Managing Uncertainty in Fashion Supply Chains: An AI-Based Analysis of Demand Variability and Forecast Precision

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Abstract -

Purpose: *This study aims to enhance demand forecasting accuracy in supply chain management using advanced techniques like genetic algorithm-optimized deep neural networks and fuzzy clustering. Accurate demand prediction enables informed decision-making for inventory planning, risk mitigation, and operational efficiency.*

Methodology: *The study adopts an empirical approach utilizing sales datasets to develop machine learning and deep learning models that effectively capture fluctuations in demand across products with varying levels of volatility. The products are classified into categories using fuzzy clustering based on demand variability metrics.*

Results: *The optimized deep neural network model, fine-tuned by a genetic algorithm, achieved the highest precision with under 3% mean absolute percentage error in forecasting demand variations, outperforming methods like linear regression and Temporal Fusion Transformer networks.*

Practical Implications: *The findings demonstrate the vital role of AI/ML in enhancing supply chain resilience through improved demand forecasting. By proactively adapting to demand changes, businesses can optimize inventory and production planning, leading to increased profitability, agility, and sustainability.*

Originality: *To the best of the author's knowledge, this is the first study incorporating genetic algorithm-optimized deep learning and fuzzy clustering to categorize retail products based on demand volatility signatures, thereby significantly improving forecast accuracy.*

Key Words: Machine Learning, Supply Chain Risk, Deep Learning, Temporal Fusion Transformer (TFT), Artificial Neural Network (ANN), Genetic Algorithm (GA)

1. INTRODUCTION

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Supply chain volatility presents significant challenges for businesses, especially in terms of its impact on demand forecasting accuracy (O'Neal, 2021). This directly affects inventory planning, risk mitigation and overall operational efficiency. While the complexity of this issue is acknowledged (Wan & Evers, 2011), prior academic works have exhibited certain limitations.

Although trend forecasting has shown to increase supply chain stability (Miyaoka & Hausman, 2008), joint forecasting models employed by Aviv (2002) rely on limited data and statistical methods. Advanced AI/ML applications for enhancing resilience have been underexplored. Despite attempts to reduce inventory fluctuations and costs using moving average techniques (Yuan et al., 2020), the bullwhip effect persists in distribution networks.

While machine learning has been recognized for improving supply chain efficiency (Aamer et al., 2020), its incorporation specifically for pharmaceutical demand forecasting has been recent (Yani & Aamer, 2022). Moreover, the impact of enhanced predictions on decentralized networks requires careful evaluation (Miyaoka & Hausman, 2008). Although information sharing between parallel supply chains boosts forecasting accuracy (Zhang & Zhao, 2009), corresponding gains for individual members remains unclear.

This study aims to address prevailing gaps by adopting an empirical approach to develop optimized machine learning models that capture complex demand fluctuations across retail products. The core objectives are:

- To classify products into categories based on demand variability and lifecycle stage using fuzzy clustering.
- To evaluate various state-of-the-art forecasting techniques in predicting future sales for differently volatile product groups.
- To determine the feasibility of tailoring forecasting models based on the unique volatility signatures identified through clustering.

By combining advanced clustering with tuned predictive models, this study endeavors to significantly improve forecast precision. Enhanced demand prediction will empower businesses to make data-driven decisions for inventory planning, risk assessment and coordinating supply chain activities.

The paper is structured as follows: Section 2 reviews relevant literature, Section 3 explains the research methodology, Section 4 presents the experiments and results, and finally Section 5 provides the conclusion and implications.

2. Literature Review

Improving supply chain resilience is a crucial objective for businesses and advanced demand forecasting techniques play a critical role in achieving this goal. Accurate prediction of demand enables businesses to ensure the availability of correct parts and products at all times (O'Neal, 2021). Trend forecasting has been found to increase supply chain stability, reduce stockouts, and reduce the bullwhip effect (Wan & Evers, 2011). Joint forecasting and replenishment processes enable supply chain members to observe market signals and forecast future demand, leading to improved forecasting accuracy (Aviv 2002). The moving-average forecasting technique has been demonstrated to reduce the bullwhip effect and increase profitability in closed-loop supply chain networks (Yuan et al., 2020).

