An AI Enabled Framework for Accurate Shoe Demand Forecasting and Supply Chain Optimization Using Enhanced Adaptive Neuro Fuzzy Inference System (EL ANFIS)

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Abstract: The study examines Artificial Intelligence enabled framework used for sophisticated demand forecasting and supply chain optimization using Enhanced Adaptive Neuro-Fuzzy Inference System (EL-ANFIS). Most importantly, accurate forecasting is a need for effective inventory management, production planning, and disruption of supply chains. The model worked on demand forecasting which collects the past sales data from the years 2016-2019, and fuzzy logic combined with neural networks handling nonlinear, dynamic demand patterns. Implemented in MATLAB using a multi-level approach of collecting data, fuzzy rule-based forecasting, and inventory adjustment forecasting. The model generates weekly forecasts about different sizes of shoes that create a real-time scenario in identifying the gaps with demand and inventories and acts before stocks are lost or sales are lost. EL-ANFIS architecture had around five different layers from which each one contributes to a high-precision outcome for demand prediction using fuzzy membership functions and firing strength normalization and consequent parameter learning activities. Comparative analysis results show that the proposed model reaches an overall accuracy of about 99% and is superior compared to the traditional models of ARIMA and SVM at both runtime and cost-effectiveness in running-on-system criteria while adapting to market changes accompanied by a minimal prediction error. Lastly, the paper demonstrates real-case applicability of this particular model in providing solutions that are scalable and intelligent with respect to the modern challenges in the supply chain not only applicable in the footwear industry but also beyond.

Keywords: Demand forecasting, EL-ANFIS, Neural Networks, Fuzzy Logic, Supply Chain Optimization, Shoe Sales, Inventory Management, MATLAB, AI in SCM, Predictive Analytics.

I. INTRODUCTION

Demand forecasting is perhaps one of the most crucial aspects to supply chain management regarding studying the potential future outcome of past sales volume data and market trend data together with external factors such as macroeconomic indicators, seasonal variations, or changing tastes and preferences of consumers. By combining historical and predictive analytics, the company can align its operations with the required demand and improve production planning, inventory control, and overall resource utilization. Accurate forecasting reduces the degree of stockouts or overstocking and enhances instant customer satisfaction and operational efficiency.

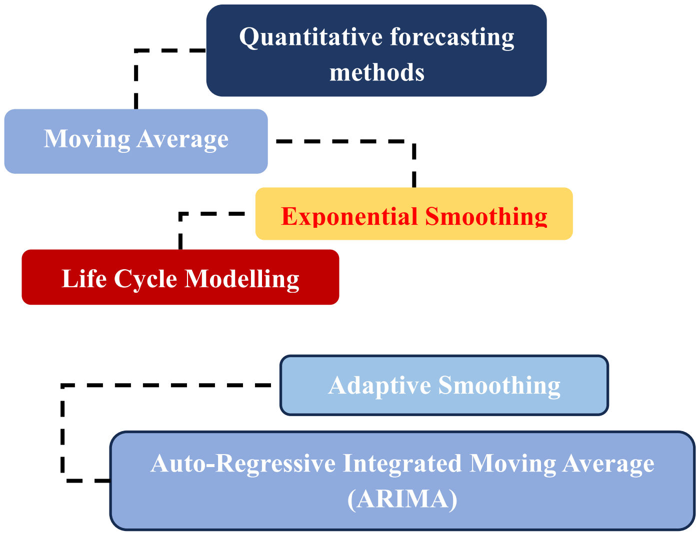

Figure 1 Method of Forecasting

Thus, advanced techniques, like statistical models, machine learning algorithms, and real-time analytics, allow the company to react to market turbulence, hence risk reduction in their supply chains [1][2]. There are generally two classified forecasting ways: quantitative and qualitative methods. Quantitative methods include moving average, exponential smoothing, ARIMA, among others, which forecast future sales volume based on historical sales data. Qualitative methods rely on expert judgment and market insights like the Delphi method and historical analysis where data is scant. Both approaches are equally very important in building a balanced forecast strategy that supports an organization in areas such as product planning, market expansion, and strategic investment, helping to secure that competitive edge when faced with dynamic marketing environments [3].

A. Types of Demand Forecasting

Demand forecasting involves predicting future demand using various methods to support business planning and decision-making. Qualitative forecasting relies on expert opinions and market research when historical data is limited. Quantitative forecasting uses statistical models and historical data for accurate, objective predictions. Short-term forecasting focuses on immediate operational needs using real-time data and AI tools, while long-term forecasting supports strategic planning over months or years with trend analysis and scenario planning. Macro-level forecasting examines broad economic and global trends, and micro-level forecasting provides detailed insights at the product or customer segment level using granular data and advanced analytics. Together, these approaches help businesses stay efficient, agile, and competitive.

1. Qualitative Forecasting

Qualitative forecasting is that technique where the historical data is missing or is not enough. It is based on judgment of experts, market survey, and consumer surveys to predict future demand. A good example is forecasting demand where there is new product launch or entering a market. Some methods apply, such like the Delphi technique, which structures expert insights through several rounds of feedback; while judgment relies on intuitive understanding of professionals regarding market dynamics. These methods allow organizations to remain responsive in uncertain environments and make qualitative forecasting a flexible tool for decision making [4][5][6].

