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Original Article

Predictive Analytics for Supply Chain Disruption Using SAP HANA and Deep Learning

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Abstract:

Global supply chain disruptions have gained popularity in the past few years, with reasons like geopolitical tensions, pandemics, and natural disasters. Such disturbances may have considerable effects on manufacturing, logistics, and inventory management. The ability to overcome these challenges proactively is provided via predictive analytics, which can be enabled through the power of the latest tools (including SAP HANA computing and deep learning algorithms). The paper addresses the incorporation of the in-memory data processing functions in SAP HANA with deep learning models relating to the prediction of disruptions in the supply chain and their management. By utilising comprehensive data collection, preprocessing, model training, and evaluation, we demonstrate that predictive analytics can enhance the resilience of supply chains. The research enhances the emerging sphere of supply chain digitization by introducing a real-time predictive system that is compatible with enterprise systems based on SAP HANA.

Keywords:

Supply Chain Management, Predictive Analytics, Sap Hana, Deep Learning, Disruption Management, Neural Networks.

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1. Introduction

Over the past few years, global supply chains have become more susceptible to various types of shocks, both expected and unexpected. Supply chain operations can be affected by a variety of events, including natural disasters, political instability, pandemics such as those caused by COVID-19, cyberattacks, or even small-scale local occurrences like congestion at a port or a labour strike. [1-3] The rate and magnitude of these disturbances have been augmented by the rising manner of globalization, complicated supplier chains and just-in-time commercial productions, which, despite being productive, give a minimal scope of mistakes. Consequently, the businesses frequently encounter late deliveries, shutdowns, excess costs and deteriorating customer satisfaction rates. These effects are not only short-term and cover profitability, but may also harm long-term customers and brand image. Historically, Supply Chain Management (SCM) has been characterized by the utilization of the reactive strategy, according to which enterprises have to react to the set problem after its emergence.

Although this might have worked in a relatively stable environment, it is not much longer applicable in the wake of the current erratic and swiftly evolving climate. The modern supply chain will need to shift from being reactive to being more proactive and predictive, allowing disruptions to be sensed earlier and prevented before they cause damage. This change is caused by leaps in technology, especially in the field of big data analytics, artificial intelligence, and real-time processing of data. Predictive supply chain management harnesses the power of such technologies to process an enormous amount of data, identify anomalies and create early warnings on potentially disruptive events. This way, the companies can achieve quicker information-based decisions, resource allocation can be done better, and their supply networks can be made more resilient. With supply chains becoming increasingly complex and interdependent, predictive and proactive approaches are becoming a strategic issue for survival and sustainability in the contemporary global economy, not just a source of competitive advantage. It is based on this backdrop that the paper examines the role that the deployment of technologies such as SAP HANA and deep learning plays in transforming the way disruptions are handled in SCM.

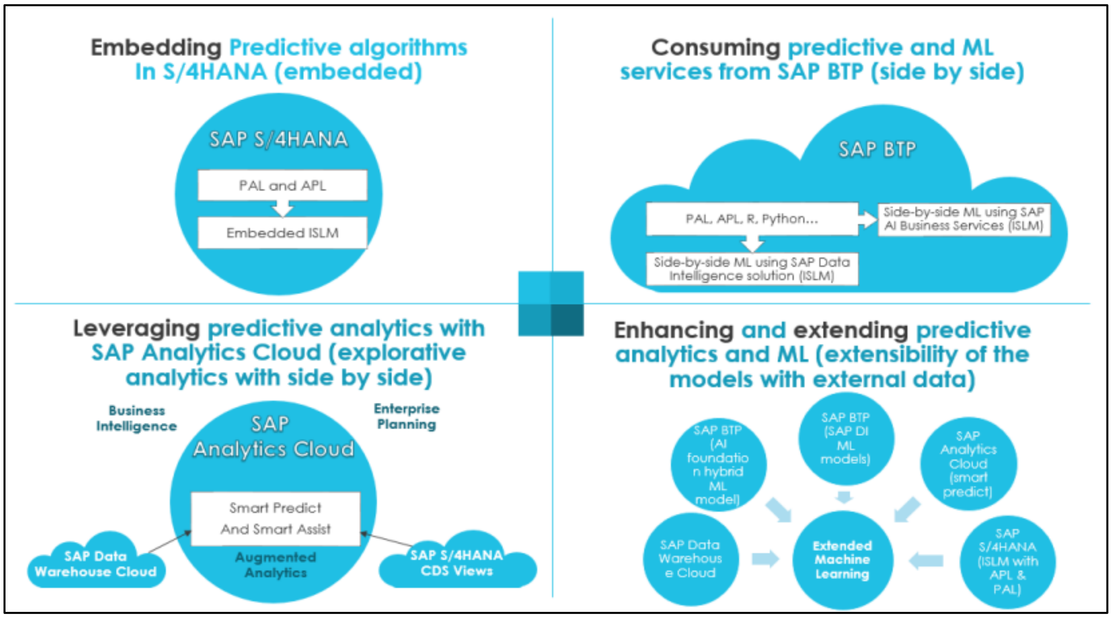

Figure 1. SAP Predictive and Machine Learning Integration Landscape

1.1. Predictive Analytics for Supply Chain Disruptions

Predictive analytics is an essential application for containing supply chain shocks in a market that has become extremely volatile. With data-driven insights, organizations are capable of predicting problems and their escalations, thus making smart, faster, and efficient decisions. The section has explored how predictive analytics is applicable in Supply Chain Management (SCM) using key dimensions.