The utilization of machine learning in demand forecasting has been acknowledged as a valuable contributor to the enhancement of supply chain management efficiency. Accurate demand forecasting is essential to mitigate the bullwhip effect and improve supply chain performance (Aamer et al., 2020). Disruptive techniques such as machine learning can be employed to enhance the resilience of supply chains, particularly in the pharmaceutical industry (Yani & Aamer, 2022). However, it must be acknowledged that improved forecasts can have both positive and negative consequences on decentralized supply chains. Although improved forecasts can lead to better coordination and reduced costs, they can also detract from the performance of individual supply chain members (Miyaoka & Hausman, 2008).

The influence of external demand information on parallel supply chains is also examined. Utilizing the demand history of other supply chains can enhance the forecasting accuracy for both suppliers and retailers (Zhang & Zhao, 2009). In the retail industry, various demand forecasting methods and algorithms have been explored, underscoring the importance of accurate demand forecasting for effective supply chain management (Vikas et al., 2021). Several demand forecasting technologies, such as the moving average, exponential smoothing, and minimum mean square error methods, have been analyzed to assess their impact on the bullwhip effect in two-level supply chain distribution networks (Yuan & Zhu, 2016).

A recent study found that incorporating base stock policies with "stale" forecasts in a two- stage supply chain can lead to improved fulfillment and reduced production-level fluctuations (Miyaoka & Hausman, 2004). Additionally, the impact of stochastic lead- times on the bullwhip effect has been investigated, underscoring the importance of considering lead-time variability in demand forecasting (Michna et al., 2020). Other forecasting methods, such as autoregressive integrated moving average and exponential smoothing, have been suggested to enhance forecasting accuracy in supply chains (Wagner, 2010). The evolution of ARMA demand in supply chains has significant practical implications for quantifying the bullwhip effect, coordinating forecasting, and evaluating information-sharing (Zhang, 2004).

Risk is an inherent aspect of life that carries consequences; however, when it specifically arises in supply chains, it is susceptible. Junaid et al. (2019) aimed to identify, assess, and develop criteria for managing supply chain risk. These results suggest that supply chain resilience is the most critical criterion for managing these risks. Additionally, Gružauskas et al. (2019) investigated the influence of information sharing on forecasting accuracy in different market sizes, types, and consumer integration, using machine learning algorithms to adapt to supply chain members' needs. Weskamp et al. (2019) examined postponement concepts and presented a case study of the apparel industry, illustrating the benefits of the model and conducting a sensitivity analysis regarding demand uncertainty and correlation. Ge et al. (2019) focused on several core components of supply chain management, including vendor management, demand forecasting, inventory management, and order fulfillment. The supply chain management field has undergone significant changes with the emergence of new business scenarios and advancements in both algorithm design and computational power.

Food supply chains are currently facing increased uncertainty in both supply and demand and are susceptible to unexpected disruptions. To design a resilient food supply chain that can withstand demand uncertainty and epidemic disruptions, a comprehensive two-stage scenario-based mathematical model has been proposed (Gholami-Zanjani et. al., 2020). To improve efficiency and reduce emissions in the downstream oil industry, the Chinese government is promoting a multiproduct pipeline network reform (Yuan et. al., 2020).

An official framework was constructed to procure comprehensive design-scale information necessary for evaluation, incorporating demand forecasting and demand reallocation within a pipeline network optimal planning model. (Siagian et. al., 2021) explored the impact of supply chain integration on business performance through supply chain resilience, supply chain flexibility, and innovation systems in Indonesia's manufacturing companies. This study found that supply chain integration enhances business performance through innovation, supply chain flexibility, and supply chain resilience in the context of the COVID-19 pandemic. (Tarigan et. al. 2021) investigated the influence of internal integration, supply chain partnership, supply chain agility, and supply chain resilience on sustainable advantage. These findings provide valuable insights for managers to improve sustainable advantage by enhancing supply chain agility, resilience, and partnerships.