2. Quantitative Forecasting

Unlike qualitative forecasting, quantitative forecasting involves the use of historical data and statistical models to predict demand, yet, thus creating fewer occasions for misconceptions about such predilection and even improving accuracy through its past consideration of trends and use of external elements. Such techniques are good for using time series, moving averages, and regression models to enable strategic planning in inventory maintenance, improving production schedules, and resource allocation that can assist in enhancing the forecasting precision [7][8][9].

3. Short-Term Forecasting

Short-term forecasting refers to the period extending from a few days to a few months. Typically, short-range forecasts deal with operational needs related to inventory, scheduling, and logistics. These forecasts are generated from real-time data and respond to sudden changes in demand or market conditions using such tools as AI, ML, and big data analytics. The most popular techniques regarding short-term forecasting are demand sensing and exponential smoothing. They predict fluctuations on a short time scale and help to ensure the best performance of warehouses and workforce. Thus, integrating ERP systems can provide greater agility in a firm's supply chain and resilience during volatile conditions [10][11][12].

4. Long-Term Forecasting

Long-term forecasts perceive future months to years ahead. Support for strategic plans, such as new capacity, investment in infrastructure, and sustainability, comes from this place. Trend analysis, regression models, and scenario planning are the primary analytical tools that enable companies to understand market shifts, macroeconomic indicators, and technological developments. AI and predictive analytics will also be essential in processing great volumes of data to identify emerging trends through pattern recognition. A good way to cut risks is to use this knowledge to inform supplier contracts and long-term inventory and procurement strategies [13][14][15].

5. Macro-Level Forecasting

This is a study of a macro-level forecast. It studies demand and supply trends, at industry or global level, keeping in mind the economic, political and environment factors indicating how they affect it. It is useful for strategic decisions supporting the governments and multinational firms, since they can prepare themselves for changes resulting from change in GDP, inflationary effects and regulatory changes. Evaluation of future risks and opportunities will be provided with econometric modeling and scenario analysis. All the planning in this way can prepare for flaring up of global crisis and would assist in sustainable practices and investment in emerging markets [16][17][18][19].

6. Micro Forecasting

Micro forecasting is characterized by specific production and customer segment forecasting on an organization level from historical sales, market trends, and behavioural data for accurate demand forecasting. Forecasting techniques basically rely on reducing stockout or overstock situations: moving averages, time series, and machine learning. It is mainly applied in areas such as retail and manufacturing, where it allows demand sensing and real-time decisions. Micro forecasting, on the other hand, is an IoT-and-cloud-based solution that enhances efficiency, responsiveness, and customer satisfaction in fast-changing markets [20][21][22].

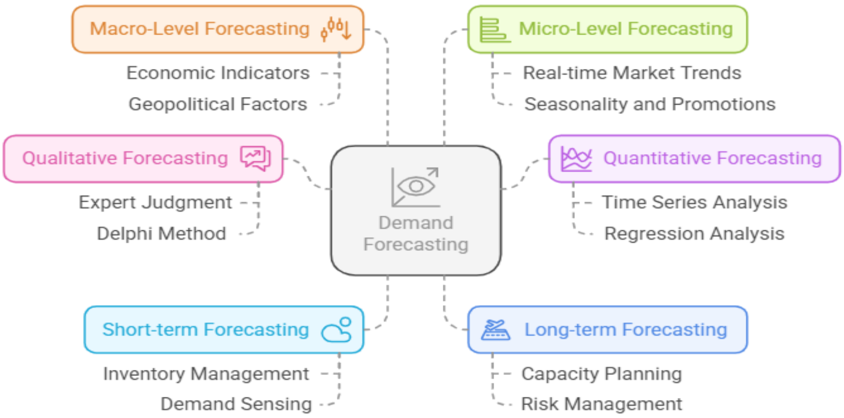

Figure 2 Types of Demand Forecasting

The figure 2 represents the range of approaches to predicting customer demand in the future. The approaches range from macro-forecasting (influenced by economic and geopolitical factors) to micro-forecasting (real-time trends and seasonality). These forecasting procedures can be bifurcated into qualitative ones (expert opinion forecasting such as the Delphi method) versus quantitative ones (statistical modelling such as time series and regression analysis). Further classification distinguishes between short-term forecasting (aimed at inventory management and demand sensing) and long-term forecasts (capacity planning and risk management). This forms a strong framework for active decision-making.

B. Methods of Demand Forecasting

There are various techniques of improving the accuracy of demand forecasts. In supply chain management, time series analysis is used to measure upward trends and down times with methods like moving averages, exponential smoothing, and ARIMA. Another prediction model is the causal model in which demand is linked with price, promotion, and other variables through regression and machine learning. AI and machine learning allow real-time or instantaneous forecasts based on current market conditions. In essence, Econometrics is a mixture of economic theory and statistics to gauge the macroeconomic effects. Together these techniques help in inventory optimization, cost reduction, and overall efficiency in supply chain operations.

