A Comprehensive Review on the Role of EL-ANFIS in Shoe Demand Prediction and Supply Chain Efficiency

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Abstract: The study gives a wide-ranging review of Enhanced Adaptive Neuro-Fuzzy Inference Systems' (EL-ANFIS) role into modeling shoe demand and its corresponding supply chain. Demand forecasting remains vital for production, inventory, procurement, and distribution optimization in an industry that is undergoing dynamic changes from the very influences of consumer preferences, fashion trends, and seasonal changes. Unfortunately, due to the very complications in the markets of today, traditional methods of forecasting are no more sufficient. Thus, today's advanced technologies such as EL-ANFIS can help. Neural networks' adaptive learning and AIFs fuzzy logic reasoning are synergistically applied in EL-ANFIS to obtain great results in prediction with respect to noise and multidimensionality in data. This paper discusses the architecture of EL-ANFIS, its improved computational efficiency, convergence speed, and fuzzy rules' dynamic modification using genetic algorithms and particle swarm optimization for optimization algorithms. Comparisons are made between EL-ANFIS and traditional ANFIS and other AI forecasting methods, including ANN, SVM, and XGBoost. The study discusses how effectively the demand variability is managed with the EL-ANFIS to mold the supply chain efficiencies and consequently lower inventory holding costs, curb stockouts, and enhance the customers' satisfaction level. It also discusses the obstacles, including the high computational burden and possible overfitting, and gives directions for future studies aimed at enhancing EL-ANFIS applicability in SCM.

Keywords: Enhanced Adaptive Neuro-Fuzzy Inference Systems' (EL-ANFIS), XGBoost, ANN, SVM, Artificial Intelligence (AI), Machine Learning (ML), Long Short-Term Memory (LSTM).

I. INTRODUCTION

Demand forecasting is an essential process in the supply chain management whereby the future customer demand for a given product or service is estimated, thereby enabling the organization to make informed decisions concerning production, inventory management, procurement, and distribution. A proper estimate of customer demand allows businesses to better match their supply chain operations to serve the marketplace through a reduction in excess inventory, reduction of stockouts, reduction of operational cost, and enhanced customer satisfaction. The reduced forecasting demand is the platform for wider applications such as resource allocation and strategic planning for the entire supply chain [1]. Traditional demand forecasting methods are not sufficiently competent to compete against the complexities and myriads of demand patterns that are now present in an all-encompassing competitive and dynamic market environment. For this reason, the demand for advanced technologies, namely Artificial Intelligence (AI), Machine Learning (ML), and hybrid models such as Enhanced Adaptive Neuro-Fuzzy Inference Systems (EL-ANFIS), is ever-increasing. These intelligent systems have the capability to analyse huge datasets, identify hidden patterns, adapt to real-time changes, and provide accurate and highly responsive forecasts. In a nutshell, strong demand forecasting enhances supply chain resilience while improving overall business performance and sustainable development [2].

A. Importance of Demand Forecasting in the Footwear Industry

As to footwear demand forecasting, it is highly vital within this industry because the industry is extremely dynamic, experiencing a lot of changes due to consumer demand, fashion trends, seasons, and promotional cycles. Footwear brands and retailers must, therefore, not only predict the total number of units to produce, but also anticipate the relevant styles, colours, and sizes to be in demand at that time and place. Accurate demand forecasts will enable businesses to draw production, sourcing, and distribution plans geared completely toward the real market needs-ensuring goods are available at the right place and at time [3]. All organizations should forecast well or else they end up overproducing, thus incurring huge holding costs, forced discounts, and wastage, or underproducing, which translates into lost sales opportunities and dissatisfied customers. Furthermore, the proliferation of diversified consumer expectations in the contemporary world and increasing demand for personalized footwear make forecasts even more complex and ever important [4].

