.

Data warehousing makes it easier to aggregate and standardise financial data, including market data, performance measurements, and historical transactions, in the context of financial information management [14, 15]. The accuracy and dependability of financial projections are improved by this centralised repository's capacity to conduct thorough analysis across several dimensions, such as time, location, and financial indicators [14, 16]. Data warehousing facilitates the integration of many data sources and makes it possible to apply sophisticated analytical methods to extensive financial datasets by offering just one single point of truth [18].

By providing a thorough examination of technology developments in a variety of fields and pointing out important research gaps, this study significantly advances the subject of sales forecasting. Our methodical approach not only documents the progression of forecasting approaches from conventional statistical methods to contemporary machine learning and deep learning applications, but it also suggests future research avenues to address identified shortcomings. This study offers practical insights for scholars and practitioners alike, strengthening their comprehension of the topic by bridging the gap between academic subject's research and practical implementation [18]. The thorough analysis and suggestions made here are meant to stimulate further innovation and highlight the increasing importance of incorporating real-time data and sophisticated analytics into forecasting for sales procedures [18].

RELATED WORK

1.1 Planning the review

The BDA-SCM cycle structure was first created in this article to include pre-process, control process, & post-process stages. The most relevant literary pieces were chosen to depict each step. Pre-process guidelines for forecasting purposes include an organised approach to forecasting and BDA techniques that aim to enable thorough demand forecasting taking into account cutting-edge technology and pertinent research [17, 18].

1.2 Search strategy

The goal of this SLR was to provide a thorough and impartial assessment of the body of research on BDA-SCM up to 2023 [18, 19], which include an examination and analysis of several SC forecasting issues as well as BDA improvements, tactics, and approaches. To reduce bias and guarantee the inclusion of a wide variety of relevant sources and information, major academic databases such as Google Scholar or Science Direct among others were searched [19].

1.3 Selection strategy

To make sure the chosen publications were both theoretically and practically relevant to the advancements in BDA-SCM research, the significance of each published was evaluated. Articles were deemed of greater importance if the search phrases were included in the abstract, title, keywords, and body of the text [19, 20].

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ES (2024) 20(2), 455-464 | ISSN:1505-4683