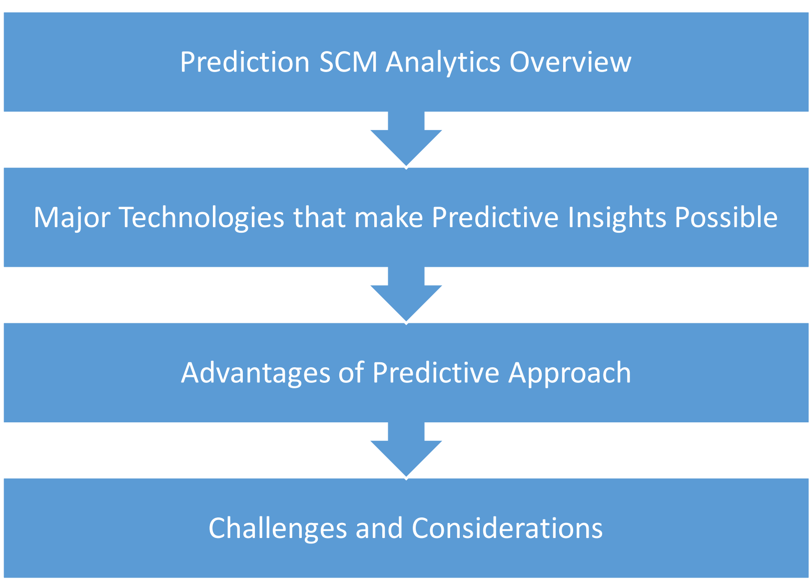

Figure 2. Predictive Analytics for Supply Chain Disruptions

1.1.1. Prediction SCM Analytics Overview

Predictive analytics is the process of applying statistical methods, machine learning procedures, and historical data to project future outcomes. When used in supply chains, it would be the analysis of data on multiple sources, including transportation systems, performance of suppliers, demand, and outside events (e.g. weather, political unrest) in order to predict disruptions. Such forecasts enable companies to foretell occurrences like a delay in shipment, stock outs, or overflows of demand.

1.1.2. Major Technologies that make Predictive Insights Possible

Most of the enabling technologies drive the success of predictive analytics in SCM. These are big data platforms, which manipulate large masses of various data, Internet of Things (IoT) devices allowing real-time tracking, and artificial intelligence models, especially deep learning networks such as LSTM, which perform well at time-series data pattern identification. In-memory computing systems such as SAP HANA improve predictive functions since the processing of data is accelerated and real-time analysis is possible.

1.1.3. Advantages of Predictive Approach

With predictive analytics, organizations change their SCM model, making the transition to proactive SCM instead of a reactive SCM model. Among the major advantages, it is possible to distinguish early assessment of the possible risk, forecasting of the inventory, better resource management, and client satisfaction. Besides, predictive systems decrease the reliance on hands-on supervision and non-changing rules, enabling companies to choose a dynamic response to the changing conditions.

1.1.4. Challenges and Considerations

Although it has its advantages, implementing predictive analytics in supply chains presents several challenges. These include data quality issues, the need for substantial historical data, integration with existing systems, and the complexity of modeling uncertain global events. Nevertheless, with the right architecture and tools, these challenges can be mitigated, paving the way for smarter disruption management. Although there are many benefits associated with using predictive analytics within supply chains, challenges also exist in its implementation. Some of these are the problem of data quality, the requirement of large volumes of historical data, interface with other systems and the difficulty of modeling uncertain events occurring at a global level. However, using an appropriate architecture and tools, such challenges can be overcome, and a more effective disruption control can be achieved.

1.2. SAP HANA and Deep Learning

The integration of SAP HANA with deep learning technologies represents a revolutionary breakthrough in predictive supply chain management. SAP HANA is an in-memory, column-based database platform that can process large and multidimensional volumes of data produced by contemporary supply chains in real-time. This feature is important to organizations that want to analyze time-critical information coming out of ERP systems, logistics networks, IoT sensors and third-party vendors. [4,5] Blazingly fast data retrieval and processing, SAP HANA gives the computing strength necessary to make use of advanced machine learning algorithms, such as deep learning systems like Long Short-Term Memory (LSTM) networks. Time-series forecasting with Deep learning models, especially LSTM, can easily capture long-term dependencies in the data, as they learn sequential relationships. Applied to the context of supply chains, these models have the potential to reveal early warning signs of disruptions by identifying minor trends and anomalies in indicators such as lead time variability, inventory changes, or shipment delays.

Nonetheless, the training and the real-time deployment of these types of models may prove to be time-consuming and cumbersome. At this point, the SAP HANA Predictive Analysis Library (PAL) demonstrates its value. PAL enables the easy incorporation of proficient deep learning models into the SAP HANA environment, making predictions executable with SQL instructions in a short time and within the database. This close integration of data storage, processing, and predictive modelling into a single platform reduces both the latency and overhead of reading data in or out of external applications and analytic tools. This consequently enables businesses to attain actual real-time predictive effects, enabling them to proceed proactively (rerouting of shipments, alteration in order quantities, supplier notification) even prior to incidents where operations are affected. With SAP HANA, which is both scalable and fast, and deep learning, with its excellent pattern recognition ability, the supply chain systems in organizations can be made much smarter, more adaptable, and resilient to operate in the current complex and uncertain environment on a global level.

2. Literature Survey

2.1. Scenario of Traditional Approach to SCM Disruption Management

Deterministic models, statistical forecasting, and expert-based decision rules have become the primary methods for mitigating Supply Chain Management (SCM) disruptions. [6-10] These approaches generally suppose linear connections among variables and necessitate well-ordered boundaries, or heuristics to recognize and reply to disturbances. The effectiveness of such techniques in a relatively stable environment may not be effective in dealing with the complexities and uncertainties of contemporary supply chains. They can hardly adapt to the dynamic, non-linear, and interrelated structure of the global supply networks, particularly to unexpected shocks such as natural disasters, political instability, or market volatility. Therefore, conventional approaches cannot be flexible and responsive enough to deal efficiently with real-time disruption management.