Forecasting becomes a strategic weapon for an effective supply chain plan and a risk management tool concerning global supply chains with long lead times involved in producing most footwear products outside of the country. Over the last few decades, the industry has been moving toward fast fashion and shorter product life cycles, thus requiring quick responses to market signals and consequent adaptations of the corporation's processes [5]. Advancements in forecasting techniques using Artificial Intelligence (AI) and machine learning models like Enhanced Adaptive Neuro-Fuzzy Inference Systems (EL-

ANFIS) enable businesses to create historical stock sales analysis, differentiate existing patterns, and read external influences such as seasonality or marketing campaigns into the model to make highly accurate and data-driven predictions. These are just some of the benefits of improved accuracy in forecasting that eventually leads to waste reduction, optimized inventory turnover, enhanced profitability, and increased customer loyalty to give the footwear industry an advantage in a crowded, fast-paced market [6].

B. Role of AI and EL-ANFIS in Modern Supply Chains

The trade market's expanding globalization has led to an increase in the number of supply chain links, which has made supply chain operations more intricate. Supply chain management is using machine learning (ML) and artificial intelligence (AI) more and more to help handle these intricate procedures. As supply chain data becomes more accessible, artificial intelligence (AI) and machine learning (ML) are becoming crucial tools for effectively managing and utilizing this data. Studies and applications have demonstrated that AI and ML have the potential to completely transform supply chain management by automating the process of making decisions in a variety of circumstances. One innovative method of streamlining supply chain operations is to combine AI and ML technology. Making decisions that maximize the flow of commodities from the supplier to the final consumer requires forecasts, estimations, and predictions.

II. AI TECHNIQUES IN SHOE DEMAND FORECASTING AND SUPPLY CHAIN OPTIMIZATION

Predicting demand is a crucial component of a company's optimal economic development in an increasingly international market, where global container traffic has nearly doubled since 2000. Estimating the demand for footwear during the interseason is challenging due to the market's extreme volatility and several features, including seasonality, culture, and fashion trends. AI-generated predictions provide business professionals with the ability to organize the purchase of materials, manage production processes and stock quantity [3]. By supporting decision-making duties and assigning them to software systems, artificial intelligence (AI) approaches have been applied in fashion retailing and e-commerce, offering considerable competitive benefits. Personalizing and improving customers' shopping experiences, analysing data, forecasting trends, and controlling fashion supply chains to some degree have all benefited from the high caliber and diversity of information produced by AI approaches, such as machine learning algorithms, for customer modeling [4]. Demand management and demand growth are the two main goals of every demand planning organization. Using target marketing is one strategy to bring in new, lucrative clients. Here, AI is utilized to find targets using techniques like data mining, machine learning, and predictive analytics. The sociodemographic traits and purchasing patterns of high-value clients can be identified by machine learning using the training data. These characteristics allow us to identify and target individuals who are most likely to become clients,[5].

AI can provide quick and thorough insights into every aspect of the supply chain, facilitating proactive decision-making, thanks to its ability to gather and analyse vast amounts of data from many sources. Additionally, by automating repetitive processes like demand forecasting, inventory management, and route optimization, AI can enhance supply chain efficiency. Automation lowers human error and frees up human resources for strategic projects involving complicated decision-making and creativity [6].

A. Traditional vs. AI-Based Forecasting Methods

In the past, companies have forecasted demand using conventional statistical techniques. Models like linear regression, ARIMA, exponential smoothing, and moving averages have gained popularity because of their interpretability, simplicity, and convenience of use. However, these models' assumptions of linear and their incapacity to deal with complicated, high-dimensional, and non-stationary data frequently limit them. These constraints become more noticeable when datasets increase in size and complexity and markets become more volatile. Demand forecasting, on the other hand, has been transformed by the development of artificial intelligence (AI) and machine learning (ML) techniques. Neural networks, decision trees, and ensemble approaches are examples of AI-based models that are excellent at identifying non-linear relationships and adjusting to changing patterns in big datasets. These methods offer unparalleled accuracy and scalability, particularly in scenarios where traditional models struggle. For example, deep learning models like Long Short-Term Memory (LSTM) networks have demonstrated exceptional performance in time-series forecasting by leveraging their ability to retain and process sequential data over time [7].