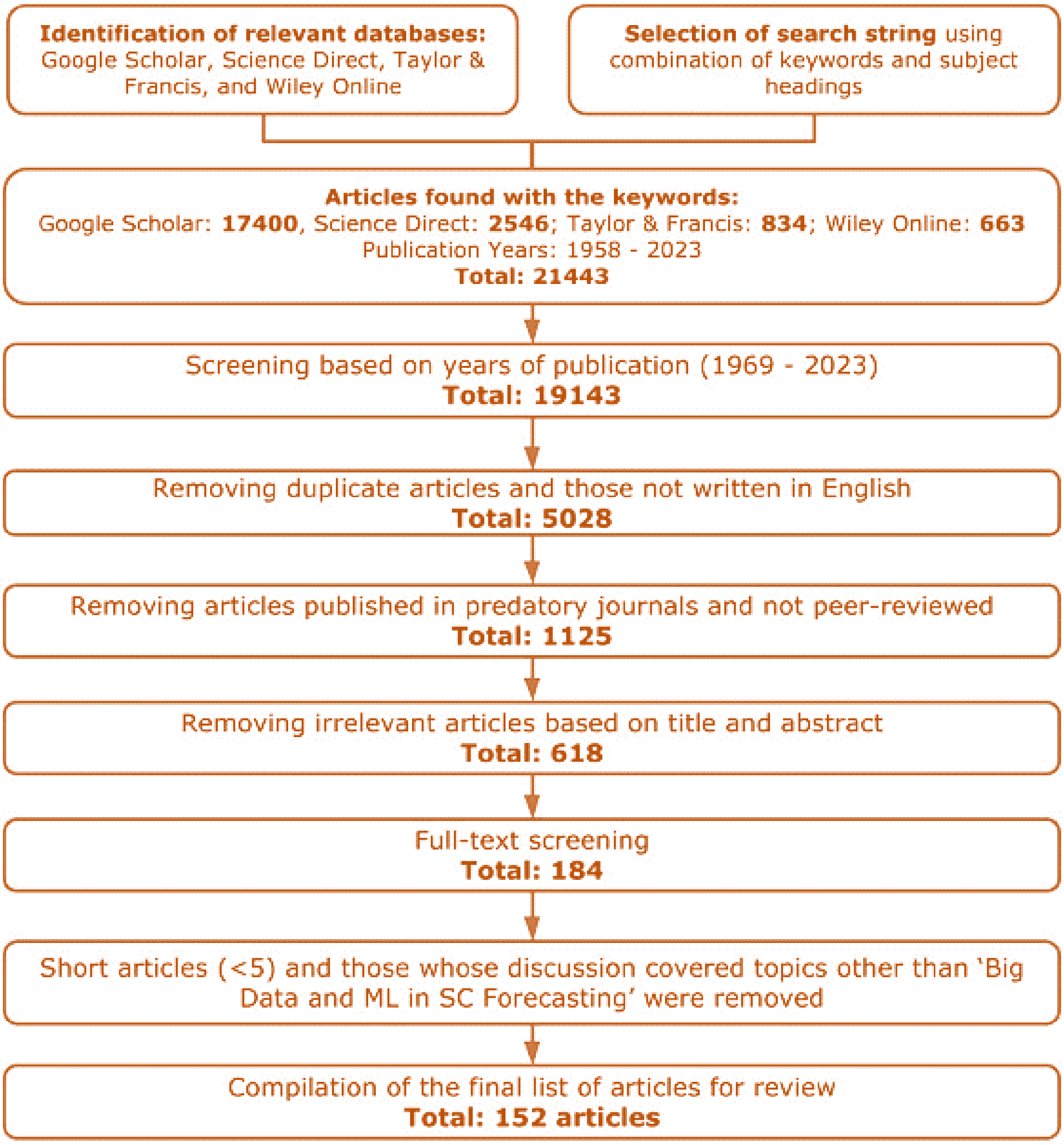

Fig. 1 The article selection procedure involving SLR on BDA-SCM forecast is shown in this PRISMA flow diagram. [20]

II. BDA-SCM FRAMEWORK

The cyclic link created by the suggested BDA-SCM system, which is shown in both Figures 2 and 3, makes it easier to continuously enhance SC forecasting. This cyclical process creates a dynamic connection that repeatedly optimises SC operations by smoothly integrating three crucial stages: pre-process, control-process, and post-process [20, 23]. Figure 2 primarily shows how data is used and flows cyclically in SC. Only the SC sections where BDA could be implicated are included [29, 30].

By discussing the techniques for appropriately cleaning, examining, and analysing data, Figure 2 enhances Figure 3 [20, 23]. In order for ML algorithms to train effectively, it uses FE approaches to choose just the most relevant & distinctive characteristics.

