

LEVERAGING ARTIFICIAL INTELLIGENCE FOR ENHANCED FORECASTING IN PROCUREMENT OPTIMIZATION

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ABSTRACT

The innovative capacity to improve forecasting skills in procurement optimization by utilizing artificial intelligence. Coordinating state-of-the-art AI computations with forward-thinking analysis emerges as a clear benefit in the rapidly evolving procurement landscape. The purpose of this article is to compare computer-based intelligence with conventional measurement approaches and demonstrate how much Artificial Intelligence may be used to improve forecasting abilities in procurement. This article simultaneously presents the standard for the Quicken exploration project. This article uses artificial intelligence to measure customer orders in medium-sized businesses. Precise measurements are essential for businesses. for planning, guiding, and managing. Estimates are used, for instance, in the development, purchasing, and retail network sectors. Medium-sized businesses face major challenges when it comes to applying the right tactics to advance their forecasting capabilities. Organizations often use tried-and-true tactics, such as the ARIMA calculation and old-fashioned metrics. In any event, when applied to complex non-straight expectations, simple measurements often yield disappointing results. The initial results demonstrate that even a simple MLP ANN outperforms traditional measurement techniques in terms of performance. Additionally, the exhibition was evaluated using the organization's gauge, the

Understanding Deals Assumption. This correlation further demonstrates the superiority of the suggested simulated intelligence approach.

Keywords: *Leveraging, Artificial Intelligence, Enhanced, Forecasting, Procurement Optimization*

1. INTRODUCTION

Procurement processes are held to high standards in the highly complex, unstable, and interconnected business environment of today. Due to the challenges posed by rapidly shifting economic conditions, organizations are increasingly turning to artificial intelligence, or "man-made intelligence," as a remarkable tool for enhancing forecasting and streamlining procurement processes. Traditional forecasting methods often fall short in capturing the complex aspects of global supply chains, supplier relationships, and the multitude of variables influencing procurement decisions. The core component of technological advancements in artificial intelligence is the promise to transform how businesses anticipate and respond to the intricacies of demand, supply, and market dynamics.

Artificial intelligence advancements bring a new level of complexity to forecasting capabilities in the procurement arena. Unlike traditional methods, artificial intelligence-driven systems can process massive amounts of data over time, sorting important events from those that could otherwise be stored away. Artificial intelligence (AI) computations, a subset of simulated intelligence, enable procurement specialists to identify patterns, connections, and anomalies within informational sets, utilizing a more sophisticated understanding of provider characteristics and market behavior. This logical depth helps organizations to go beyond responsive leadership and promotes a proactive approach to procurement, which is essential for examining the weaknesses of the global commercial hub.

Furthermore, the integration of artificial intelligence into forecasting seamlessly adapts to the ongoing trend of sophisticated change in the procurement domain. As organizations come to understand the critical value of information, artificial intelligence emerges as a fundamentally powerful tool that provides an advantage in the efficient management of supply chains. Insightful computerization enabled by simulated intelligence not only increases forecasting operations' accuracy and speed, but also enables procurement teams to focus on crucial navigation. Essentially, forecasting powered by artificial intelligence becomes the

cornerstone of a wider automated approach, positioning organizations to thrive in an era where adaptability and promptness are critical.

The basis for an extensive analysis of the specific components and advantages associated with the integration of artificial intelligence into procurement optimization. It emphasizes the necessity for associations to accept artificial intelligence as a revolutionary force in examining the complexities of modern procurement, with its potential to transform forecasting processes and maintain the adaptability of the store network across the board in a continuously evolving business landscape.

2. LITERATURE REVIEW

The work of A. D. Fiore (2018) examines how artificial intelligence, or intelligence created by humans, is progressing in dynamic cycles within associations. According to the author, computer-generated intelligence is pushing traditional navigation from the back burner to the foreground. The article highlights how artificial intelligence advancements are encouraging workers at all levels to make more informed decisions by delving into real models and contextual investigations. Fiore's experiences provide an important perspective on the possibility for computer-based intelligence to democratize dynamic and to foster a more nimble and adaptable hierarchical culture.