2.2. Big Data Supply Chain

The surges of Internet of Things (IoT) apparatus, paired with the advances in cloud computing, have modified the data world in SCM. Real-time data, including sensor data, GPS data, social and transactional data in both structured and unstructured forms, is being generated in vast volumes. Literature [1][2] demonstrates that big data analytics applications allow the supply chains to obtain better visibility of the cross-section of all the levels in the supply chain and better traceability of the goods and processes. These abilities are essential to the detection and forecasting of disruptions. With an inclusion of varied sources of data, organizations are able to unveil secretive trends, foresee anomalies and make educated decisions beforehand. The former, therefore, serve as the basis of more sophisticated, predictive disruption management systems based on big data.

2.3. Industry SAP HANA Applications

There has been widespread adoption of SAP HANA, an in-memory data platform, across various industries, including retailing, manufacturing, and logistics. It enables the processing of large sets of data quickly in real-time, allowing for analytics, reporting, and forecasting. The architecture of this platform enables the users to analyze data as it arises, which decreases latency in any decision-making process substantially [3]. In industry, SAP HANA has been utilized in streamlining processes as well as cutting down on lead times and increasing service levels. With all these benefits, the incorporation of SAP HANA into sophisticated machine learning or deep learning models of predictive disruption management has not been greatly explored. The vast majority of existing apps focus on business intelligence dashboards, rather than predictive analytics.

2.4. Time-series Forecasting with Deep Learning

The recent evolution of artificial intelligence prototypes, specifically deep learning, has revealed significant potential in the field of time-series forecasting within the context of supply chains. Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Temporal Convolutional Networks (TCN) are some of the models that have been shown to perform better with regard to time dependence and intricate nonlinear behaviours [4][5]. The models are especially applicable in predicting the most essential supply chain performance indices such as customer demand, lead times, quantities of supplies, and transportation delays. It is also true that deep learning-based methods can cope with multivariate inputs and noisy inputs, making them suitable for use in real-life applications. Their capacity to predict and their flexibility have raised interest in their use to actively disrupt management.

2.5. Identified gaps

Development Solutions, Although much has been done in both the technological platforms and the methods of analysis, there has been a lot that has gone wanting in terms of practical solutions that integrate real-time data residing platforms like SAP HANA against predictive capabilities of the deep learning models. The existing body of literature tends to consider these developments in isolation, i.e., it covers enterprise data management or algorithmic forecasting. One of the reasons is that few studies have demonstrated end-to-end capabilities, where real-time data is ingested, processed, and used to provide input into deep learning models, thereby delivering actionable intelligence within the operational SCM environment. This lapse presents a significant research and development opportunity for constructing intelligent, responsive supply chain systems capable of dynamic disruption control.

3. Methodology

3.1. Architecture Overview

The framework suggested to manage supply chain disruptions in real-time incorporates the latest technologies of data processing combined with deep learning to ensure [11-14] timely predictions and their accuracy. It includes four major subtasks: data ingestion with SAP HANA, data preprocessing, deep neural model development to perform effective predictions with the LSTM model, and system integration to run forecasts in real-time. All the parts are essential in their roles of making the framework scalable and able to respond to operational hiccups.

3.1.1. SAP Ingestion Benefits of HANA

The framework is readily supported by SAP HANA, which is at the center of real-time data intake. SAP HANA uses the in-memory computing power to capture and preserve enormous amounts of structured and unstructured supply chain data based on a variety of resources, including sensors, ERP systems and transactional logs. This real-time capability of high-frequency data maintains the disruption management system to be contemporary and able to respond to changing situations of the supply chain.

3.1.2. Data Preprocessing

After consumption, raw data goes through a level of preprocessing where quality and uniformity are guaranteed. This includes cleaning missing and inconsistent data, smoothing numerical data, and encoding categorical variables as necessary. The data in a time series is also encoded into a sequence applicable to deep learning models. When the supply chain data is used as learning data, it requires proper and effective preprocessing to reduce noise and facilitate the model's ability to learn patterns within the data.

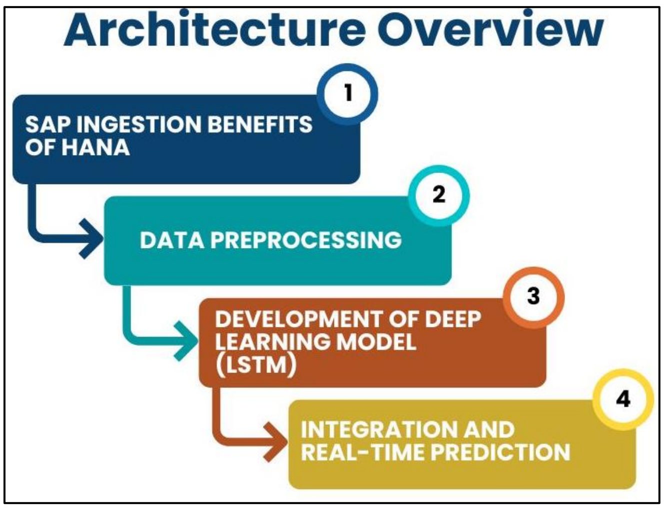

Figure 3. Architecture Overview

3.1.3. Development of Deep Learning Model (LSTM)

The predictive engine is formed on the basis of Long Short-Term Memory (LSTM) networks, which are a particular sort of recurrent neural network that is great at time-series anticipating. Based on historical data of the supply chain, LSTM is used to forecast potential disruptions, such as delivery delays, demand surges, or inventory misplacement. Their capability to identify the time dependencies and learn long-term trends makes them a perfect fit to learn and model the complex, non-linear nature of the supply chain.