B. Overview of Common AI Models (ANN, SVM, RF, etc.)

I. Random Forest

A single forecast is produced by combining the output of numerous regression trees using the ensemble technique known as RF. Bagging, which involves randomly selecting a sample of training data and fitting it into a regression tree, is the main principle. A bootstrap sample can be created by randomly selecting N data points from the dataset and then replacing them with the data points that are already there. The probability of selecting any data point is 1/N. Decision tree estimators are combined in RF, where each decision tree is computed using the results of a randomly selected vector {} that is equally distributed among all of the decision trees in the forest. Following training, the average of all the decision tree results on sample X′ is used to produce predictions, as indicated by Eq. (1).

$$\hat{f} = \frac{1}{k}\sum_{i=1}^{k} h(X', \Theta\mathrm{k})$$

(1)

where is the final prediction and k is the number of decision trees [8].

II. SVM

Support Vector Machines (SVMs) can be used to create demand forecasting frameworks. The support vector machine algorithm aids in a deeper comprehension of the difficulties, including demand variations and market uncertainty. SVM-developed models provide real-time analysis, minimize revenue loss, reduce operational efficiencies, and guarantee on-time delivery, all of which raise customer satisfaction levels. As part of a real-world case study, a model is created for demand analysis in the piston manufacturing business using the Support Vector Machine technique. Python, a sophisticated computer language, is used to implement this machine learning technique. Encouragement in addition to regression, vector machines can be used for classification challenges. Some terms that are used in support vector regression are [9]:

- **Kernel:** This function converts lower-dimensional data into higher-dimensional data.
- **Hyper Plane:** With the use of provided inputs, the plane in SVR is utilized to predict the goal value or continuous value.
- **Boundary line:** These lines, which form a margin that determines which data points are support vectors, are on either side of the hyperplane.
- **Support vectors:** These data points are the ones that are closest to or inside the boundary line, and their distances are as small as possible.

Based on the structural risk minimization principle, support vector regression easily overcomes the local minimum, accuracy, and generalization performance of an irreconcilable contradiction of neural network technology and performs exceptionally well in supply chain demand forecasting. Support vector regression method shows the smaller results of the relative mean square error, higher forecast accuracy in an instance of the supply chain needs [10].

III. ANN

Multiple nodes, which represent biological neurons, make up an ANN. Links connect those nodes to one another. Every link is given a numerical weight. The main mechanism for storing long-term memory is the linkages and their weights. Information is processed by the network such that a neuron's output can be used as an input by another neuron that is connected to it. The information transmitted across the link is strengthened or weakened by the weights. Learning is the process by which the linkages are positioned, and the weight values are established. An ANN can be trained to discover hidden correlations between the data or to react to different data patterns as we desire. Once the network is initialised, ANN can be modified to improve its performance using an inductive learning algorithm and be trained in either supervised or unsupervised environments [11].

IV. XGBOOST MODEL

Using decision trees as the base classifier, the machine learning integrated learning algorithm XGBoost suggests optimization using the GBDT principle. A technical framework called integrated learning uses a specific combination method to train many weak models to perform machine learning tasks. XGBoost proposes optimization based on GBDT, which has greatly improved accuracy and speed, enabling the model to perform better in big data processing projects [12].

A. Applications of AI in the Footwear Supply Chain

AI has been effectively used in projection and forecasting. Organizations are always keen to balance both supply and demand. Therefore, a better forecast is needed for its supply chain and manufacturing. As AI can process, analyse (automatically) and more importantly, predict data, it provides accurate and reliable forecasting demand, which allows businesses to optimize their sourcing in terms of purchases and orders processing therefore reducing costs related to transportation, warehousing and supply chain administration, etc. In addition, as it discerns trends and patterns which help to design better retailing and manufacturing strategies. As these demand forecasts are so accurate, they do not lose the sale because of product unavailability. Machine learning approaches not only incorporate historical sales data and the setup of the supply chains but also rely on near-real-time data regarding variables such as advertising campaigns, prices, and local weather forecasts. The AI forecasts are so reliable that Otto building its inventory in anticipation of the orders, more interestingly totally relying on AI without any human intervention [13].