A. Nandan's thorough analysis of artificial intelligence (AI), deep learning, and computer-based intelligence (edureka!) in 2019 is a helpful resource for understanding the nuances and distinctions between these important developments. The article explains the fundamental concepts, uses, and implications of artificial intelligence (AI), profound learning, and man-made intelligence. The explanation of terminology and basic understanding provided by Nandan's work are important for experts, professionals, and enthusiasts venturing into the field of artificial intelligence. It is an essential resource for anyone wishing to delve deeper into the nuances of these interrelated subjects because of its well-organized and accessible information.

"The Universe of Tomorrow: How the Following Modern Unrest Will Change Our Lives in General," interpreted by E. Brynjolfsson and A. McAfee, Plassen, (2014), provides a forward-looking analysis of the cultural implications of the impending modern upheaval. The authors explore the profound shifts brought about by innovation, such as robotization and

artificial intelligence, and they offer recommendations about several aspects of human life. Based on a thorough analysis, the book provides a thorough understanding of the potential disruptions and opportunities that the next modern insurgency may present. The work of Brynjolfsson and McAfee serves as a thought-provoking resource for understanding the wider cultural implications of artificial intelligence and its role in shaping our future.

Min, H. (2010) In this unique work, Min explores the potential applications and plausible setups of artificial intelligence (AI) in the field of production network management. The article provides a thorough overview of the combination of artificial intelligence techniques, such as AI and optimization calculations, to handle challenges with production network planning, forecasting, and navigation. Min's analysis serves as a primary source of information for comprehending the potential impact of computer-based intelligence on enhancing the effectiveness, readability, and adaptability of store network operations.

IfM Bonn (2019) The IfM Bonn explains the definition of Mittelstand, a concept deeply ingrained in the German corporate environment. Mittelstand refers to small and medium-sized enterprises (SMEs) as a vital component of the German economy, assuming a crucial role in propelling financial development and development. This resource from IfM Bonn clarifies the characteristics and meaning of Mittelstand, which is essential for placing discussions on how innovations—including artificial intelligence—are received inside the SME system in perspective.

In 2019, M. Hänlein and A. Kaplan: A comprehensive account of the history and evolution of artificial intelligence, or computer-based intelligence, is provided by Hänlein and Kaplan. They cover everything from the technology's plausible origins to its modern uses. The piece covers real-world accomplishments and provides tidbits of information on the present and potential futures of artificial intelligence. The authors contribute to a more nuanced understanding of the more widespread implications and possible cultural repercussions of simulated intelligence by examining the advancement of man-made intelligence advancements and its reconciliation into various enterprises. For individuals seeking a well-rounded perspective on the various aspects of simulated intelligence within the context of executives and business strategy, this study serves as a valuable resource.

3. STATE OF THE ART

Future interest rate forecasting, even with the greatest of caution, may have significant financial value. An inaccurate estimate might have a lot of negative effects. If the request is denied, revenue will be lost because special orders cannot be fulfilled. Inaccurate request evaluation may result in excess inventory, fixed capital, and stockpile expenses. As a result, one should avoid the two scenarios.

When it comes to predicting techniques, scientific advancements differ greatly from those being made in industry. While most firms use factual and critical forecasting methodologies, such as Autoregressive incorporated moving normal (ARIMA). For these and other purposes, Artificial Brain Organizations, or Ann's, have been used in study since the year 1000. Man-made intelligence forecasting techniques have been gradually making their way into the strategic plans of large corporations for a long now.

The following are the main reasons someone would want to start practicing:

- **Big Data** –The cost of storing vast volumes of data is coming down as the amount of data is growing quickly.
- **AI Democratization** –AI techniques are made more readily available through packages like TensorFlow, which lowers the complexity barrier to using them.
- **Low-cost computing power** – Simple applications can be computed on nearly any computer because to the ongoing advancements in computing power. AWS (Amazon Web Services) and other flexible cloud computing services lower the high investment requirements of businesses in their own data centers.

According to several analyses, medium-sized businesses view digitization as a major trend, but their execution of the strategy differs greatly from that of large corporations.

It raises the question of why, in particular, medium-sized businesses haven't yet adopted cutting edge forecasting techniques like artificial intelligence. The reasons for this are multifaceted, but they ultimately boil down to central specialized weaknesses in the IT framework, the lack of a computerized system, mental barriers to advancement, and a shortage of skilled IT workers.