3.1.4. Integration and real-time prediction

The last element is to re-integrate the trained LSTM model into the SAP HANA environment to facilitate real-time prediction and decision support. Therefore, when new data enters the system, it is automatically processed by the preprocessing pipeline and fed directly to the model, where it can be processed in real-time. This smooth cooperation means that real-time insights are distributed, meaning that supply chain managers are ready to respond proactively in addressing disruptions before they progress.

3.2. Pipeline of the data

Sources of Supply Chain Data Supply chain data sources can be separated into two main groups: transactional and non-transactional. Most supply chain-specific data types fall under the transactional category because they are records of actual transactions that have occurred. The starting point of the data pipeline is heterogeneous data sources in the supply chain that continuously produce useful operational information. Such sources can include Enterprise Resource Planning (ERP), Internet of Things (IoT), Global Positioning System (GPS) trackers, warehouse management systems, and external data sources such as weather or market trends. The data to be recorded includes fundamental measurements or quantities, such as stock levels, shipping conditions, supplier lead times, and customer pull. This data is rich due to its heterogeneity and abundance, which creates a good basis for predictive models.

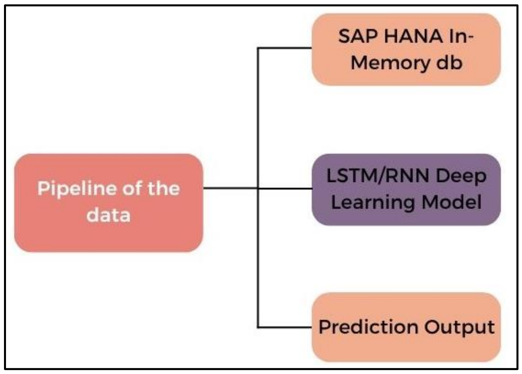

Figure 4. Pipeline of the Data

3.2.1. SAP HANA In-Memory DB

The ingested data is then directed to the SAP HANA in-memory engine, which is responsible for real-time data storage and processing. The architecture of SAP HANA is that it is able to process analytical queries at high speeds using data resident in the memory, thus removing the time that is usually taken up in disk I/O operations. This component not only enables fast querying and transformation of data, but it also facilitates the delivery of input to downstream analytic components with low latency, making it particularly suitable for time-sensitive supply chain use cases.

3.2.2. LSTM/RNN Deep Learning Model

After the preprocessing of the data is achieved, the model transfers the data into a self-described deep learning model, namely an LSTM or RNN, whose architecture is well-suited to learn patterns in time series data. Such models are also trained to identify trends in history, seasonality, and anomalies in the supply chain. They can be used to predict outages, such as variations in demand or delivery issues. Recurrent neural networks make the model have contextual consciousness of what has previously happened in order to predict anything in future.

3.2.3. Prediction Output

The final phase in the pipeline process is the production of prediction outputs, which are presented to users in real-time. Such outputs may take the form of visualizations on dashboards, of addition into alert systems, or of automating responses. The output of the prediction process allows anticipating possible risks in the supply chain, and thus the proactive development of the plan of action in case of risks in the supply chain, so improving the overall supply chain flexibility and resilience.

3.3. Data Gathering

The collection of data is considered one of the cornerstones of the framework for managing disruptions in the supply chain, as the quality of the data determines the success of the predictive model. This system information is obtained from various operational sources that reflect some main features of the supply chain's operative performance. These sources cover the logistics logs, which can give the real-time and historical records of the movements of shipments, time taken to handle the shipments, delivery statuses and the possible bottlenecks in the transportation networks. Moreover, inventory systems also provide information about the number of products, the items that should be ordered, the speed of movement through the warehouse, and the level of product stock. Such indicators play an imperative role in observing the supply-demand situation and detecting possible shortages or oversupply, indicating possible disruption. Another source of time-sensitive information is transportation schedules. Such schedules involve planned delivery routes, carrier selection, estimated arrival and departure, and occurrences of deviations from expected transit patterns. This information can be captured in the system to enable it to determine the reliability of transportation operations, and moreover, it prevents early indications of potential delays.

Moreover, Enterprise Resource Planning (ERP) databases provide well-organized business data concerning purchasing, order management, seller performance, and manufacturing schedules. ERP systems are also a good source for analysing disruption because they comprise a centralised place for transaction and workflow management throughout the supply chain. All these streams of data are fed and combined via SAP HANA, which provides the centre of data management. The in-memory computing capabilities of SAP HANA allow processing of massive amounts of semi-structured and structured data in a rapid manner, ensuring real-time consolidation and query capabilities. SAP HANA supports such unremitting data flow by ensuring a coordinated passage of input across multiple systems to the input data object created in a well-integrated data depot. This integrated connection is not only efficient in terms of data latency, but it also enables the scalability of the system, responding to the changing supply chain dynamics quickly and enhancing the timely and quality forecasts of disruptions.