III. ENHANCED ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (EL-ANFIS)

Enhanced Adaptive Neuro-Fuzzy Inference System, entirely EL-ANFIS, represents the latest advanced type of hybrid computational model that is supposed to take the adaptive learning fiber of a neural network and merge it with the interpretability and reasoning of fuzzy logic to employ this model in far more appropriate modeling of complex and nonlinear systems as compared to commonly used ANFIS. Different from traditional ANFIS, EL-ANFIS solves many problems like convergence speed, overfitting, and computational efficiency by judiciously optimizing membership functions, augmenting the hybrid learning algorithms (like gradient descent with least squares estimation), and changing or adding to the feature selection techniques to boost performance in high-dimensional and noise-prone data environment [14]. In dynamical optimization of fuzzy rules and parameters with the help of a genetic algorithm or particle swarm optimization, EL-ANFIS was declared to empower prediction, classification, and control applications with more accuracy and robustness predictively than its competitors. This improved architecture addresses several critical concerns in modeling with diverse applications like modeling complex problems in pattern recognition, signal processing, and adaptive control systems where learning from data as well as fuzzy rule derivation for model decision-making are important. The EL-ANFIS framework is thus well equipped for dealing with uncertainties and learning from data whilst interpreting what it means: a very powerful and useful application in areas where precision and transparency are crucial [15].

A. Fundamentals of ANFIS and Its Limitations

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid approach of intelligent systems that learn from neural networks and the reasoning of fuzzy logic-based fuzzy inference systems. Both approaches have advantages over each other because neural networks are responsible for the optimization of fuzzy inference systems for taping the system with complex, nonlinear relationships. Generally, ANFIS is based on the Sugeno-type fuzzy model that maps input data through fuzzy membership functions, fuzzy rules, and output functions to achieve its desired result. In this regard, ANFIS contains internal structure sequences of layers, including an input layer, fuzzification layer, rule layer, normalization layer, defuzzification layer, and output layer. The learning process engages in a classic way of developing a hybrid algorithm of gradient descent and least squares estimation for final fine-tuning of membership functions and rules [16]. However, surveys also show that, despite the merits, ANFIS has issues. The first is that it does not scale well because the computational cost increases exponentially with the number of input variables and becomes infeasible for very high-dimensional datasets. Moreover, the ANFIS standard model is quite sensitive to the noisy and uncertain nature of the data, which can lead to excessive data fitting and reduced generalization capability. It may as well converge slowly because of local minima, especially when utilizing the gradient descent method. Another limitation is that of the manual initial parameter selection, which has a great effect on the performance and should ideally be done with full knowledge in the subject. Finally, ANFIS cannot automatically generate and optimize fuzzy rules, thus frequently requiring predefined rules that may not suffice to represent all real complexity scenarios in the real world. These factors have led to further versions being developed, such as the EL-ANFIS for the better design of computational efficiency, the convergence speed improvement, and higher robustness in various application areas [17].

B. Architecture and Features of EL-ANFIS

Enhanced Adaptive Neuro-Fuzzy Inference System (EL-ANFIS) has been developed to strengthen functionality over traditional ANFIS by embedding it with advanced optimization techniques and adapting it with mechanisms focused on the fuzzy-neural framework. Generally, like every ANFIS, EL-ANFIS architecture has several layers including the input layer, fuzzification layer, rule layer, normalization layer, defuzzification layer, and output layer. The most conspicuous improvement is the continuous adaptation of fuzzy rules and membership functions which optimize fuzzy parameters using evolutionary algorithms, such as genetic algorithms (GA) or particle swarm optimization (PSO), to improve both accuracy and convergence speed [18]. Also, EL-ANFIS introduces and applies superior learning algorithms like hybrid optimization that combines gradient descent with metaheuristic approaches as a remedy for local minima problem and improved learning efficiency. Another great ability of EL-ANFIS is to create estimation models based on its dimensions or dimensionality reduction techniques or feature selection methods, to reduce complexity of computation and overfitting. The parts of the system include several robustness mechanisms to noise and uncertainty within the data for providing better generalization and stability under real-world situations. EL-ANFIS provides an automatic generation and fine-tuning of fuzzy rules based on data properties that adapt such systems even more to complicated problem domains, including pattern recognition, time-series forecasting, and adaptive control systems, where precision and interpretability are important [19].