Thus, the Vitalize exploratory project aims to assist small and medium-sized businesses in implementing artificial intelligence. As a result, the focus of this next section is on how artificial intelligence is portrayed as a cutting-edge method of forecasting.

3.1. Description of the currently used methods in the field of forecasting

A brief analysis of the current forecasting methodologies used by corporations is provided. Organizations today really use crucial forecasting tactics in view of involvement rather than quantitative techniques, according to studies conducted with organizations.

Studies have shown that quantitative approaches are superior to critical approaches in terms of ideality and accuracy. Furthermore, it has been demonstrated that human tendencies—such as inconsistent behavior, an inclination to overestimate, and living in a fantasy world—have an impact on the assessment of figures.

The usefulness of these tactics for businesses relies on how widely they have been applied over a long period of time and how much businesses value them above artificial intelligence methods. The conventional factual approaches have a vast array of possible applications and can produce reliable results. These approaches are obviously constrained and fail in complex applications since they rely on linear connections. Artificial intelligence techniques, akin to brain networks, achieve significantly better outcomes because they are able to recognize intricate non-direct causal relationships.

The introduced tactics have all been validated previously, but due to the incredibly resilient advancements in programming, innovation, and analysis, companies now have new and improved avenues to direct predictions. Generally, it can be said that companies' ongoing plans are something that can be practically worked on. Organizations should always improve and modify their methods based on the importance, influence, and conditions of sound hypotheses.

3.2. Artificial Intelligence for forecasting purposes

The traditional definition of artificial intelligence includes the additional subfields of machine learning and deep learning, as shown in Figure 1.

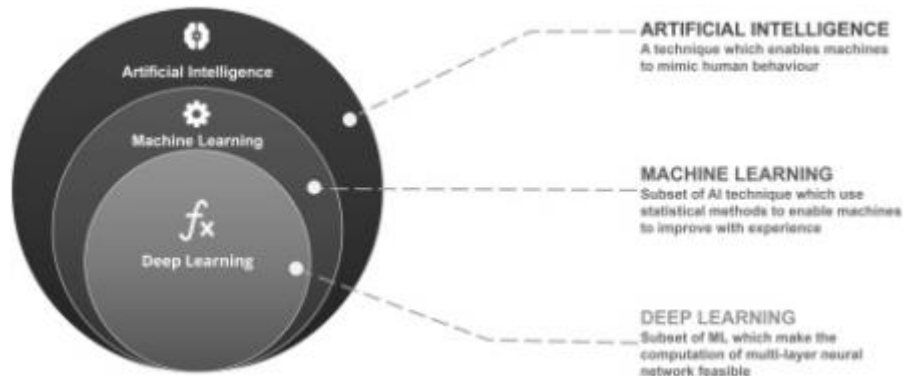


Figure 1: Deep learning, machine learning, and artificial intelligence

AI gives robots the ability to learn from their experiences. By adapting to new data sources, the machines are able to perceive designs in them and process large amounts of information in a manner similar to that of a person. Artificial intelligence has a subset called machine learning. It gives the robots the ability to learn and build expectations based on their experiences (data). ML makes use of explicit computations such as Numerous Direct Relapse and Gullible Bayes. A branch of machine learning called deep learning is motivated by the practicality of human synapses. All it does is take the information associations among all artificial neurons and modify them in accordance with the information design. If the informational index is complex and non-linear, then additional neurons and layers are needed. It provides learning at multiple levels of reasoning naturally, allowing a framework to learn intricate utilitarian mappings without being constrained by a particular computation. Various brain network architectures are used, such as Convolutional Brain Organizations for image processing.

Over 5,000 scholastic distributions have been ranked by ISI (Global Science Ordering) in the subject of man-made intelligence forecasting, demonstrating the growing interest of man-made intelligence in forecasting.

Zimmermann has shown that ANNs are particularly appropriate for solving nonlinear problems with a large number of parameters. They extend the capabilities of standard methods for direct polynomial math, which make sense for the organization of linear conditioning structures with a large number of direct factors, and the methods for

indispensable and differential analytics, which make sense for the organization of nonlinear conditioning structures with a small number of factors.

ANNs are therefore particularly suitable for conjectures of time series and complex, non-straight, but also direct conditions. The truths discussed earlier are illustrated in Figure 2.