The essential techniques considered for enhancing the accuracy of forecasting demand in supply chain management are time series analysis, AI and machine learning, and Causality models. In terms of data, time series methods use historical data to define trends and estimate seasonality through moving averages, exponential smoothing, and ARIMA, making it well-suited for stable markets [23][24][25]. The technique for forecasting based on AI and machine learning deploys real-time learning with algorithms such as neural networks and decision trees, to analyze both structured and unstructured data, going towards adaptive and very high precision predictions particularly in fast-paced industries such as retail and e-commerce [26][27][28]. Causal relations capture demand according to some of its driving exogenous factors, such as price, promotions, and market trends, by applying regression analysis combined with advanced ML tools, making them particularly useful in environments where demand is affected significantly by external variables [29][30]. The aligned forecasting approaches improve inventory management, enhance production planning, and improve overall efficiency in the supply chain by such methods.

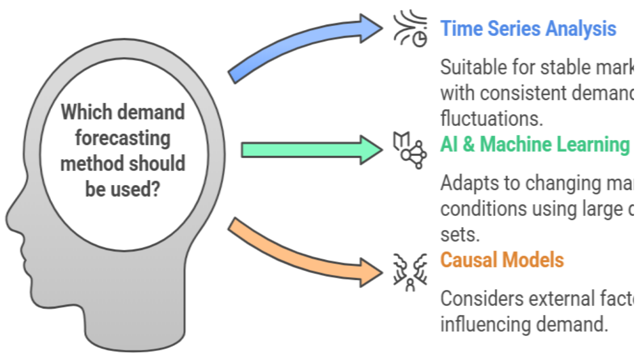

Figure 3 Enhancing Demand Forecasting Accuracy

C. Importance of Demand Forecasting in Supply Chain Management

Prediction of future demand is one of the most critical parts of supply chain management, which enables a company to optimize its inventory, production, and distribution processes. Accurate forecasting aids in aligning production-related activities to meet customer requirements; it helps reduce stockout and overstock problems and assures efficient operations throughout the supply chain [31]. It also improves decision-making through uncertainty reduction and aids one between seasonal changes, promotions, and market shifts. Beyond inventory, it benefits enhanced production planning, more efficient logistics, and supplier collaboration; reducing lead times and operational waste, it improves capacity and resource management [32]. Demand forecasting also acts on strategic areas for decision-making like market expansion and new product launches with trend analysis from future needs. It improves customer satisfaction in product availability and time, boosting loyalty and competitive advantage [33]. Modern-day forecasting tools integrate the application of AI understanding-the ability of machine learning and predictive analysis-and have therefore translated real-time insights, and enhanced accuracy, into the possibility for sophisticated, cost-effective, and agile supply chain operations that can withstand modern market dynamics [34].

D. Challenges in Demand Forecasting

Indeed, forecasting demand is greatly beset by challenges that hinge mainly on data accuracy and availability. Forecasting becomes so unreliable when integrity of data is marred with inconsistent or incomplete historical records, and forecast data sources remain eternally fragmented without real-time updates; when political instability, natural calamities, or spontaneous market upheavals intervene, forecast models become redundant [35]. Fast changes in consumer behaviour instigated by economic conditions, social media, and global events further muddle demand patterns in fast-evolving sectors, such as e-commerce. These sudden variances will, therefore, trigger more frequent change in forecasting models while increasing confidence in adaptive AI and machine-learning tools [36]. Seasonality and product lifecycle variations, both prominent in fashion or electronics, disrupt reliable long-term forecasts- especially about new product launches or heavily-promoted ones that have uncertain demand [37]. Disparate demand cycles and influencers are other layers of complexity added to multi-product businesses. Global disruption to supply chains-from raw material shortages to logistics delays and labor unrest-can mismatch supply and demand and breed inefficiencies and increased costs. With such perils come the need for companies to switch to real-time forecasting with agile models that can do scenario analysis and contingency planning for supply chain resilience [38].

II. LITERATURE REVIEW

Pasupuleti et al. (2024) [39] studied the advanced machine learning techniques that can be applied to understand the complexities of the modern global supply chain. Much of the traditional approaches ultimately fell short and encouraged regression, classification, clustering, and time series analysis on historical data collected from a multinational retail firm. And they have stated that machine learning models improved demand forecasting accuracy by 15%, stockouts, and overstock reduced by about 10%, and 95% accuracy in estimating order fulfilment dates. The methodology also facilitated customer segmentation as well as the early warning for at-risk shipments. All in all, the study proved that machine learning considerably increased the supply chain responsiveness with a 12% increase in lead time efficiency, an 8% decline in replenishment errors, and a clustering silhouette coefficient of 0.75.

One of the hardest markets to predict demand for is fashion, as stated by **Swaminathan, K., & Venkitasubramony, R. (2024) [40].** Our investigation offers a thorough analysis of the literature on the various forecasting methods applied in the fashion sector. Innovations in artificial intelligence and machine learning techniques for forecasting the demand for fashion items receive special attention. Based on the forecasting approach used, carefully curated literature is analyzed and the studies are categorized into qualitative, statistical, artificial intelligence (AI), and hybrid techniques.