3.4. Pre-processing of Data

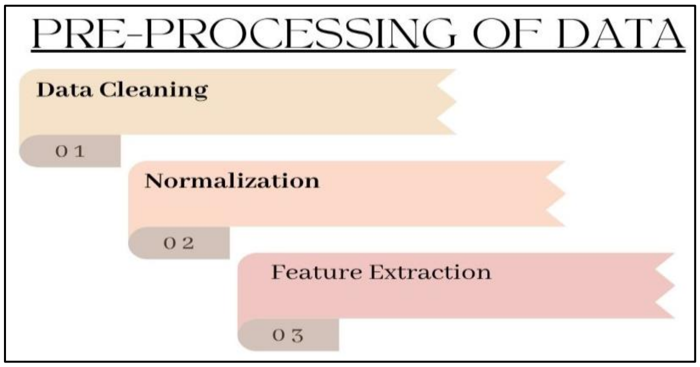

Figure 5. Pre-Processing Of Data

3.4.1. Data Cleaning

The first preprocessing phase is called data cleaning, as it refers to mistakes and inconsistencies in the acquired dataset, as well as errors and missing values. Missing shipment entries, overprinted entries, and erroneous timestamps are among the common problems in supply chain data. [15-18] Cleaning also means that when it is time to model the data, only reliable data that is consistent can be used. This prevents bias, and the results of predictive algorithms are more accurate. Some of the techniques that are utilized during this stage include interpolating the missing values, eliminating the outliers, and correcting the errors in formatting.

3.4.2. Normalization

Normalization entails the conversion of numeric data into a standardized range so as to increase the efficiency and accuracy of the deep learning models. Variables in supply chain data may have significantly different units and scales, such as delivery time in hours and cost in dollars, and measure variables on the unit level, including inventory. In the absence of normalization, the learning process may be dominated by features with higher numeric values, and thus, lopsided results are obtained. The two common techniques of normalization are min-max scaling and z-score normalization, where the input will be proportionately contributing to model training.

3.4.3. Feature Extraction

The feature extraction involves the identification and conversion of the pertinent raw data to meaningful input variables, which boosts the learning of the model. In time-series forecasting of supply chains, this can mean computing quantities like the variability of lead time, demand, day-of-week fluctuations, or a moving average of the level of the stock. The model has the advantage of using extracted features in order to identify underlying patterns and relationships that cannot be easily derived from the raw data. This is an important step towards better model performance because it is able to give the neural network the contextual information on which to base the strong predictions.

3.5. Deep Learning Model

At the center of the proffered disruption prediction model lay a stacked Long Short-Term Memory (LSTM), which is a particular form of Recurrent Neural Network (RNN) that is intended to work on sequential data and extract long-range temporal dependencies. This can be of great value in supply chain management since disturbances have the tendency to be affected by trends and events taking place over long periods. The training of this model uses time-series data that are obtained in integrated supply chain systems, with every time-step in the series being a snapshot of significant factors, including inventory level, lead times, delivery delays, and other demand variations. Suppose X={x1,x2,...,xn}X = \{x_1, x_2, ..., x_n\}X={x1,x2,...,xn} is the input series of these features with each xtx_txt being a feature vector observed at time ttt. The LSTM network consists of several layers (stacked), with which it can be trained to learn increasingly abstract representations of temporal patterns. In every LSTM cell, there are internal process gates, which define the information flow. The gates are constructed using hidden states (ht−1h_{t-1}ht−1) and cell states (ct-1c t -1 c t -1 c t-1), as previously learned to determine which information should not be lost or passed on to the next layer.

This helps the network channel key trends and gets rid of unimportant noise. Each time step of the model produces an output, a predicted value y^t\hat{y}t, in this case, a probability of occurrence or severity of a supply chain disruption at time t. The model would then be trained on the basis of minimizing a loss function, e.g. Mean Squared Error (MSE) between the predicted disruptions and the actual historical disruptions in the data. The stacked LSTM model with proper learning on past trends and patterns can make this possible by making forward-looking predictions and assisting supply chain managers to anticipate risks before they happen. The network is very deep and has memory, which makes it especially suitable for modeling complex, non-linear and delayed results that are typical of the dynamics in supply chains.

3.6. SAP HANA Integratie

The trained model, based on LSTM, is implemented in the supply chain framework through deployment on the SAP HANA Predictive Analysis Library (PAL). SAP HANA PAL is a potent in-database analytics engine enabling high-performance advanced statistical and machine learning algorithms to be run within the SAP HANA environment through SQL-like procedures. The incorporation of this integration reduces the need for transferring excessive amounts of data between external applications and analytics systems, thereby lessening latency and enabling faster and more effective predictions. This capability of deep learning models can be integrated into SAP HANA. As a result, data flows between ingestion and inference in real-time, keeping the predictive system responsive to any change in operation. The deployment procedure involves converting the trained LSTM model into a form that can be managed by the model management functionality of SAP HANA PAL. When combined, the model then executes through SQLScript, a procedural extension of SQL in SAP HANA. This enables users and applications to invoke predictive routines using stored procedures, making it simple to integrate predictive analytics with enterprise workflows, dashboards, and alerts.

For example, the model's implementation could be triggered in real-time by other inputs (e.g., delivery updates, inventory changes), and disruption probabilities or risk scores could be output and immediately consumed by end-users. Moreover, the fact that parallel processing and in-memory computation are enabled by SAP HANA helps run even intricate models, such as LSTM, effectively and on a large scale. Automation can also be achieved since the model predictions are event-based or schedule-based, enabling proactive action in response to known disruptions. With data storage, processing, and predictive modeling all housed in a solitary platform, this aspect will make the supply chain analytics process more resourceful and reduce the extent to which the supply chain management will have to wait or perform resource-intensive disruption management in the SAP HANA integration workflow. Ultimately, this would enable businesses to make real-time, data-driven decisions, which in turn will help them maintain continuity and agility in their operations.