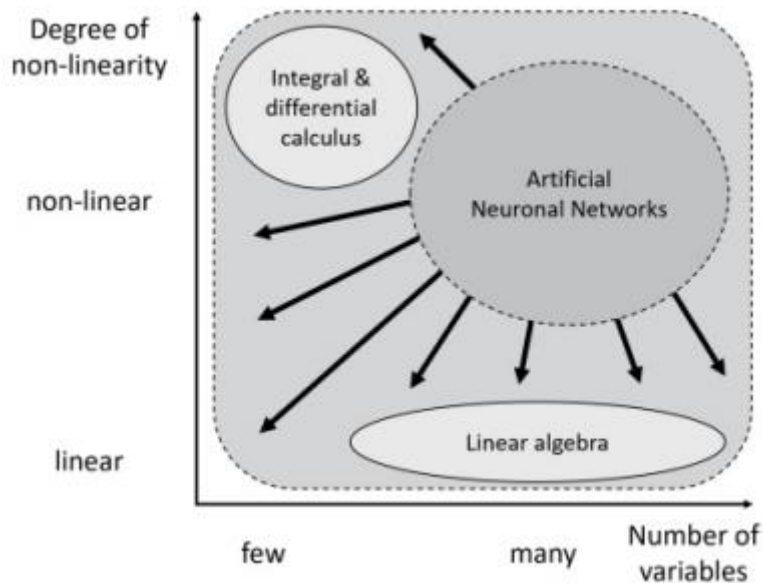


Figure 2:Application domains for artificial neural networks

Recently, neural organization-based computations have gained immense popularity and are the main focus of artificial intelligence. Artificial Neural Networks (ANN) are data-handling frameworks composed of multiple simple elements. They can be altered individually, or preparation and visualization can be done using an ANN system that is already in place. The usage of ANN is also generally relevant in initiatives because of the abundance of freely or almost free projects that can be used by people without a lot of experience in software programming.

Artificial intelligence can be used in a variety of areas, such as customer loyalty, executive forecasting of customer flights, credit board financial soundness checks, scale gauge swapping, advertising for deals and request forecasting, controlling for early notice, or energy supply, load estimates, power cost conjectures at day-ahead power costs, and CNC turned part cost prediction based on specialized drawing.

Figure 3 (attached) depicts an Artificial Neural Organization.

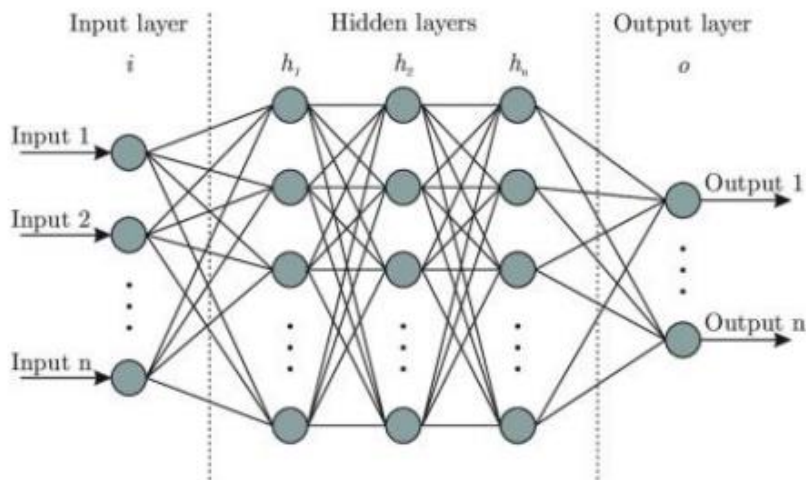


Figure 3:Architecture of Artificial Neural Networks

The result layer, the secret layers, and the information layer make up the organization that is displayed. The network that is displayed includes multiple hidden layers, indicating that it is a purported Deep Learning entity.

The Vivify research project's significant potential for artificial intelligence to produce visuals is illustrated in the section that follows.

4. SOLUTION APPROACH

The REIFF Gathering has a number of challenges. The company works with a wide range of customers in different industries and on a variety of products. Administration is regarded as a very important component. As such, increasing stock levels and reducing client delivery times are very desirable to REIFF.

The methodology for integrating an Artificial Neural Organization into the Quicken research project is explained in greater detail in the accompanying design in the accompanying section.