According to **Abolghasemi et al. (2020) [41],** demand forecasting is a difficult task owing to the volatile nature of demand, created by having promotions which cause high variability across different time series, having different coefficients of variation (CoV). By analyzing 843 real-life demand series, they proposed a hybrid model that first decomposed the demand into baseline and promotional components. The advanced hybrid model, with improved forecasting for different levels of volatility, managed to boost the accuracy of the forecasts and the inventory performance. It is found that ETSX had been poor for highly volatile data, whereas ARIMAX, DLR, and SVR showed more reliable forecast performance, with ARIMAX and the hybrid models being preferred for the best inventory outcomes at the least cost. Improvements in performance indicate that a 95% accuracy rate in the fulfillment dates was achieved, 15% in demand forecast accuracy, 12% lead time reduction, 10% stockouts and overstocking reduction, and 8% reduction in replenishment errors, proving operational benefits of advanced forecasting approaches.

Ahmed, H. et al. (2024) [42] investigated creative methods of Sustainable Supply Chain Management (SSCM) in the manufacturing industry, a field that is becoming more and more important because of moral obligations and financial rewards. We assessed research from PubMed, Web of Science, and Scopus while following stringent qualifying requirements that emphasized the relevance of SSCM to manufacturing. Out of the 381 papers that our investigation and screening procedure found, 46 were chosen for a more thorough examination of technical advancements and teamwork tactics. According to preliminary research, there is a good correlation between SSCM integration and cost-effectiveness, environmental sustainability, and operational efficiency. Notwithstanding possible drawbacks such publication bias and methodological variation across research, the results emphasize the value of cooperation and technology in enhancing SSCM. This study highlights the need for additional investigations on the durability and flexibility of SSCM in diverse industrial settings.

A systematic review and content analysis were undertaken by **Mugoni, Kanyepe, and Tukuta in (2024) [43],** to examine the incidence of Sustainable Supply Chain Management Practices (SSCMPs) on environmental performance. The authors analyzed 140 journal articles spanning a period of 11 years between 2012 and 2022, across various databases including ScienceDirect, SCOPUS, ProQuest, and DOAJ, and established ample evidence of a significantly positive effect of SSCMPs on environmental outcomes, although very little had been written about operational performance and social sustainability. Recommendations were made for future research to extend in these areas as mediating aspects and to encourage robust industry-specific methodologies, such as mixed approaches, to help grow understanding of the larger effects of SSCMPs.

In another study**, Sahebi, Barzinpour, and Gilani (2024) [44]** extracted a material bibliometric representation from a total of 7394 papers indexed in the Web of Science Diary (1978-2021) in order to clarify the connection between sustainability and oil and gas supply chain management in the wake of increased global energy demand caused by an increase in population levels. Clear visual and analytical mappings were put out to identify research trends and featured some major topics including greenhouse gas emissions, life-cycle assessment, sustainability, as well as green fuel, carbon management, Industry 4.0, and circular economy as emerging topics for future study. The findings create a good foundation for future research, gaps, and guidance for research activities related to sustainable practices in the oil and gas supply chain for both academics and practitioners.

As **Khan et al. (2022) [45]** studied in the study, traditional supply chains can be endowed with automation, intelligence, and decision-making capabilities through their integration with smart objects and IoT technologies. The authors reiterated that IoT provides such technologies as RFID, cloud computing, middleware, and short-range communication, which significantly enhance operational efficiencies, safety, cost savings, and inventory management. The research also proposes IoT solutions for smart distribution such as transportation, warehousing, and packaging. The paper further discusses the concepts of customer tracking and store optimization via IoT with a view to increase sales.

Table 1 Comparative Analysis of Supply Chain Studies

Reference	**Method**	**Parameters**	**Key Findings**	**Outcomes**
[39]	Machine Learning (regression, classification, clustering, time series)	Historical data, demand trends, segmentation, fulfilment rates	Improved forecast accuracy, reduced stockouts/overstock, enhanced responsiveness	15% forecast accuracy, 10% fewer stock issues, 95% fulfillment accuracy, 12% lead time improvement
[40]	Literature Review and Categorization	Forecasting techniques (qualitative, statistical, AI, hybrid)	AI/ML plays a key role in fashion forecasting; methods categorized	Better understanding of forecasting approaches in fashion
[41]	Hybrid Forecasting (ARIMAX, DLR, SVR)	Baseline and promotional demand decomposition, CoV variation	ARIMAX and hybrid models outperformed ETSX for volatile demand	Higher forecast accuracy, better inventory outcomes, reduced replenishment errors
[42]	Systematic Review and Screening	SSCM relevance, cost-effectiveness, environmental impact	SSCM improves environmental, operational performance and cost savings	Proven SSCM impact in manufacturing; emphasis on collaboration and technology
[43]	Systematic Review and Content Analysis	SSCMPs, environmental and operational outcomes	Strong positive link between SSCMPs and environmental outcomes	Need for further study on social/operational impacts of SSCMPs

[44]	Bibliometric Analysis	Sustainability, emissions, green fuel, Industry 4.0	Identified sustainability trends and emerging research gaps	Framework for future research in oil & gas supply chain sustainability
[45]	IoT Integration with Traditional Supply Chain	RFID, cloud computing, middleware, logistics data	IoT enhances efficiency, safety, cost, and smart distribution	Improved logistics, inventory control, and customer tracking

III. OBJECTIVE

- The study is an exercise in forecasting shoe demand.
- Demand forecasting will be weekly in nature.
- An analysis will be made to discover the most frequently demanded items.
- The common sizes used for each item will be looked into.
- Analysis of seasonal and monthly demand patterns for particular items will be done.
- A Fuzzy Logic approach will be used to minimize shortages and reduce through waste.