Manufacturers and retailers are key players in supply chain management. However, inaccurate demand information from retailers can negatively affect supply chains. To address this issue, Sardar et al. (2021) proposed a machine-learning approach for on- demand forecasting in the context of smart supply chain management. The pandemic has accelerated digitalization trends and the use of functional materials in the textile industry, presenting an opportunity to overcome supply chain disruptions and other challenges. Ivanoska-Dacikj et al. (2023) discuss the advancements in developing smart textiles through the use of electrospun nanofibers and nanogenerators for monitoring and sensing purposes. Mittal et al. (2008) developed a physics-based method that utilizes nonlinear differential equations and a tailored objective function for forecasting a company's throughput. Their approach highlighted the potential of physics-based tactics for forecasting. Mittal et al. (2023) study focuses on the intricacies and vulnerabilities inherent in supply chains, which are often influenced by external disruptions such as pandemics, conflict scenarios, and inflation. The aim is to devise an AI-driven system that can accurately appraise these intricacies within the domain and mitigate their vulnerabilities effectively.

In conclusion, advanced demand-forecasting techniques play a crucial role in enhancing supply chain resilience. By employing accurate prediction methods, businesses can optimize inventory levels, minimize stockouts, and mitigate bullwhip effects. Several techniques, including trend forecasting, collaborative forecasting, machine learning, and forecasting technologies, have been explored to enhance forecasting accuracy and supply chain performance. However, it is essential to consider the potential impacts of improved forecasts on decentralized supply chains and the significance of lead time variability in demand forecasting. Precise demand forecasting is vital for effective supply chain management.

3. Methodology

The primary aim of this study is to investigate the influence of demand volatility on the performance of forecasting models commonly used in supply chain management. Our objective is to examine the feasibility of incorporating demand variability into a robust forecasting framework, considering how this volatility changes over the product lifecycle and in relation to the key product offer characteristics. The goal is to develop a hybrid forecasting approach that can account for significant differences in volatility across products and time periods, thereby enabling the creation of a more comprehensive and accurate system for supply chain planning and management.

To achieve this objective, the research methodology outlined in this study adopts a two- pronged approach, as shown in Figure 1. The initial phase involves clustering products into groups based on lifecycle stage, margin of value, and multiple demand volatility metrics. By categorizing the products in this manner, homogeneous volatility profiles can be identified within each cluster. The second phase involves developing tailored forecasting models for each defined product cluster. This allows unique volatility signatures and demand behaviors to be incorporated into each cluster-specific model through the model structure and parameters. By combining advanced clustering techniques with cluster-tuned forecasting models, the hybrid approach aims to capture variability in a robust manner, beyond the capabilities of traditional one-size-fits-all forecasting systems.

The performance and viability of the proposed hybrid methodology were evaluated through an empirical analysis using real-world retail sales data.

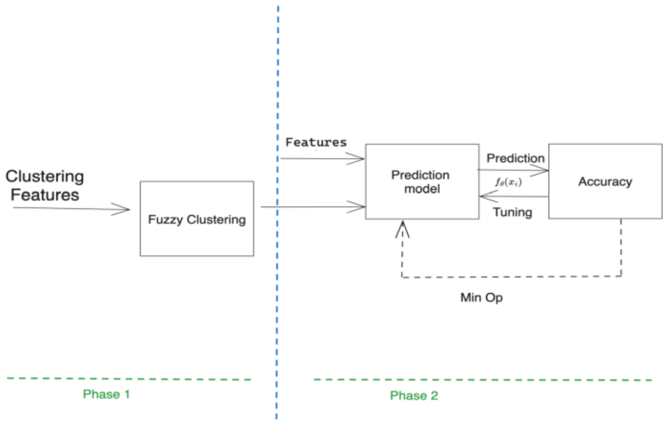

Fig -1: Two Phase Model Architecture

4. Data Understanding

The data used for this analysis were sourced from a large retailer that produces numerous product lines across multiple categories. The company provides a comprehensive dataset that includes five years of aggregated point-of-sale demand data and current and historical pricing information. The demand data are compiled across all the company's sales channels, including brick-and-mortar stores, e-commerce, and wholesale or third-party retail partners, encompassing 10,000 individual stock-keeping units (SKUs).

A crucial aspect of the data is that demand levels vary significantly based on the product lifecycle stage. Products in

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the introduction and growth phases typically have higher demand than those in the maturity and decline phases do. This discrepancy is primarily attributed to how product offerings contribute to the measurement of variation (MoV) at each lifecycle stage. Newer products bring greater MoV, while demand tapers for aging products as MoV decreases. The variation of the demand with different covariates is demonstrated in Fig2 and Fig3.