The exploring interaction is introduced first. The clarification of the objective figure, the information structure, and the model preparation process come next. The model engineering and its limitations come next. Finally, the capacity to forecast is evaluated.

4.1. Research Process

The REIFF team provided the review team with stock counts on a monthly basis as well as all incoming requests from 2008 to 2019. The data was used to develop and test machine learning calculations that speculate on the interest of item groups and industry areas after it was combined from multiple.csv information documents into a SQL information base.

To examine how closely the application forecasted with the usual, a pattern was placed. The mid-term and transitory estimations isolate the extent of the forecasting. The midterm statistics focus on time periods ranging from three months to six months for different types of items. Brief speculations revolve around determining the unique goods' interest on a fourteen-day basis. The first step in implementing the center term gauges was to create a Multi-LAYER perceptron (MLP) using the data provided by REIFF and a few external variables.

In addition, through a number of arbitrary master meetings, we will investigate the current business cycles of REIFF in order to conceive how a simulated intelligence application could be integrated into the standard business procedures.

4.2. Explanation of the target forecast

Eight branch divisions, such as drive innovation, water power, fixing innovation, plastics, and so on, make up the current information structure. Deals mostly consist of the number of orders placed and the items that are sought on a monthly basis. A consistent mid-term assessment of the deals of the internal components of REIFF is made in the first step. The project manager from the partner company REIFF brought up the medium-term estimate. This stands for the related challenges. Currently, medium- to long-term conjectures at the item level ($n > 140,000$) are challenging to carry out due to the lengthy estimate time frame and the vast number of completely different things and consumers.

Mid-to long-haul gauges are therefore recognized at the branch level. We shall continue to increase the momentary statistics at the item level as long as the mid-term estimations at the branch level are carried out with a sufficient error rate. This relationship between short-term, medium-term, and long-term estimations is depicted in Figure 4.

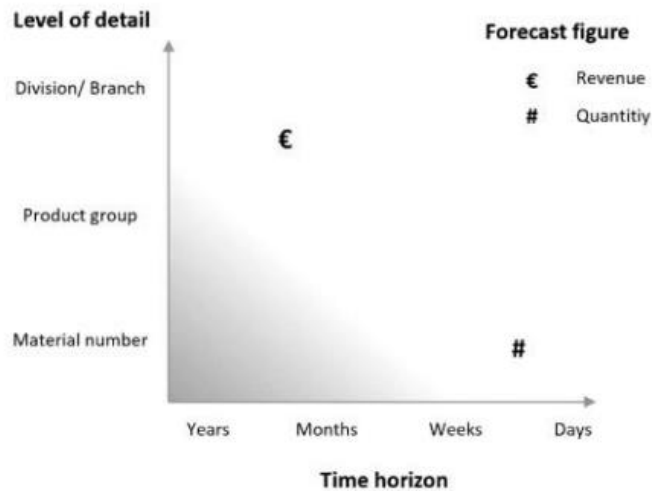


Figure 4:A comparison of the temporal horizon for forecasting

The chart is intended to illustrate the need for a very short time frame skyline gauge that contains the most notable data content at the lowest detail level. Therefore, it is possible to make an industry-level conjecture about a fundamentally longer gauge period.

4.3. Structure of the data

The information structure is currently analyzed for a superior receiving it, as this contributes to the estimate (yield). When ML and DL computations can leverage a massively compliantly marked data layout, they perform optimally. However, in real-world situations, information consistency and accessibility are put to the test because informational collections are often incomplete or boring.

The information structure is essentially divided into branches, such as drive innovation, hydrodynamics, fixing innovation, plastics, and so forth, as it is currently referred. The client request includes information about the request, including information about the client, branches, organized item, amount, and so on. We handle all of the client orders beginning in 2008 and the stock quantities on a month-to-month basis.

We will receive regular updates during the task period, which suggests more up-to-date data on upcoming quarters as well.

In addition to the REIFF data, the following external data has been included: ifo Business Environment Record, De Statis financial data, and Google Patterns (using catchphrases such

as "PVC," "REIFF," or customer names). A Python script then compiles this data into a single.csv file. Next, the data is pre-processed using the machine learning library and Standard Scaler technique. After determining how to normalize the data, Sk learns to use the Min Max-Scaler to rescale the data to values between 0 and 1.