IV. METHODOLOGY

In short, strong supply chain management is supported very heavily through accurate forecasting of demand and sales so that manufacturing and the reselling and merchandising strategies can be solidly laid down. Just-in-time balancing of supply and demand is vital to keep the company from incurring high costs due to overstocking or stockouts. The final outcome of demand overestimation is presence of surplus goods in stock and storage costs; while demand underestimation will lead to loss of sales as well as poor satisfaction among customers. Forecasting techniques such as the traditional time series are known to be valuable but fail in modelling nonlinear dynamic data-badly thereby reducing profit and efficiency. This gave rise to increasing attentions toward modern advanced techniques of forecasting such as Artificial Neural Networks (ANNs), which are expected to break complex and hidden patterns within huge amounts of data and thus exhibit higher precision and adaptability in dynamic changes of the market environments. ANNs would be particularly excellent where traditional models fail. ANNs, thus, have been seen as a strong weapon for demand prognosis in modern supply chains. In recognition of these shortcomings in traditional methods, this research proposes novel AI-based forecasting methodologies focusing on neural network techniques designed for multi-level complexities in the supply chain. These futuristic models, as a result, proffer an upsurge in predictive accuracy and responsivity alongside giving rise to companies optimizing their forecasting processes while still being competitive in fast-evolving markets.

A. Forecasting

Efficiently diffuse and put learning into practice with different classes of neural networks based on computational parameters, which can quickly solve logistics and optimizations that are complex in areas such as load planning, warehouse management, and transportation routing. This adaptability to real-time constraints affords them a great advantage, enabling quick, precise decisions, which in turn enhances organizational performance and increases customer satisfaction. One of the major uncertainties that plague supply chains is demand variability; however, that first problem is loss-related uncertainty caused by transportation delays and unexpected disruptions in the movement of parts in supply chains; these uncertainties render largely ineffective traditional methods-that include expert systems and statistical models-because of their linear assumption. Neural networks overcome those hurdles because these networks can process non-structured or dynamic data and analyze partial or uncertain data, making them more versatile and robust. Unlike conventional models, they learn and adapt over time, improving forecast accuracy and significantly reducing uncertainty. With its attribute of ever-evolving capability, neural networks form fierce weapons to construct resilient, flexible, and effective supply chain strategies in this volatile and fast-paced market.

B. Decision support

When managers make decisions, they face two problems: the first problem lies in the fact that the amount of information regarding the decision is too large, and the second is that information regarding the decision is in reality incomplete. The two above-mentioned factors constitute a serious obstacle to the exploiting of expert systems and statistical methods. Neural networks, in comparison, act like human brain thinking. They have a kind of "creativity" capable of making more rational and precise decisions from incomplete information. Now the greatest part of research on decision support systems is concerned about the management and analysis of decision-making data. Neural networks possess unique identification capability, data classification ability, and self-organization, making it the ideal technology for supply chain management data research. A neural network system had been developed to identify potential customers during selling. Another important problem for the decision support system relates to determining the relationships innately embedded between the data from the huge mound of data available. Self-organizing and generalizing capabilities of neural networks seem to fit well in order to carry out the demanded tasks undoubtedly.

C. Proposed Algorithm

Given: n = Number of weeks
m = Number of items
t= Number of sizes available
a= Number of iterations
for i=1:n
for j=1:m
for k=1:t
for x=1:a

Forecast Demand (Fd)
Calculate Error
If error > threshold value
Update internal parameters of algorithm
else
Final forecasted demand= Fd
end
end
end

A multi-level methodology was employed to structure demand forecasting, beginning with data collection that included historical sales figures, shoe sizes, and corresponding item codes. This dataset formed the foundation for model design, with its accuracy being critical for reliable forecasting. Key parameters—such as sales trends, seasonality, and customer preferences—were identified for use in a fuzzy rule-based approach to handle uncertainty and enhance forecast flexibility. These parameters enabled the model to generate weekly demand forecasts for various shoe sizes, allowing proactive inventory planning by highlighting potential demand variations. Each forecast was compared against current stock levels, and any identified gaps prompted immediate inventory adjustments to prevent stockouts and lost sales. This dynamic approach aligned supply chain operations with market needs, improved customer satisfaction, and offered opportunities for early interventions like production rescheduling or timely reordering. The entire process, from data collection to inventory adjustment, is illustrated in Figure 4.