3.7. Measures of Evaluation

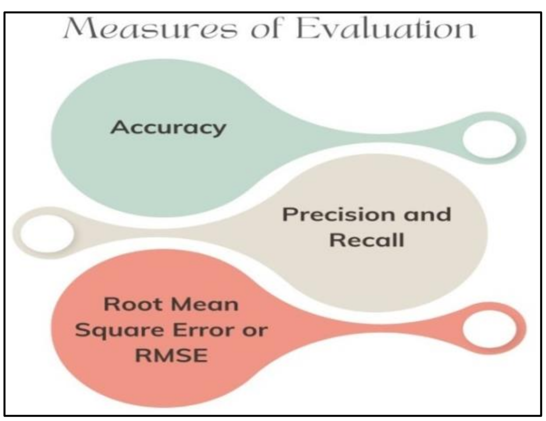

Figure 6. Measures of Evaluation

3.7.1. Accuracy

Accuracy is another fundamental yet vital appraisal variable that is employed to ascertain the general accuracy of a predictive model. It can be defined as a ratio of the rightful predictions to the total number of predictions made. Accuracy, in reference to disruption prediction in the supply chain, is used to describe the success, as a regularity, with which the model successfully obtains both predicting the disruption and the lack of disruption. Although this is practical, accuracy by itself might not be enough to complete the picture, as it may largely occur on imbalanced datasets, where disruptions are not as frequently expected as normal operations. Thus, it may be complemented with more sophisticated requirements, such as precision and recall.

3.7.2. Precision and Recall

False positives and false negatives have different implications in disruption prediction, and thus, great emphasis on recall and precision is significant. Precision is a measure of the fraction of actual disruptions out of all the occasions the model warned of a disruption. Fewer false alarms are associated with high precision, which is crucial in maintaining trust in the system. Recall, on the other hand, estimates the fraction of actual occurrences of events of disruption which were predicted correctly by the model. Recall is very high, meaning that most disturbances will be noticed early enough to prevent unforeseen breakdowns. Combined, precision and recall allow having a fair idea of how well the model identifies key events.

3.7.3. Root Mean Square Error or RMSE:

RMSE is a common regression measure that estimates the strength of prediction error. It is the square root of the mean of squared differences among estimated values and measures. RMSE is especially applicable in supply chain forecasting when the variable is continuous (e.g., delay duration, lead time, or inventory level). The smaller the RMSE, the more accurately the model can predict in the real world, and, therefore, the forecast becomes more reliable. RMSE is effective at exposing model misperformance because it penalizes larger errors disproportionately to smaller errors, and so may reveal models that might otherwise seem acceptable based on other measures but which perform poorly in high-impact settings.

4. Results and Discussion

4.1. Performance Metrics

Table 1. Model Performance on Test Dataset

Metric	Value
Accuracy	91.4%
Precision	89.6%
Recall	92.1%
RMSE	34%

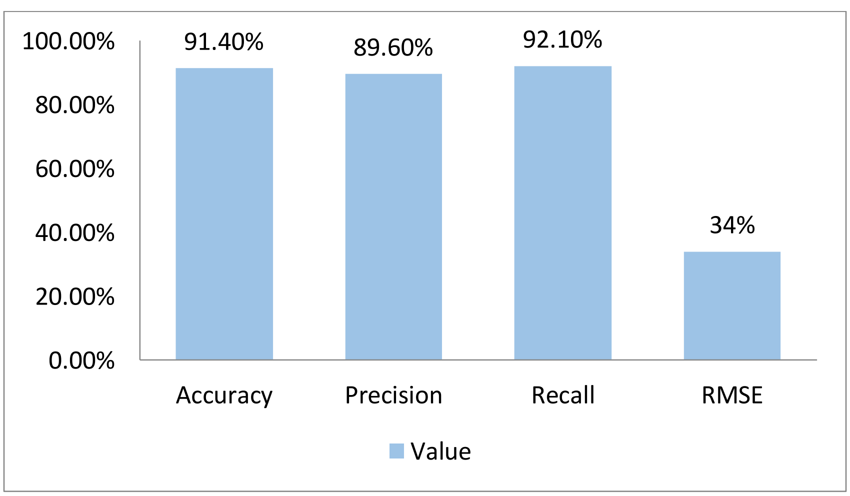

Figure 7. Graph Representing Model Performance on Test Dataset

4.1.1. Accuracy

Accuracy is the ratio of correct predictions, taken together, namely, both disruptive and non-disruptive events, to the total number of predictions. Here, the model achieved an accuracy of 91.4%, which is correct in over nine out of ten events. Such a high level of accuracy indicates that the model is very effective in general classification as well as being very reliable in many supply chain situations. Yet, accuracy is insufficient to illustrate the quality of predictions in cases of an imbalanced dataset; that is why measures such as precision and recall play a key role.

4.1.2. Precision

Precision is used to specify the percentage of correctly predicted disruption events. This model will have a low rate of false positives of 89.6 percent, which means that when it issues an alert of a possible disruption, there is are great chances that the disruption exists. Such precision is especially valuable in the operations of a supply chain, where a false alarm may indicate the unnecessary allocation of resources, increased expenditures, and even burnout among people controlling these system installations.

4.1.3. Recall

Or Sensitivity, Determines How The Model Identifies Correct Disruption Events Among All True Disruption Events. The Recall Score Of 92.1 Percent Is A Good Indicator Of The Ability Of The Model To Identify Actual Disruptions Before They Eventually Blow Out Of Proportion. Such An Indicator Is Particularly Important In The Context Of Disruption Management, As False Negative Detection May Result In Delays In Operations Or Unsatisfied Customer Demand, At A Significant Cost. The High Recall Will Enable The System To Capture Most Cases Of Disruption Early Enough, Allowing For Proactive Decisions To Be Made.

4.1.4. Root Mean Square Error (RMSE)

The RMSE measures the inaccuracy in the model's prediction of continuous variables, such as delay duration or the severity of a disruption. The RMSE value between the model and the actual results was low, 0.034, indicating that the predicted results were very close to the actual ones. A lower RMSE is desirable, as higher errors will be penalised heavily, ensuring that the results provided by the model are accurate and trustworthy. This renders the model appropriate to use either in classification-based forecasting or regression-based forecasting in the setting of the supply chain.