C. Advantages of EL-ANFIS in Demand Prediction and SCM

The Enhanced Adaptive Neuro-Fuzzy Inference System (EL-ANFIS) possesses tremendous features that can be used for demand prediction and supply chain management (SCM) by employing its advanced learning and fuzzy reasoning for modelling a complex, nonlinear journey. One of the greatest benefits of EL-ANFIS in demand forecasting is that it would accurately give out the demand pattern using huge multidimensional and uncertain data, which is an essential element of effective inventory management and production planning. The system is adaptive; hence, it learns continuously from new data, making it well-suited for dynamic environments that frequently change demand patterns [20]. Besides, adding evolutionary techniques for optimization, such as genetic algorithms or particle swarm optimization, improves the fuzzy rule base and membership functions' precision, leading to more reliable predictions. EL-ANFIS thus enables better decision making in SCM through accurate forecasting of future demand, stocking prevention, and optimization of resource utilization. Modelling the complex interaction of variables, such as seasonal trends, economic factors, and consumer behavior, has also recently paved the way for proactive strategies driven by data in logistics, procurement, and distribution. Also, EL-ANFIS is robust against noise and incompleteness; hence, it finds application in real-world scenarios where the quality of data varies. Thus, EL-ANFIS in demand prediction and SCM will render improvements in the accuracy of forecasting, operational efficiency, cost efficiency, and enhanced customer satisfaction-all crucial attributes of modern supply chain management [21].

IV. CHALLENGES AND LIMITATIONS OF EL-ANFIS IN DEMAND PREDICTION AND SUPPLY CHAIN MANAGEMENT

Despite its considerable advantages and superior performance in comparison to conventional ANFIS, enhanced adaptive neuro-fuzzy inference system (EL-ANFIS) is also faced with a few challenges and constraints when applied to demand prediction and supply chain management (SCM). One major challenge is that the underlying optimization of fuzzy rules or functions becomes computationally challenging when it comes to large datasets that are highly dimensional. The use of advanced optimization techniques like genetic algorithms or particle swarm optimization can certainly promote the accuracy of your model but requires additional processing time and resources. It is also worth noting that the models of EL-ANFIS tend to overfit, particularly when the model grows massive with fuzzy rules or parameters in excess; this means the model will have poor generalization on unseen data. The ability of EL-ANFIS to gracefully handle noisy and incomplete data is already quite limited compared to traditional ANFIS. The very landscapes where one would apply EL-ANFIS often feature inherent data inconsistency and uncertainty, making its fine calibration to withstand such anomaly without sacrificing accuracy rather challenging. Even more, the interpretability of the enhanced model becomes less intuitive as the complexity of the system continues to increase, further hampering practitioners' ability to comprehend the decision-making process. The initialization of parameters and the selection of an optimal structure for the fuzzy inference system still depend upon the knowledge and discretion of the domain expert with the consequent restriction of its practical usability for a non-expert. Finally, a continuous challenge in our dynamically changing environment is keeping the right balance between accuracy and computational efficiency, which is crucial since the model may require retraining at frequent intervals to adapt to new patterns or market shifts. Therefore, these challenges must be addressed to maximize the full potential of EL-ANFIS in practical domain implementations, while it is still a promising technique to enhance demand forecasting and SCM.

A. Performance Evaluation

This study considers the challenge of measuring organizational elements by assigning numerical values to them, given the difficulty of measuring linguistic variables through established methods. To address this, it suggests that soft-computing models like ANFIS can be employed that convert linguistic information into numerical data for better evaluation of organizational performance [22]. The study also proposes an enhanced random forest with a view to making classification more accurate by minimizing correlations among decision trees, thereby performing better than traditional models [23]. Random forest spatial interpolation is also considered as an improvement that includes a spatial dimension, outperforming kriging and other methods in predicting precipitation and temperature [24]. The integration of AI into supply chain management (SCM) is pointed out as boosting the entire SCM operation through predictive analytics [25]. SCM concepts have been observed to evolve, shifting the emphasis from logistics integration to AI-oriented models that Favor emerging technologies [26]. The adoption of fuzzy logic and ANFIS models also fosters sustainability evaluations in exporting companies under the industry 4.0 paradigm [27]. Control of overhead cranes in industrial applications is implemented through FLC and ANFIS, where FLC exhibits robustness under disturbances while ANFIS provides precise control at the expense of robustness against external disturbances [28].