4.4. Training structure

The information explained above is used in the neuronal organization preparation process. It should be emphasized that a moving cross approval preparation technique (Time Series Split) has been used in place of an antiquated preparation strategy. The informative index is often randomly divided into a preparation set (80%) and a test set (20%) when using an outdated preparation method. The model has always been close to the entire preparation set.

The preparation set (80%) is divided once more into preparing information and approval information using the time series split technique. The test set (20%) is used in a subsequent evaluation. Iteratively, the model is built with an increasing amount of data. This benefits from the reduced opportunity of a hastily created "basic" informational index or division. In addition, the effects of overfitting make the model less helpless.

This is a preparatory technique that is very helpful for time series expectation since time series predicting and demonstrating are fascinating and challenging. Techniques for cross-approval should be applied to improve model quality and reduce potential overfitting. A type of k-overlap known as "Time Series Split" yields the (k+1) crease as the test set and the first k folds as the train set. The idea behind the Time Series Split is to divide the preparatory data into two halves.

Every emphasis uses the preparation set to get the model ready, and at the same time, a portion of the set is used directly for approval, providing information that the model hasn't yet used.

For example, it is typical to anticipate that the model is built using data from January through spring. The anticipated month of April serves as approval. The model is developed using the months of January through April in the upcoming cycle, and it forecasts the approval of May. A schematic representation of the preparation strategy is provided in figure 5.

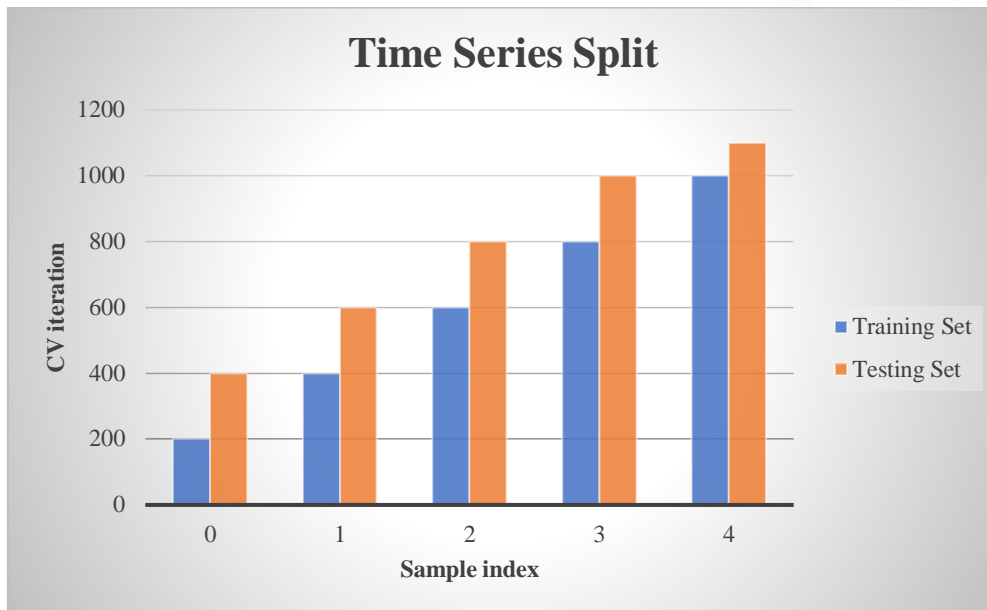


Figure 5:An example of a rolling time series split diagram

4.5. Model architecture and parameters

First, a Diverse Perceptron (MLP) model organization design is attempted. The neural organization is built using the Python programming language and the open-source scikit-learn module. The pre-owned capability/class goes by the significant name sklearn. neural_network. MLP Regressor.

The model has an information layer, a result layer, and three secret layers with 500, 100, and 10 neurons apiece. ReLu, an enactment capability rectifier, is employed. Adam is used to optimize stochastic goal capabilities based on slope.

4.6. Outcome and Evaluation

The neural organization is compared with conventional forecasting methods and a pattern that addresses the presentation of REIFF in order to evaluate the quality of the model. The stockroom stocks are used to measure deals assumptions because there is currently no clear deals arrangement. This is how the REIFF benchmark is established.

$$I = \frac{s[\text{€}]}{p[\text{months}]} \quad (1)$$

We apply SARIMA and direct relapse as representative figure approaches. Root Mean Square Error (RSME) and Coefficient of Assurance (R^2) are used to analyze the correlation between the methods.