The large timespan and extensive number of SKUs represented in the data provide a robust real-world dataset for analyzing demand patterns and lifecycle curves across a broad range of retail fashion products. This will enable the modeling of demand during key transitional lifecycle phases and provide insights into optimal forecasting approaches based on the lifecycle stage. The following data features (Table 1) were used to forecast the demand.

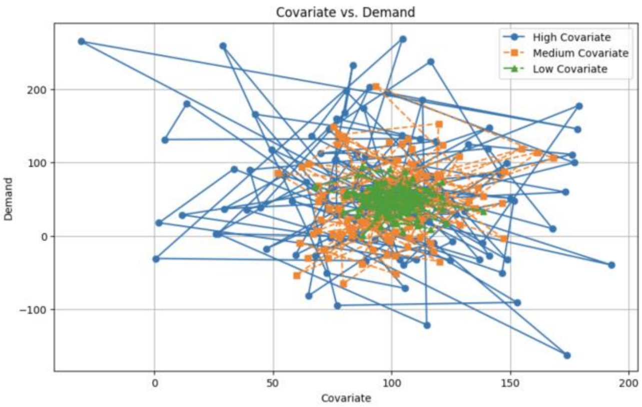

Fig -2: Covariate vs Demand

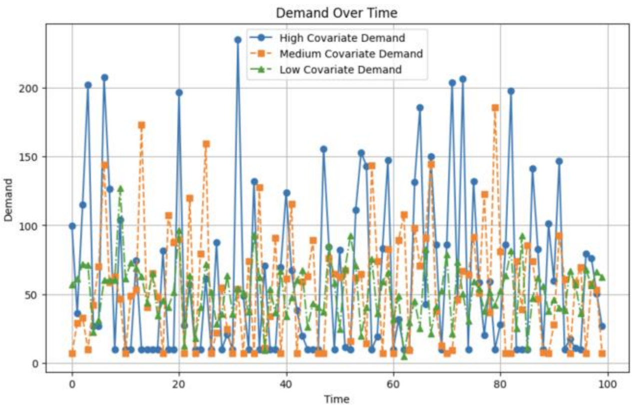

Fig -3: Demand Over Time

5. Phase 1: Product Categorization Using Fuzzy C-Means Clustering

The product data were initially grouped into primary, secondary, and tertiary clusters based on the product life cycle and measure of variance (MoV). The products were then assigned membership grades to each cluster, with the primary representing the highest MoV products and tertiary representing the lowest MoV products. This classification is crucial for further analysis, as it allows for a distinct examination of the demand variation and product lifespans in each cluster, which impacts demand forecasting differently.

Algorithm 1 Fuzzy c-means clustering for demand volatility

Dataset $X = \{x_1, x_2, ..., x_N\}$ where each x_i has: - Seas code $S \in$ {Basic, Fashion, Seasonal Basic} - Covariates Number of clusters C (set to 9) Cluster labels $L = \{l_1, l_2, ..., l_C\}$ (Basic, High MoV, etc.) Initialize cluster centers $V = \{v_1, v_2, ..., v_C\}$ randomly Initialize fuzzy partition matrix $U = [u_{ij}] = 0$ **while** *not converged* **do**- **end** **for** $i \leftarrow 1$ *to* N **do** − **end** j $\leftarrow 1$ to C $u_{ij} = \frac{1}{\sum_{k=1}^{C}(\frac{\|x_i - v_j\|}{\|x_i - v_k\|})^{2/(m-1)}}$ **for** $j \leftarrow 1$ *to* C **do**- **end** $v_j = \frac{\sum_{i=1}^{N}(u_{ij}^m * x_i)}{\sum_{i=1}^{N}(u_{ij}^m)}$ **if** *objective function converging* **then**- **end** *break* **for** $i \leftarrow 1$ *to* N **do**− **end** c $= \text{argmax}_j u_{ij}$ Assign x_i to cluster c Label each cluster based on L and seas code/covariance patterns