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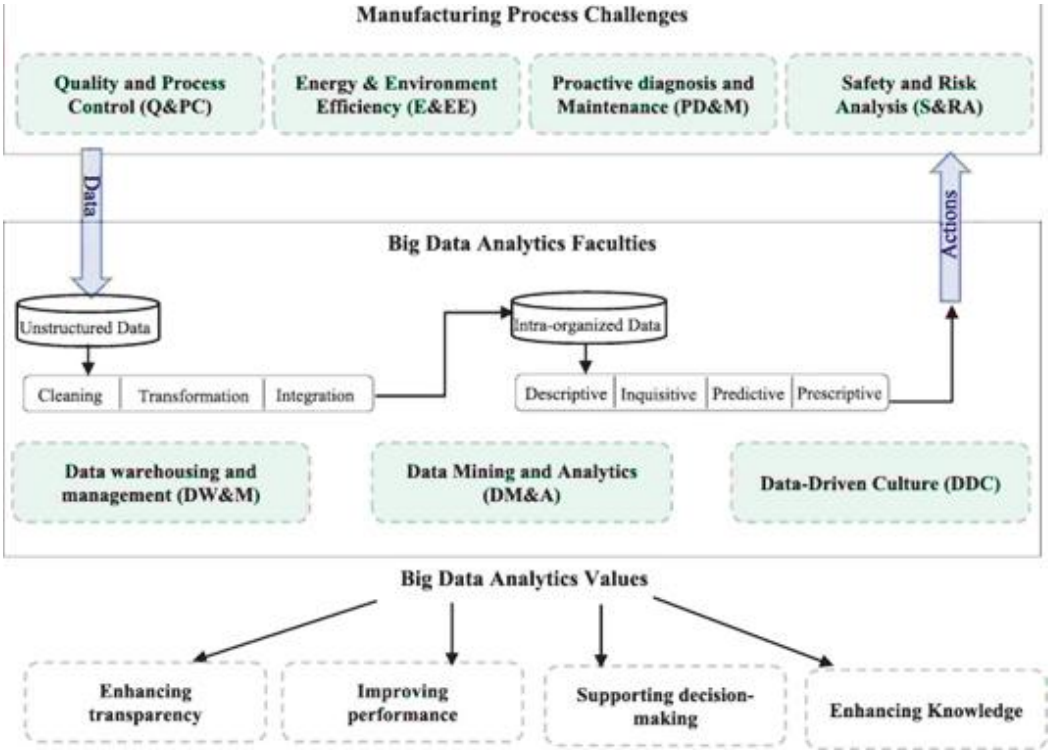

Fig. 2 Supply chain operations using big data analysis (pre-, control-, and post-process). [22]

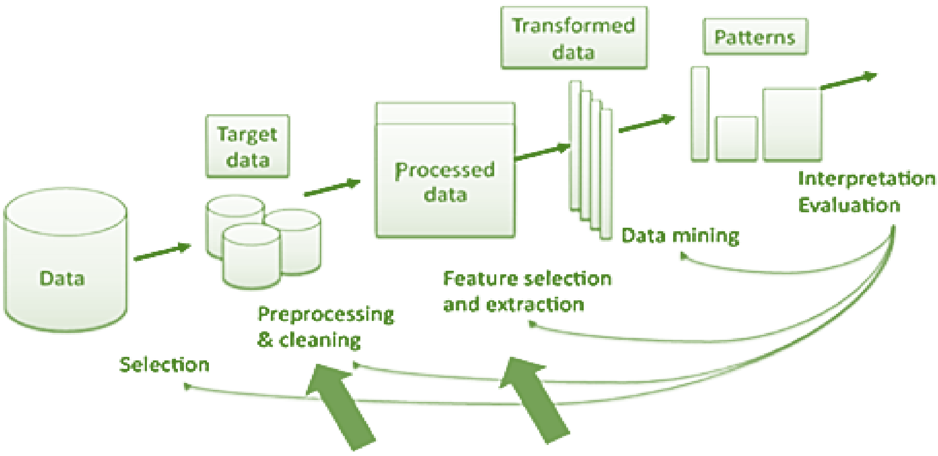

Fig. 3 Data reduction, exploratory analysis of data, engineering of features, and pre-processing. [24]

$$b' = \frac{(b-min_F)}{max_F-min_F}.(new - max_F - new - min_F) + new - min_F. \text{............}1$$

$$b' = \frac{(b-\bar{x})}{S_x} \text{..................}2$$

$$\bar{\bar{x}} = \frac{1}{n}\sum_{i=1}^{n} b_{i,} \text{...............}3$$

$$S_x = \frac{1}{n}\sum_{i=1}^{n}(b_i - \bar{\bar{x}}) \text{..............}4$$

$$L = \prod_{i=1}^{n} f_i\left(y_{i1,}y_{i2,\dots\dots\dots}y_{i1,}k_i;\theta\right) \text{.......}5$$

$$f_i * \left(y_{i3,\dots\dots,}y_i k_i;\theta\right) = \prod_{y_1}\prod_{y_2} f_i\left(y_{i1,\dots,}y_i k_i \theta\right) \text{............}6$$