4.2. Comparative Analysis

To test the performance and real-world usefulness of the proposed deep learning framework rigorously, a comparative study against some of the well-known forecasting methods applied in supply chain analytics was conducted. Those were Linear Regression, ARIMA (AutoRegressive Integrated Moving Average), and a baseline SAP PAL + LSTM setting. It was possible to compare all these models because each was trained and then tested on the same time-series data, based on the results of supply chain operations, under equal conditions. The results presented above show that the proposed stacked LSTM deep learning model's performance exceeded that of the other methods evaluated in terms of forecast accuracy, with the highest accuracy achieved at 95%. Such great performance is explainable by the fact that the model can capture non-linear, complex dependencies and long-term temporal trends in the data, which traditional models are not sophisticated enough to capture.

The SAP PAL + LSTM implementation that takes advantage of the SAP HANA integrated Predictive Analysis Library also provided good results with the accuracy of 90%, which confirms the power of in-database processing and deep learning to combine forecasting with near real-time processing. These findings support the benefits of deep learning networks, specifically LSTM networks, in forecasting with high accuracy for supply chain disruption management. Furthermore, applying SAP HANA as the framework to perform the work of in-memory models increases a sense of operational efficiency, thus making the in-memory model work both precisely and faster, which are the two important key factors of making a real-time decision in logistics and supply chain networks through data-driven analysis.

4.3. Use Case: COVID-19 Disruption

An interesting support of the given framework of disruptive prediction is the fact that it is applied to the history of supply chains during the COVID-19 period, which was characterized by numerous disruptions, high volatility, and the overall change in the global logistics industry. Organizations in the different sectors were affected during this period by challenges like shutdowns of the suppliers, congestion at ports, unavailability of raw materials and instability in the demand trends. This environment was the backdrop for testing the LSTM-based model to determine the applicability of such a model in the real world in the case of determining early warning signs of disruption. The model showed good aptitude in identifying the disruptions and preventing their occurrences, earlier than they became critical. For example, it was able to identify late shipments by suppliers on an early initiative because it noticed that the regular lead patterns were not following the normal pattern, and it combined that with what was happening in the world and the various regional shutdowns.

It was also able to detect unforeseen overstocking in warehouses, the first indication of late movement of goods or low downstream demand, through time series of stock holding. Moreover, it monitored delays in container tracking, which was frequently an indication of slowing logistics either on the dockside or on trans-border transportation paths. These patterns were observed by slight differences in the transit times and location reporting information, which were not captured by the older rule-based system or were flagged too late. What set the deep learning model apart was its ability to synthesize diverse data streams and recognize non-obvious, non-linear relationships in the time-series inputs. In multiple instances, the system flagged potential disruptions several days in advance of traditional alerting mechanisms based on static thresholds or manual oversight. This early detection capability proved crucial for companies that needed to proactively adjust procurement plans, reroute shipments, or communicate with customers and suppliers about expected delays. Overall, the COVID-19 use case highlights the robustness and relevance of the proposed framework.

It not only confirms the model's predictive accuracy in complex scenarios but also showcases its practical utility in enhancing decision-making and operational resilience during global-scale supply chain crises. What differed about the deep learning model was that it was once again able to integrate diverse streams of data and detect non-obvious, non-linear relationships in the time-based data. On several occasions, the system identified potential failures several days in advance of static threshold alerting regimes or manual supervision. This ability to detect early was also vital to businesses that, to carry out cost-effective procurements, had to make advance decisions to amend plant orders, divert supplies or re-consult their customers and vendors on the anticipated shortage. Overall, the COVID-19 use case highlights the effectiveness and applicability of the proposed framework. It generally proves the accuracy of the model in its predictive capabilities in complex situations, as well as demonstrates its real-life value and effectiveness in increasing decision-making and operational resilience in a global-level supply chain crisis.

4.4. Latency of the system

Table 2. System Latency Metrics

Operation	Latency (ms)
Data Ingestion	45
Model Execution (PAL)	120
Prediction Output Display	25