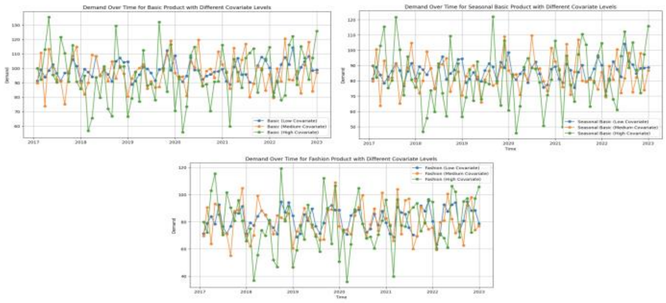

Fig -4: Demand Variation by different product and covariates (After Fuzzy Clustering)

6. Feature Engineering

The feature set comprises a range of variables related to inventory levels, sales trends, product attributes, discounts, and holidays. The inventory indicators, such as the opening and closing inventory quantities, provide insights into the current stock levels and is used in combination with sales data to determine the inventory turnover rate and the number of weeks of supply on hand. High inventory levels (exceeding 0.6 quantity indicator) indicate excess stock buildup or poor sales velocity for specific products.

The sales aggregates at the department, class, and sub-class levels allow for the analysis of broader demand trends and performance for various product groupings. Issues with lower aggregate sales for certain departments can be identified for further investigation.

The moving averages of sales with different lookback periods (4, 8, 12, 28, and 52 weeks) capture both short and long-term sales trend cycles. The 28- and 52-week averages smooth out weekly/monthly fluctuations, while the 4-week average acts as a momentum indicator of recent sales changes. Comparing the moving averages at different cycles highlights sales trajectory.

The markdown features help optimize promotional pricing and anticipate discounting effects. The time since markdown started (mkd time) provides context on where a product is in the markdown cadence. Markdown indicators (mkd ind) flag the start of discounting periods. Cluster IDs group products with similar demand profiles and markdown optimization needs.

The holiday indicators account for seasonal demand spikes, while the lagged holiday values represent post-holiday demand drop-off. Incorporating this seasonality into the model intuitively provides more accuracy. The product attributes (style, color, seasonality codes) allow for custom forecasting by product segment and characteristics.

Feature	Description
Opening Inventory Qty	Quantity indicator if opening inventory is greater than 0.6
Closing Inventory Qty	Quantity indicator if closing inventory is greater than 0.6
Replenishment Qty	Closing inventory quantity + Sales quantity - Opening inventory quantity
Replenishment Qty Lagged 1	Replenishment quantity lagged
Replenishment Qty Lagged 2	Replenishment quantity lagged
Replenishment Qty Lagged 3	Replenishment quantity lagged
Moving Average 4	Moving average of 4 weeks sales
Moving Average 8	Moving average of 8 weeks sales
Moving Average 12	Moving average of 12 weeks sales
Moving Average 28	Moving average of 28 weeks sales
Moving Average 52	Moving average of 52 weeks sales
Sales Quantity Sum Sub Class	Aggregated sales quantity
Active SKU Sub Class	Active (existing) SKU count within hierarchy
Sales Quantity Sum Class	Aggregated sales quantity
Active SKU Class	Active (existing) SKU count within hierarchy
Active SKU Department	Active (existing) SKU count within hierarchy
Week Sine	Sine encoded fiscal week number
Week Cosine	Cosine encoded fiscal week number
Month Sine	Sine encoded month number
Month Cosine	Cosine encoded month number
Quarter Sine	Sine encoded quarter number
Quarter Cosine	Cosine encoded quarter number
Discount Chain/Plan	Either last year's actualized discount or plan discount for SKU at brand fashion type level
Plan Discount Style Ratio	Planned discount ratio of style to BMC
Discount Chain Style Ratio	Actualized discount or planned discount ratio of style to BMC
Holiday	
Lagged Holiday	
Leading Holiday	
Markdown Time	Time in weeks since beginning of markdown (0 if not in markdown)
Markdown Indicator	Markdown indicator
Closing Size Coverage Indicator	Indicator SKU inventory weighted week closing size coverage greater than 0.6
Opening Size Coverage Indicator	Indicator if SKU inventory weighted week opening size coverage greater than 0.6
Style Color ID	Global style color ID
Department	Product hierarchy
Class	Product hierarchy
Sub Class	Product hierarchy
Style	Product hierarchy
Cluster ID	ID associated with MOV and Product Life Cycle cluster
Product Life Cycle	Basic (12 months offering), Fashion (3 months offering), Seasonal basic (6 months offering)

Table -1: Model Features

7. Phase 2: Demand Forecasting.

The product categorization process commences by implementing a Fuzzy C- means clustering algorithm, which assigns each product a membership grade for each cluster. This "soft clustering" method allows products to belong to multiple clusters, but with varying degrees of membership. The resulting fuzzy cluster assignments are then combined with additional numeric and categorical features such as sales history, color, and other product-specific attributes to create an enriched dataset. This enriched dataset serves as input for the subsequent time series forecasting models designed to predict future product demand.