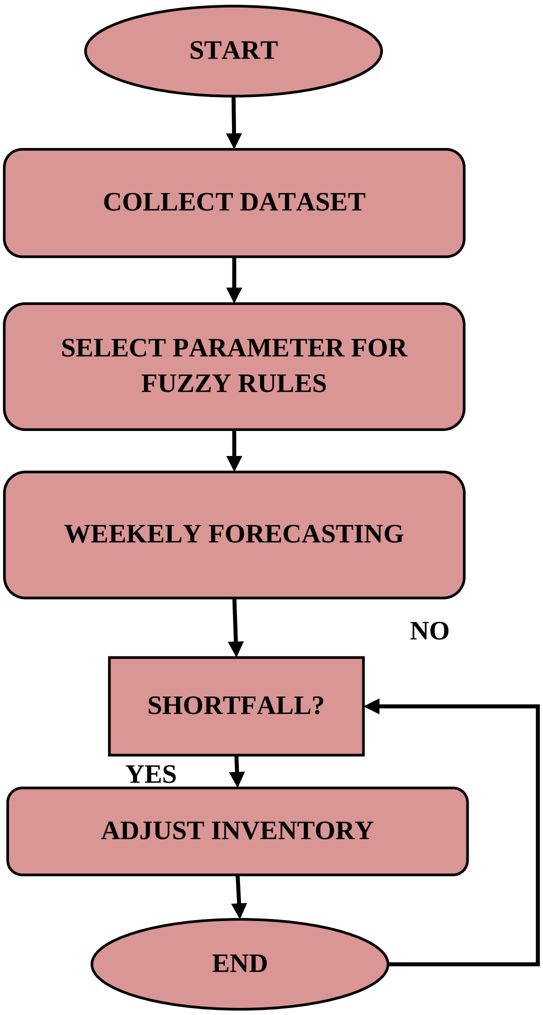

Figure 4 Flow Chart of Work

D. Approach Used

1. The methodology employs the Adaptive Neuro-Fuzzy Inference System (ANFIS), which is capable of universal approximation and is widely used for function approximation. ANFIS combines the learning ability inherent in neural networks with the knowledge representation act provided by fuzzy logic.
2. The incorporation of Extreme Learning Machine with Neuro-Fuzzy systems has simplified the computational complexity. EL-ANFIS, based on Takagi–Sugeno–Kang fuzzy inference system, thus produces highly accurate models.
3. Extreme Learning ANFIS (ELANFIS) has suggested good performance in solving regression problem.