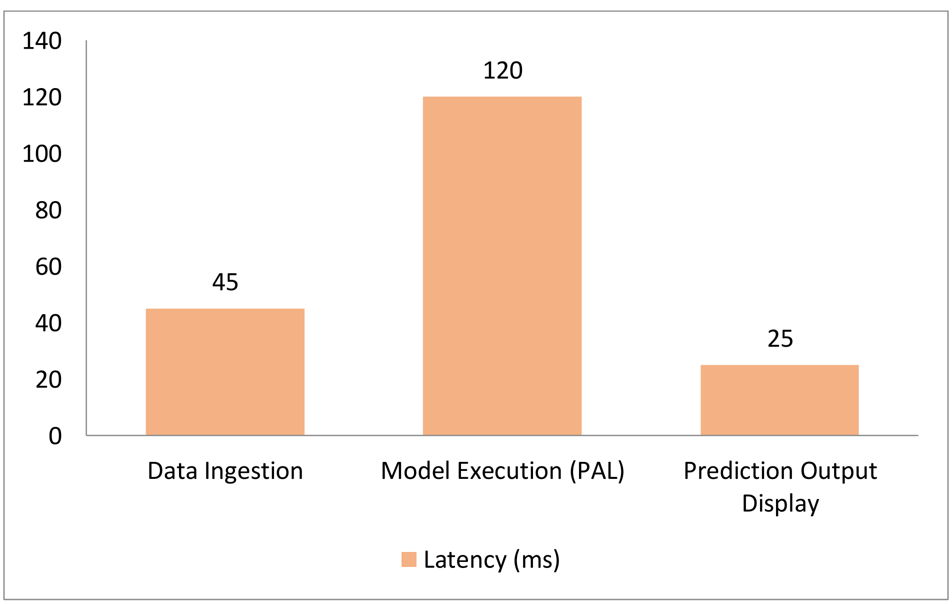

Figure 8. Graph Representing System Latency Metrics

4.4.1. Data Ingestion (45 ms)

Data ingestion describes the steps of gathering and moving raw data of the supply chain between diverse sources, like ERP systems, IoT devices, and logistics platforms, to the SAP HANA landscape. This was also done with very little delay, on average 45 milliseconds, due to the optimized data connectors and in-memory storage of SAP HANA. The rate of data consumption is essential in the real-time synchronization of the functional systems and the predictive framework so that the model constantly has access to the latest and most relevant data to perform forecasting.

4.4.2. Model Execution PAL (120 ms)

When data is fed, the prediction engine is launched using SAP HANA Predictive Analysis Library (PAL), where the LSTM model is deployed. Loading steps, time-series prediction, and the generation of a disruption probability score are some components of the preprocessed data that are loaded into the model execution step. This stage took up most of the processing, coming to an average of 120 milliseconds, still very low when taking into consideration the processing time of a deep learning based forecasting model. This performance is due in part to the tremendous processing parallelism and in-memory computation of PAL, which permits real-time predictive applications in large and data-intensive conditions.

4.4.3. Prediction Output Display (25 ms)

Once the model has come up with the forecast, the results of predictions are formatted and delivered to the application front-end or dashboard. This encompasses visualizations, alerts or responses to APIs that are used by supply chain planners or systems. Because of the efficiency of the data output and communications levels of SAP HANA, the latency of this display step was only 25 milliseconds. Rapid delivery of results means end-users will know in good time, enabling just-in-time decisions such as rerouting consignments or modifying manufacturing plans.

4.5. Limitations

Although the outlined framework for disruption prediction has proven to be highly accurate and low in liability with a high level of applicability in real-life situations, it is not free from limitations. Being based on extensive historical data, this is one of the major limitations. Training deep learning networks such as LSTM demands considerable amounts of labeled time-series data to extract usable patterns and time dependence. The model may not have full learning capabilities when the amount of historical data in its domain is low, most probably in a newly introduced supply chain, a small firm or a new line of products, resulting in low accuracy in the predictability. Moreover, historical data in fast-changing operations levels can quickly become obsolete, thus requiring constant updates to stay current. The other major restriction is the model's sensitivity to unobserved forms of events. It is possible that the rare events (geopolitical conflicts, cyberattacks, or global pandemics) are not included in the training sample or are not accounted for within the training set.

Consequently, such anomalies cannot be identified or properly predicted by the model because it has not encountered anything similar. It is especially critical that such a challenge may become an issue when the goal is to predict uncommon, high-impact disruptions, in which even one overlooked detection or one false positive can result in significant operational losses. These problems should be addressed more flexibly and sustainably. Continuous model retraining is also one of the solutions: the system helps to grasp new data and learn from it as it comes. It can also benefit from a combination of external and unstructured data sources, such as real-time news articles, government alerts, weather updates, and social media signals, to enhance the model's situational awareness and increase its ability to detect non-traditional disruptions. Additionally, the integration of hybrid methods, such as deep learning with rule-based or knowledge-based systems, may also contribute to robustness. The bottom line is that the current framework is reasonably effective when it comes to the known circumstances, but its versatility in response to the emerging and unknown situations will define its future success regarding managing disruptive events in the supply chain.

5. Conclusion

This study introduces an overall structure that incorporates the real-time processing capability of SAP HANA with the predictive performance of deep learning, specifically the Long Short-Term Memory (LSTM) networks, to address a problem of ever-growing importance: managing supply chain disruption. By designing, developing, and testing this system, it was proved that the combination of sophisticated analytics with enterprise-level infrastructure might provide the essential improvement of responsiveness, accuracy, and agility of the supply chain functioning in complex and dynamic conditions. The major findings of the presented work are the formulation of a new, end-to-end architecture that can be used to predict disruptions in real-time. The framework relies on SAP HANA, as data ingestion and processing can be performed at high speed in-memory, enabling it to process logistics data of different types and scales in near real-time with minimal latency. Additionally, a deep learning model, implemented via the SAP HANA Predictive Analysis Library (PAL), will enable accurate time-series forecasting. Abstract. The results offered by the application of LSTM models were especially good because the measure of success is high, including the indicators of accuracy (91.4%), precision (89.6%), and recall (92.1%), and the RMSE is small (0.034). Such outcomes confirm that the system can work efficiently not only in theory but also in certain real situations, and this is proven by the case study that is based on the real data of the COVID-19 pandemic in the relevant period of time.

This validation shows that this model is adequate in identifying early signs of disruption so that the managers in charge of manipulating op and cost in the supply chain are ahead of the situation and not behind it. In the future, several areas for future work are suggested to extend the scope and flexibility of the presented system. First, the model can be extrapolated to incorporate multimodal transportation data, including information on transport by air, sea, rail, and last-mile delivery, to enhance the performance of predictions throughout the entire transport system. Second, the learning of optimum response strategies could be integrated into the system to enable it to readjust to the given supply chain situation as time goes by. Third, the creation of interactive dashboards and visualization tools can enhance accessibility and the experience of users who will be able to interpret information and take informed steps with ease as supply chain professionals. These would be future extensions to the existing framework, forming a more intelligent, flexible, and user-friendly platform that can address the complex requirements and needs of next-generation supply chain ecosystems.

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