The time series models evaluated for their forecasting accuracy include the Temporal Fusion Transformer (TFT) model, which is robust to outliers, and the Deep Artificial Neural Network (ANN) model. The TFT model uniquely combines multiple decision tree models, each built on de-trended time series segments, to provide a reliable prediction. The model's performance is optimized using hyperparameters that are tuned using Randomized Search to identify the optimal number of trees, seasonality Fourier order, and other significant parameters.

The Deep ANN model is optimized using a Genetic Algorithm, which fine-tunes the number of nodes, dropout rate, and other topology parameters by mimicking the process of natural selection. The evaluation of these models utilizes various accuracy metrics like Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), which are calculated on a validation set to ensure the model's accuracy. Statistical testing is then employed to determine the significance of accuracy improvements.

Based on a comprehensive evaluation, the Temporal Fusion Transformer and the Deep ANN models have exhibited remarkable efficacy. Specifically, the neuro evolved ANN model has consistently recorded the least error across multiple experimental trials. As a result, these exceptional models are retraining on the entire dataset to generate the most dependable and robust predictions. This thorough process thus ensures optimal product categorization and precise demand forecasting, which are crucial for effective inventory management and business planning.

8. Evaluation metrics:

The three error measurements of root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) are used to evaluate the predictive accuracy of the models. RMSE is computed by taking the square root of the average squared differences between predicted and actual values, and it measures the magnitude of the error. MAPE is the mean of the absolute percentage errors, calculated by taking the absolute difference between each prediction and actual value, dividing by the actual value, and averaging these percentages, and it expresses accuracy as a percentage of the error. Finally, MAE is the mean of the absolute differences between predictions and actuals, providing an absolute measure of the typical magnitude of the errors. These three metrics offer a comprehensive assessment of the deviations between the models' predicted values and the true empirical values. Analyzing RMSE, MAPE, and MAE enables a robust evaluation of the models' predictive capabilities.

$$MAPE = \frac{\sum_{t=1}^{k} |\hat{y}_t - y_t| / y_t}{k} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{k} (\hat{y}_t - y_t)^2}{k}} \quad (2)$$

$$MAE = \frac{1}{k} \sum_{t=1}^{k} |(\hat{y}_t - y_t)| \quad (3)$$

n = the number of observations

yhat = the predicted value

y = the actual value

Σ = the summation symbol, representing the sum of all observations from 1 to k

9. Experiments:

9.1 Temporal Fusion Transformer (TFT)

The Temporal Fusion Transformer (TFT) is a highly advanced model that employs the Transformer architecture to process the complex temporal dynamics present in multiple time sequences. It comprises five critical components, each with a distinct function. Firstly, the gating mechanism is utilized to eliminate unnecessary elements and customize the depth and complexity of the network to suit various datasets and conditions. Secondly, the variable selection network selects the relevant input variable for each time step. The static covariate encoder plays a dual role by assimilating static features into the network and regulating temporal dynamics through the encoding of context vectors. Fourthly, the TFT is equipped with temporal processing capabilities that extract both short- term and long-term temporal associations from observations or time-varying inputs known in advance. This is achieved through sequence-to-sequence layers for local processing, as well as a novel interpretable multi-head attention block for long-term term extraction. Finally, the model utilizes multi-level prediction interval prediction, which employs quantile prediction to determine the range of potential target values within each prediction interval. This comprehensive structure, despite its complexity, allows the TFT to effectively capture the intricate temporal dynamics present in multiple time sequences.