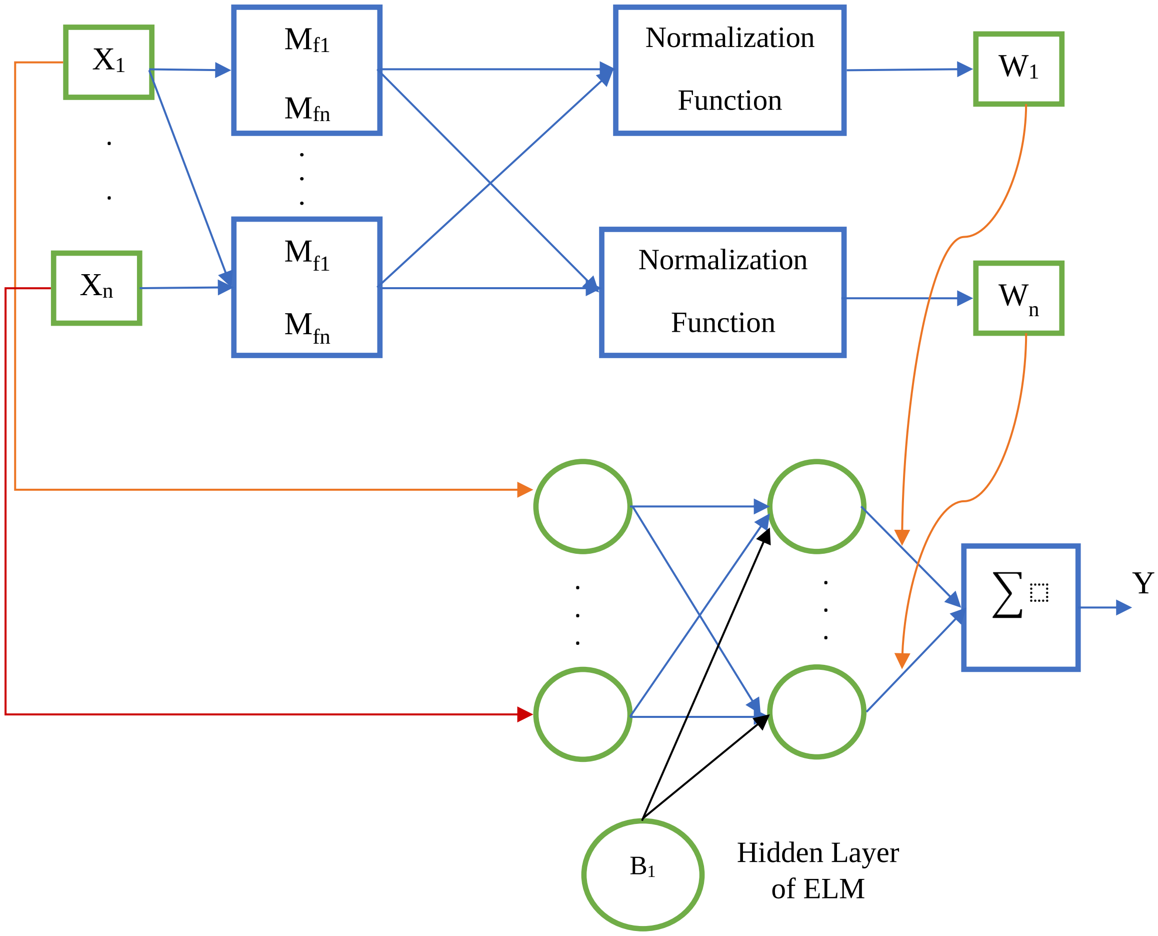

Figure 5 EL-ANFIS Architecture

With five layers, the modified EL-ANFIS network architecture of Figure 5 represents the fifth prototype. The input layer receives data pertinent to the analysis, while the activation layer evaluates fuzzy rules. Rule weights are normalized to sum to one in the normalization layer, thereby assuring balance in the system. Consequences from the TSK fuzzy logic output layer are influenced by normalized values, whereas the output layer sums these to yield the overall result. Here neural network learning is blended with flexible fuzzy logic to form a model that is robust for generalization towards complex systems.

The modified architecture of the EL-ANFIS network encompasses certain critical layers through which it collaborates to offer an accurate fuzzy-based prediction system. The input layer shall receive all the input variables that will then be fuzzified with the fuzzification layer, where two-sided Gaussian membership functions will evaluate the extent of membership concerning the input, through their parameters $c_{ijL}, \sigma_{ijL}, c_{ijR}, \sigma_{ijR}$. This function is defined as:

$$g(x_j) = \begin{cases} e^{-\frac{(x_j - c_{ijL})^2}{2\sigma_{ijL}^2}}, x_j < c_{ijL} \\ 1, c_{ijL} \le x_j \le c_{ijR} \\ e^{-\frac{(x_j - c_{ijR})^2}{2\sigma_{ijR}^2}}, x_j > c_{ijR} \end{cases} \quad (1)$$

Strength of every rule being fired is calculated as:

$$w_i(x) = w_{1c_i}(x_1) \otimes u_{2c_i}(x_2) \otimes \cdots \otimes u_{nc_i}(x_n) \quad (2)$$

where ⊗ represents the fuzzy AND operation. These initial firing strengths are normalized in the firing strength normalization layer:

$$\overline{w}_i(x) = \frac{w_i(x)}{\sum_{k=1}^{L} w_k(x)} \quad (3)$$

The consequent parameter layer entails a neural network trained with extreme learning for the computation of rule outputs.

$$\beta_i = p_{i0} + p_{i1}x_1 + p_{i2}x_2 + \cdots + p_{in}x_n \quad (4)$$

Each type of logic by averaging the ways in which they handle the undetermined-"A or both A and all B"-possibilities.

$$y = \sum_{i=1}^{L} \beta_i \, \overline{w}_i(x) \quad (5)$$

That intelligent idea was one where it suggested the interaction of multilayer perceptron techniques and fuzzy logic systems to address the uncertainty and nonlinearity of the input data.

V. RESULT ANALYSIS

A. Implementation Details

The Enhanced Adaptive Neuro-Fuzzy Inference System (EL-ANFIS)-based demand forecasting model was implemented in MATLAB using historical shoe sales data from 2016 to 2019. Its objective was to provide forecasts on monthly demand trends that would directly influence inventory and production considerations. Custom M-file programs were generated which utilized modern computation methods to enhance prediction accuracy and the reliability of the forecasts. Neural networks were fused with fuzzy logic to effectively model the exceedingly complex patterns present in the data. Throughout the model, continuous monthly evaluations were made comparing the predicted sales and actual sales, therefore, improving the forecasting process. Sample data in Table 2 were presented to confirm the applicability and accuracy of the model in real-life settings.

Table 2 Data Sample

Date	Company Name	Item Code	Shoe Size	Quantity	Price
4/8/2016	KHADIM INDIA LTD	10211210250	6/1	1	999
4/8/2016	KHADIM INDIA LTD	16504716560	9/1	1	450
4/8/2016	KHADIM INDIA LTD	16504816550	8/1,9/1	2	450
4/8/2016	KHADIM INDIA LTD	27400127460	5/1	1	649
4/8/2016	KHADIM INDIA LTD	27405227460	4/1,5/2,9/1	4	499
4/8/2016	KHADIM INDIA LTD	28001828060	9/1	1	499
4/8/2016	KHADIM INDIA LTD	28013928090	9/1	1	499
4/8/2016	KHADIM INDIA LTD	28322528362	9/1	1	999
4/8/2016	KHADIM INDIA LTD	28520052151	1/1	1	699
4/8/2016	KHADIM INDIA LTD	28520442550	1/1	1	799
4/8/2016	KHADIM INDIA LTD	28719628760	1/1	1	799
4/8/2016	KHADIM INDIA LTD	28936928950	6/1	1	399
4/8/2016	KHADIM INDIA LTD	29429029450	4/1	1	199
4/8/2016	KHADIM INDIA LTD	34527234560	6/1	1	499
4/8/2016	KHADIM INDIA LTD	34527434550	5/1,7/1	2	499
4/8/2016	KHADIM INDIA LTD	34527634560	6/1	1	649
4/8/2016	KHADIM INDIA LTD	34527834560	5/1	1	699
4/8/2016	KHADIM INDIA LTD	35826535820	7/1	1	899