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$$f_i * (y_{i3,\ldots\ldots,} y_i k_i; \theta) = l_{y_1} l_{y_2} (y_{i1,} y_{i2,\ldots} y_{ik}) dy_2 dy_1 \quad \ldots\ldots\ldots\ldots 7$$

$$L = \prod_{i=1}^{q} f_i \left((y_{i1,} y_{i2,\ldots} y_{ik}; \theta \right) \prod_{i=q+1}^{p} f_i * (y_{i3,\ldots,} y_i k_i \theta) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 8$$

2.1 Top Forecasting Models

Our studied literature [24] has used a number of time-series forecasting of demand models, which are included in Table 1. a thorough analysis of the most current machine learning models that have been presented for use in various forecasting applications, together with the performance indicators that have been assessed in each of the relevant literature. When it came to accuracy and precision in predicting future time-series lags, the ARIMA model fared better than the SES (Simple Exponential Smoothing), MA (moving average), and AR (Auto-Regressive) models.

Table 1 List of Models for Forecasting Time-Series Demand for goods in the Literature Review. [22]

Models	**Ref.**
LSTM	[25]
RBFNN	[11]
ARIMA	[2]
Adaptive Network	[3]
Winter Models With SVM	[2]
Fuzzy Reasoning Strategy and ANN	[23]
XGBoost	[14, 25]
Ada Boost	[22]
MLP	[7, 9]
CNN_LSTM	[19, 23]
EGD-SNet	[22, 29]
Swish Activation	[28, 30]
Temporal Convolutional Network	[2]
Extreme Learning Machine (ELM)	[8]
Adaptive Neuro-Fuzzy Inference System (ANFIS)	[21]
SARIMAX	[11]
Prophet	[2,16]
RNN	[5]
GRU	[6]
AU-NN	[14]
M-GAN=XGBOOST	[6]

III. CONTROL-PROCESS

Real-world procedures don't always go as expected. Changing degrees of efficiency give rise to variations in performance [11]. Ideally, the staff and available capacity can accomplish the objective as intended. However, performance levels vary depending on the product mix, machine utilisation, work-in-progress inventory, and queueing system, and they are inconsistent with people. It is impossible to forecast such variations in efficiency [17, 18].

3.1 Information Flow

Decisions on forecasting have an impact on subsequent SC planning [9]. Information thus moves between the SC process's various stages. Information about demand may flow from downstream members to upstream ones, and information about production plans and deliveries can flow from upstream members to downstream ones, enabling improved logistics and faster stock level synchronisation [11, 22].

3.2 Production efficiency

Production efficiency is increased by having real-time production data. By integrating data in real time into SC operations, firms may reduce mistakes and waste inside production facilities while managing the processing of orders across SCs and organisations [10, 19]. The availability of data from distributors and suppliers further improves this efficiency.

3.3 Employee productivity

Generally speaking, the manufacturing process is either overstaffed or understaffed; the issue is how to lessen the ineffectiveness [18, 19]. Without data analysis, workforce scheduling under changeable output needs requires spending money on cross-job training to help employees be more efficient and productive at work.

3.4 Inventory management

Lowering inventory costs may lower the company's total expenses. A variety of models have been developed to help with material planning processes, stock-out forecasts, inventory level projections, and many other tasks in an effort to reduce expenses and increase revenues [5].

Data's function by time period Despite the fact that BDA may increase the efficiency of SC operations [11,19], the same forecast cannot be used. Storage size and capacity planning are examples of for a long time strategic choices that need for either aggregating short-term forecasts or long-term projections [22].