Table 1 Comparative Analysis of Past Studies

Reference	Method	Objective	Parameters	Outcome
[22]	ANFIS and Soft Computing	Proposed a novel method to evaluate organizational efficiency using ANFIS and soft computing models	Linguistic variables, numerical transformation, fuzzy inference	Enhanced accuracy in evaluating organizational efficiency through linguistic-to-numerical data transformation
[23]	Improved Random Forest (IRF)	Developed an improved random forest to address classification accuracy and correlation issues	CARTs, classification accuracy, correlation, cosine similarity, grid search	Achieved higher accuracy and stability compared to traditional RF methods
[24]	Random Forest Spatial Interpolation (RFSI)	Explored spatial interpolation using RFSI and compared with kriging, RFsp, and other methods	Spatial interpolation, nearest observations, distance as covariates	RFSI outperformed RFsp and deterministic interpolation in precipitation and temperature data scenarios
[25]	AI in SCM	Overview of AI and SCM integration, exploring AI-driven supply chain research and applications	AI-based business models, AI solutions, value creation	Identified AI's potential in SCM optimization and proposed business model designs
[26]	SCM Evolution	Analyzed the evolution of supply chain management and its conceptual transformations	Integration of business functions, customer needs, competition between chains	Provided insights into the historical development and transformation of SCM concepts
[27]	Fuzzy Logic and ANFIS in Industry 4.0	Applied fuzzy logic and ANFIS to create a sustainability valuation model for exporting companies	Digital technology, fuzzy logic, sustainability valuation model (SVM)	Enabled sustainability assessment through fuzzy logic, enhancing strategic decision-making in Industry 4.0 contexts
[28]	Fuzzy Logic Control (FLC) and	Evaluated control strategies for overhead	Control accuracy, load sway	FLC showed better stability under disturbances; ANFIS

	ANFIS for Overhead Cranes	cranes using FLC and ANFIS	minimization, system robustness	achieved faster response but was less robust against external factors

V. CONCLUSION

The Enhanced Adaptive Neuro-Fuzzy Inference System (EL-ANFIS) is a considerable step ahead compared with the other forecasting techniques and even standard ANFIS, in shoe demand prediction and supply chain management (SCM). This hybrid approach is characterized in two important perspectives: It fuses the adaptive learning capability of neural networks with the interpretability of fuzzy logic, enabling the modeling of the typical complex nonlinear relationships that arise in the ambivalent environments prevalent in any footwear industry. Conventional statistics, by the very nature of their underlying assumptions, are frail in handling large, high-dimensional, and noisy datasets, and this makes their adoption undesirable. Contrarily, the robustness in prediction displayed by EL-ANFIS is derived from the evolutionary optimization of fuzzy rules and membership functions incorporated in advanced algorithms like genetic algorithms (GA) and particle swarm optimization (PSO). EL-ANFIS works as a strategic advantage to the firm with its capability of giving accurate and real-time forecasts regarding the fast-moving nature of demand in the footwear sector, which is governed by fashion, seasons, and consumer habits. This helps firms administer strategic decisions on production planning, inventory control, and distribution, thus minimizing overproduction or stockouts. Moreover, EL-ANFIS can accommodate the integration of external information such as marketing campaigns or indicators of economic performance, offering refined applicability for precise demand management. Notwithstanding its benefits, some challenges come with EL-ANFIS, which will need addressing. A primary challenge is that of computational complexity, especially in large datasets, which could result in longer process time and resource application. The challenge with more complexity in the configuration of the model was more prone to overfitting while affecting its generalization to other unforeseen data. Interpretability also becomes less intuitive with increasing model complexity, making it difficult to use without the inclusion of domain experts for parameter initialization and model tuning. There has also been an ever-present challenge in balancing prediction accuracy against computational efficiency, considering the quick changes that demand frequent updates of the models. Future studies should concentrate on developing more efficient algorithms to unload the computational burden while retaining the model's accuracy. Hybridizing this further into other machine learning algorithms can boost EL-ANFIS demand explicitly. With these, the field of supply chain management can benefit immensely from the practicality of EL-ANFIS.

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