B. Comparative Result Analysis

Table 3 Comparative Performance Analysis

Model	Accuracy	Runtime	Cost (in terms of loss)
ARIMA [1]	87%	0.28s	0.18%
SVM [1]	99%	0.57s	0.72%
RNN [1]	98%	0.71s	0.63%
LSTM [1]	96%	0.5s	0.54%
Proposed	99%	0.1s	0.16%

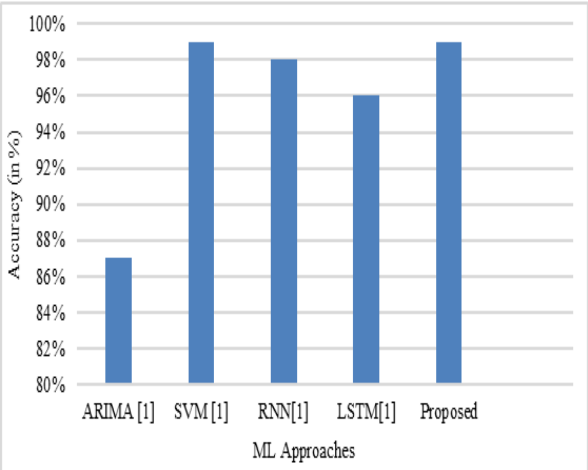

Figure 6 Comparative Accuracy Analysis

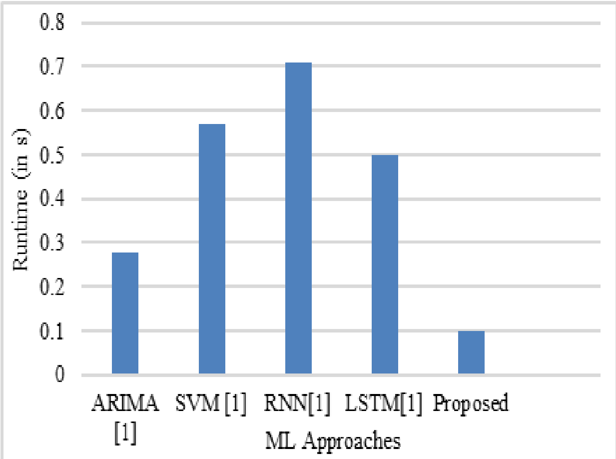

Figure 7 Comparative Runtime Analysis

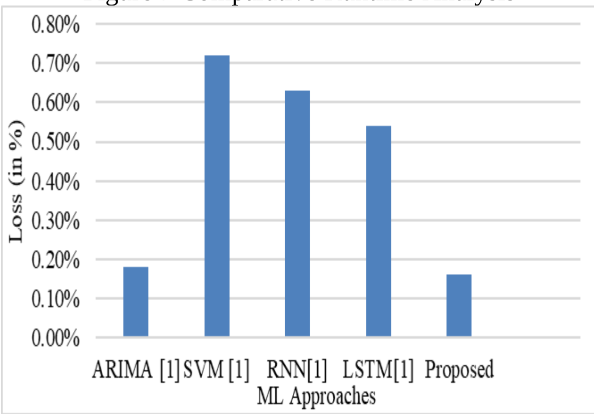

Figure 8 Comparative Loss Analysis

VI. CONCLUSION

The study presents a strong and intelligent demand forecasting framework in the form of EL-ANFIS which combines the adaptive learning strengths of neural networks with the interpretive flexibility given by fuzzy logic. Model trained on historical shoe sales data and proved successful in forecasting weekly demand which helps in précising inventory planning and improves supply chain efficiency. EL-ANFIS was highly effective compared to conventional models such as ARIMA, SVM, RNN, and LSTM based on the ability to capture non-linearity and uncertainty of data with an exceptional 99% accuracy, 0.1 s runtime in computational efficiency, and the lowest forecasting errors with 0.16% loss. The study explores how the modern artificial intelligence approach of eliminating the techniques of fuzzy rule-based modeling and neural learning algorithms addresses the inherent limitations of statistical forecasting in such high-variance, real-time retail environments. The dynamic forecast cycle runs on a weekly basis, which makes the system capable of quickly identifying shifting demands in advance of when the adjustments must take place in inventory replenishment as well as production scheduling and rescheduling during supply chain replenishment. Thus, there will be a reduction in waste and expenses in operations while improving service levels and satisfaction when stockouts and overstocks are reduced. In addition, the continuous assessment and improvement of the model on performance and data ensure the swiftly managed business operations are in tune with market demand. The research output hence proves that there is scalability and applicability of EL-ANFIS in retail and other sectors, where the need is for responsive, accurate forecasting systems. EL-ANFIS represents the award-winning efficient solution for the modern supply-chain challenge, granting a clear roadmap towards a digital transformation of demand forecasting. It becomes faster for companies to adapt to the rapidly changing behavior of consumers and fluctuations in the market, giving them the advantage of a smarter supply chain strategy as a competitive advantage. Future opportunities can explore hybrid concepts through IoT integration with blockchain or real-time data feeds for optimizing predictive power and adaptability in this model further.

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