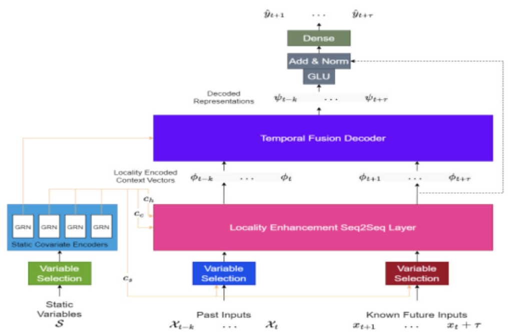

Fig -5: Temporal Fusion Transformer Architecture

Algorithm 2 TFT Demand Forecasting with Fuzzy Clustering

Input:
X: product demand time series data
F: fuzzy cluster assignments from Fuzzy C-Means

Preprocess(X):
  Resample X to frequency f
  Impute missing values in X
  Normalize features in X
  Decompose X into trend, seasonality, residuals

EnrichData(X, F):
  $X_{enriched}$ = concat(X, F)

TrainTFT($X_{enriched}$):
  split $X_{enriched}$ into X_{train}, X_{val}
  define static_encoder, temporal_encoder
  decoder = TransformerDecoder(static_encoder, temporal_encoder)
  model = compile(decoder)
  fit(model, X_{train})
  tune_hyperparameters(model, X_{val})

Evaluate(model, X_{test}):
  forecasts = predict(model, X_{test})
  error = calculate_metrics(forecasts, actuals)
  visualize(error)
  statistical_test(error)

Retrain(model, $X_{enriched}$):
  model = fit(model, $X_{enriched}$)

Output(model):
  forecasts = predict(model, X_{new})
  quantify_uncertainty(forecasts)

9.2 Deep ANN with Genetic Algorithm

The Artificial Neural Network (ANN) comprises 144 input neurons, two hidden layers with 150 and 60 sigmoid neurons respectively, and two output neurons for class prediction. The layers are fully connected and contain more than 17,000 trainable weights. These weights are optimized utilizing a Genetic Algorithm (GA), wherein each solution embodies all ANN weights in three separate one-dimensional vectors. These vectors are reshaped into weight matrices during the evaluation of fitness. The GA employs tournament selection, single-point crossover, and Gaussian mutation to evolve a population of 100 solutions for 100 generations, with the aim of discovering the globally optimal set of weights that maximizes prediction accuracy.

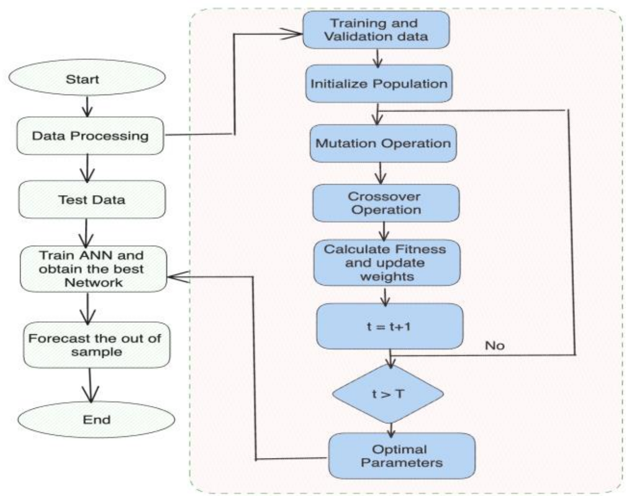

Fig -6: GA Optimized ANN

10. Results

Table 2 displays the performance of two models, TFT (Temporal Fusion Transformer) and GA Optimized ANN (Genetic Algorithm Optimized Artificial Neural Network), across three different covariate conditions: High, Medium, and Low. The models' performance is evaluated using three metrics: MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), and RMSE (Root Mean Squared Error). For the TFT model, the MAPE percentages range from 4.91% to 10.04%, the MAE ranges from approximately 83,560 to 189,110, and the RMSE ranges from around 92,460 to 183,138. As the covariate conditions decrease from high to low, the MAPE, MAE, and RMSE values tend to decrease, indicating an increase in forecast accuracy. For the GA Optimized ANN model, the MAPE percentages range from 3.1% to 5.83%, the MAE ranges from approximately 76,834 to 121,363, and the RMSE ranges from around 89,274 to 131,487. Similarly, as the covariate conditions decrease from high to low, the MAPE, MAE, and RMSE values tend to decrease, indicating better forecast accuracy.

The three product categories examined - Basic, Seasonal, and Fashion - exhibited varying levels of forecast error. The Fashion category had the highest forecast error, likely due to the volatile nature of fashion trends. The Low Covariate dataset, coupled with the GA Optimized ANN model, produced the most precise forecasts overall.