3.5 SC performance

To find the gaps between the planning models, the performance of a SC process must be evaluated once it is finished. Measuring activities in two basic dimensions—effectiveness and efficiency—is known as measuring performance. [23].

3.6 Forecasting error measurement

When the hold-out set or actual sales data are available, our suggested cyclic structure is compared to the expected sales [24]. However, the hold-out set could prove to be ideal for practical situations, thus we promote a continual and cyclical growth process based on insight from the examination of real-sales data.

$$MAE = \frac{1}{m}\sum_{t=1}^{m}|e_t| = mean(|et^2|) \text{ …………...9}$$

$$MAE = \frac{1}{m}\sum_{t=1}^{m}et^2 \text{ ………………10}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}et^2} = \sqrt{mean}\ (|et^2|)$$
…………11

$$MASE = \frac{\frac{1}{j}\sum_J |E_J|}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_t(t-m)|}. \text{ ………………12}$$

$$Algebric\ Sum\ of\ Forcast\ error = \sum_{t=1}^{m}|e_t|.$$
…………………13

$$Tracking\ Signal = \frac{Algebraic\ Sum\ of\ Forecast\ error}{Mean\ Absolute\ Error}$$
……………...14

IV. CHALLENGES

With an emphasis on the preparation of data and machine learning approaches, this section attempts to provide a thorough overview of the difficulties faced during the examination of 152 works from 1969 to 2023 in the area of BDA-SCM for forecasting [24, 25].

- The problem of data reliability and quality is one of the major issues noted in the literature study. Numerous investigations recognised that SC databases had inaccurate, inconsistent, and missing data. [26].
- Performance and scalability have become major issues in SCM due to the exponential rise of data [26, 27]. Frequently, the examined papers lacked information about how their suggested method.
- Preparing data and extracting features are made more difficult by the wide variety of data sources, including semi-structured, unstructured, and structured data. The literature assessment revealed a dearth of research on methods for managing the complexity and diversity of data.
- Automated FS, reduction of dimensionality, and representations of features techniques to determine the most relevant characteristics for forecasting in the SC context and to increase accuracy in forecasting [28].
- Some machine learning models' black-box nature restricts their interpretability and interferes with decision-making.
- Real-time monitoring & decision-making skills are essential for SCM. Nevertheless, the reviewed literature showed a scant investigation of real-time data analysis and processing methods for forecasting [28].

The first step in putting the BDA-SCM paradigm into practice for SC practitioners is to match methods for gathering information with particular

SC goals. This entails taking a methodical approach to obtaining information that is specifically pertinent to the particular dynamics and difficulties faced by the SC ecosystem. Practitioners may take use of BDA's potential at many phases, from issue identification to performance assessment, by incorporating its framework into their operating procedures.

V. CONCLUSION

This systematic review carefully examined 152 works from 1969 to 2023 in order to identify and compare the most advanced SC forecasting methods and technology within the specified temporal frame. With its state-of-the-art technology solutions and thorough BDA-SCM architecture, this research has made great progress in tackling the difficulties associated with SC forecast.

- **Pre-process:** The need of precise data in line with SC goals was underlined throughout the pre-processing phase of SC forecasting. The paper gave suggestions for SC analysts, included employing EDA, FE, hyperparameter tweaking, and latest ML model training methodologies to increase predicting accuracy.
- **Control-process:** The research covered the ways in which BD may support effective managerial decision-making in a number of SCM domains, including inventory management, manpower needs, production management and capacity planning. Making use of predicted data insights enables decision-makers to optimise allocation of resources and SC operations.
- **Post-process:** The assessment of SC performance and the function of BDA in enhancing model predictions were highlighted in the post-process part. SC practitioners may identify areas for development and adjust their financial projection models appropriately by examining performance indicators and using BDA approaches.

These results should be expanded upon in future studies to improve our understanding and use of BDA in SCM. Although this Systematic Review of the Literature (SLR) used a thorough and impartial assessment methodology, it is important to recognise its limitations.

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