The following table 1, which takes artificial intelligence into account, illustrates the techniques' results (the MLP ANN is indicated by the line that is black).

Table 1: Comparing various R^2 and RMSE values for several models

Model	RSME	R^2
Baseline	99 k€	80%
Lin. Regression	88 k€	89%
SARIMA	137 k€	72%
MLP ANN	46 k€	97%

To provide a better understanding of the visualization quality, Figure 6 visually introduces the actual trades and the MLP ANN gauge for 2018.

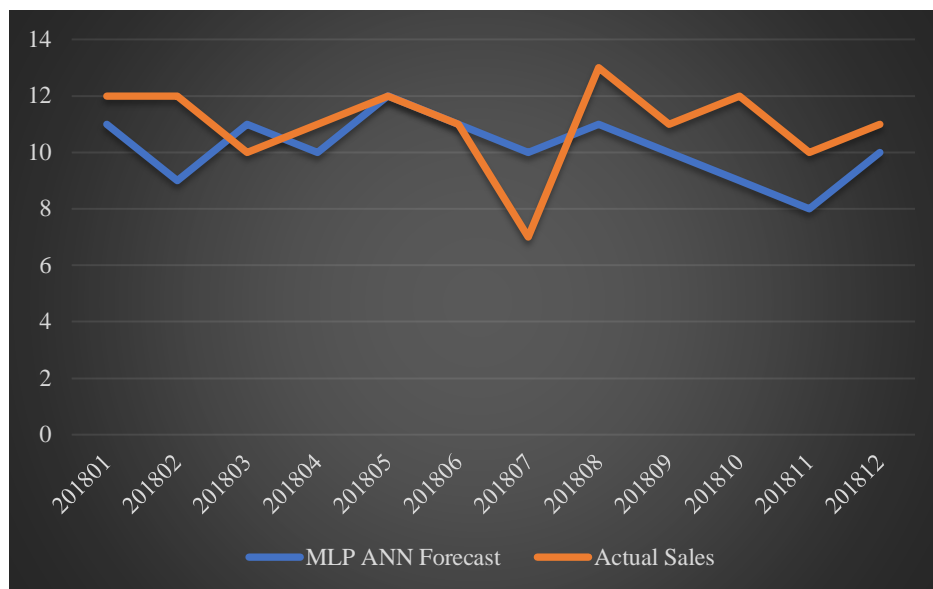


Figure 6: A comparison between the 2018 sales figures and the MLP ANN prediction

The sketch demonstrates that the MLP ANN's patterns are essentially the same as those of the current transactions. However, it is also evident that the line separating supposition from

factual knowledge need to be drawn sooner rather than later. Furthermore, the July exception was misidentified by the ANN. A vacation period could explain the real exception.

In conclusion, it's common to say that gauges are the field where artificial intelligence has its strongest protection.

From one point of view, compared to traditional static methods, the MLP ANN could produce better outcomes, such as more precise conjectures (see Table 1). In addition, the result isn't yet satisfactory. It is anticipated that additional research will improve the result. The first is to expand on the informational premise. Building the amount of information using insider knowledge from REIFF is one aspect of this. External details, including occasion periods, are added concurrently. Other deep learning architectures are also being tested, such as the convolutional neural network Channel Net.

5. CONCLUSION

The integration of artificial intelligence (AI) with procurement optimization to improve forecasting is a major advancement in modern business practices. The procurement scene is rethought by the innovative capabilities of computer-based intelligence, which are demonstrated by their accurate calculations and foresightful investigation. These capabilities give unparalleled experiences and precision. Associations can investigate the complexities of dynamic business sectors, provider connections, and internal activities with exceptional readiness by using artificial intelligence-driven arrangements. The critical application of intelligent automation and machine learning streamlines forecasting procedures and empowers procurement specialists to make data-driven, well-informed decisions. This increases the store network's overall strength and improves its functional efficacy. As businesses increasingly recognize the critical value of information in the digital age, using AI to improve forecasting becomes essential to staying competitive, fostering adaptability, and ensuring supported outcomes in the expanding global marketplace.

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