When comparing the two models, the GA Optimized ANN model outperformed the TFT model in all covariate conditions, as indicated by its lower values of MAPE, MAE, and RMSE. This suggests that the GA Optimized ANN model is more accurate in its forecasts.

Model		Basic			Seasonal Basic			Fashion		
		MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE
TFT										
	High Covariate	7.62	144,162	124,617	9.12	160,141	152,106	10.04	189,110	172,616
	Medium Covaria	6.43	100,888	142,408	8.52	144,130	183,138	9.46	154,195	182,839
	Low Covariate	4.91	83,560	92,460	5.37	100,918	133,612	7.73	132,456	150,469
GA Optimized ANN										
	High Covariate	3.1	76,834	89,274	4.63	82,498	90,760	4.95	102,493	99,870
	Medium Covaria	4.45	88,693	94,328	5.21	108,432	100,493	5.51	112,789	120,632
	Low Covariate	4.9	90,762	97,892	5.11	113,453	119,116	5.83	121,363	131,487

Table -2: Model Performance Results

The recurrence plots in Fig. 7 show the complex and irregular texture patterns of demand from the GA optimized ANN, actuals, and TFT model. The plot from the GA optimized ANN model and the actual demand exhibits complex and intriguing patterns, while the TFT model reveals high noise. The blue and yellow shades in the plot indicate the nonstationarities in the signal. The GA optimized ANN model captures the underlying patterns of the measured demand data more accurately than the TFT model. The color map indicates the recurrence points identified at different neighborhood sizes. The patterns along the vertical segments between two consecutive marked time indices are similar and nearly shifted versions of each other, suggesting that the recurrence patterns from the GA optimized ANN model closely capture the dynamics of the actual data compared to the TFT model.

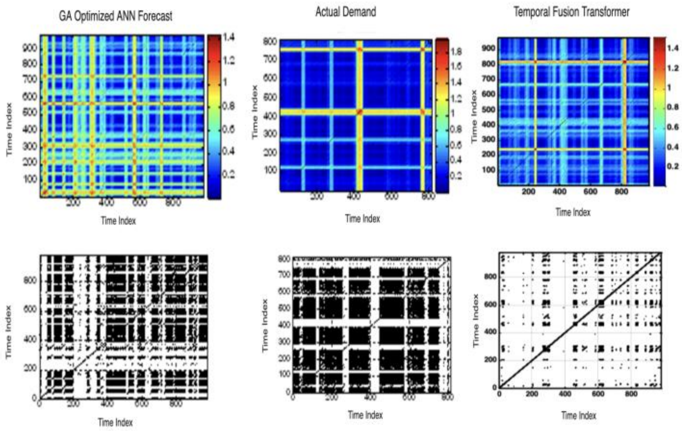

Fig -7: Comparison of Recurrence Plots for GA Optimized ANN, Actual and TFT

11. CONCLUSIONS

This article presents a study that aims to enhance supply chain resilience through the implementation of advanced demand forecasting techniques utilizing genetic algorithm-optimized deep artificial neural networks and fuzzy clustering. The research adopts an empirical approach, constructing machine learning and deep learning models to predict demand fluctuations. The results indicate that the optimized deep neural network regression model, refined using a genetic algorithm, outperforms other models in forecasting demand. The findings underscore the significant role of machine learning and deep learning techniques in improving prediction accuracy and providing valuable insights for strategic planning and procurement. The study classifies products into three categories based on market availability and variability, and it evaluates the accuracy of various state- of-the-art forecasting techniques in predicting demand series across different levels of variability. Overall, the study showcases the potential of artificial intelligence methods to strengthen supply chain resilience through improved demand forecasting.

12. Key Highlights

- The study aims to enhance the precision of demand forecasting in supply chain management using advanced techniques.
- The study adopts an empirical approach and constructs Machine Learning and Deep Learning models to predict demand variations.

- The optimized Deep ANN Regression model, fine-tuned using a Genetic Algorithm, outperforms other models in forecasting demand.
- A fuzzy clustering and Genetic Algorithm-optimized Deep ANN model categorizes products based on variations in demand.
- The findings provide crucial knowledge for management involved in strategic planning and procurement.

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