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Predicting E-commerce Sales Forecasting and Inventory Management Based on Fuzzy LIM-CNN Technique

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***Abstract* –Online shopping's share of the market has grown over the last decade, even if retail as a whole has slowed. Logistical costs for EC are higher than for other retail models due to a variety of problems with inventory management. Even though EC makes inventory management more difficult, it works well with EC because consumers can easily compare prices, which is important because goods demand is very price sensitive. Three stages, including preprocessing, feature selection, and model training, make up this suggested approach. The term "data preprocessing" refers to the steps used to remove any anomalies or noise from the chosen data. Using feature selection, we may sift through different datasets and extract the most unnecessary and superfluous information. A Fuzzy LIM-CNN was employed for the purpose of training the model. The proposed approach outperforms CNN and Fuzzy LIM with an average accuracy of 91.67%.**

***Keywords*—Sales Forecasting, Fuzzy Local Information Means Algorithm (FLIM), E-Commerce.**

I. INTRODUCTION

Raw materials, WIP (work in progress), and finished items (inventory) are the three basic commodities that a business keeps on hand to fulfill orders. Due diligence is essential for its management because of the magnitude of the investment and the potential for waste it may generate. A business maintains an inventory of goods in case they are required at a later date. An efficient inventory management system is essential for company owners of all sizes. Implementing a system that tracks inventory levels, orders, and sales can help reduce issues with running out of stock or having too much. This paves the way for demand forecasting through predictive analysis. Making sure the warehouse has the optimal amount of merchandise to keep the firm functioning well without draining its limited financial reserves is an important part of proper inventory management. Those in charge of inventory must foresee every demand of the company and find answers to most emergency calls. Without putting every cent into fixed assets, we were able to pull this off. Demand forecasting is a key challenge for every retail business. Due to the growth of e-commerce, more and more people are buying things online. However, E-commerce businesses confront a big threat from the unpredictability of online goods sales, which are on the rise. There are two sides to the coin: if vendors are prepared to meet demand, inventory costs will go down, and if producers aren't, inventory costs will go up, which means online users may have to go elsewhere. Consequently, making accurate sales predictions is a huge difficulty for e-commerce manufacturers when it comes to managing inventory and creating marketing plans. However, with demand for products being so unpredictable, it is very difficult to forecast sales. Academics and online merchants have recently centered their attention on sales forecasting. A lot of various methods have been proposed for sales forecasting. A model for sales forecasting that integrates econometric and neural network approaches. This was a break from previous research, which had used data mining frameworks to provide predictions based on online user behavior. There has been no technological advancement since the industrial revolution that can be compared to the internet. A significant number of Indians go beyond simple web browsing, emailing, and social network chatting when they connect to the internet, according to recent studies on internet prevalence and usage in the nation. We expect this number to grow as internet security measures are implemented and refined. There are now more opportunities for entrepreneurs and a changed competitive landscape for online merchants as a result of the proliferation of online platforms. Faster trade and a more interconnected supply chain are two results of globalization brought about by the rise of the internet. Online business transactions are complex and include numerous stakeholders that must work together closely. In light of customers' demands for a perfect supply chain, merchants are under increasing pressure to cut costs by incorporating lower inventory operations into demand and supply management systems. Businesses and IT organizations are becoming increasingly concerned about the storage and security of the massive amounts of data produced by various industries, including online retail.

Department, Warehouse, Raw Materials, Suppliers, and Employees are just a few of the inventory system modules that can be a real pain for administrators to manage in terms of information and connections. Data from various modules can be easily stored, deleted, searched, and updated using this framework. Everyone who came into contact with an item during storage will have their department, the dealer who gave it to them, and the original warehouse all documented in the system. Even the commodities themselves can be distinguished by this model, thanks to the warehouse's two distinct sections for raw materials and finished goods. Lastly, there's the amount of item in the latter. We can find out which department a supplier or dealer belongs to using the Supplier and Dealer modules. Fields in the Employee module include things like Employee ID, Name, Department Head, Joining Date, and Salary, among others, and can be used to store information about individual employees. Each section has its own unique identifier, manufacturing date, and amount. Organizing what needs to be sold and what can be saved for later is the purpose of this section.

II. Literature Survey

We require replenishment automation and inventory forecasting to save costs and waste in the supply chain. Because of the complexity and amount of data required for demand and sales pattern forecasts, replenishment automation presents a significant difficulty. To improve inventory forecasting, [1] used a neural network model to reduce inefficiencies. Big data's worth in SCM is often contingent on company procedures and decision-making frameworks. [2] investigated the role of AI at critical nodes in the textile manufacturing process. Research suggests that by utilizing information and theoretical concepts such as genetic algorithms, fuzzy set theory, and neural networks, the textile and clothing sector may effectively establish a sustainable textile supply chain.

[3] It is important for organizations to consistently assess and monitor their suppliers' key performance indicators (KPIs) to guarantee seamless product delivery. This involved identifying critical aspects such as cost, timeliness of delivery, controls for quality assurance, leadership, budget, capacity management, environmental factors, transportation options, technical assistance, and so on [4]. This is a crucial component of managing a group of preferred or pre-qualified providers. This could lead to technical competence being used as an extra factor in choosing suppliers, which could affect variables like inventory forecast and delivery schedule [5]. The existing methods for predicting sales are connected to approaches that use parameter prediction models based on time series, machine learning, and deep learning. [6] There are two main categories into which time series-based parameter prediction approaches fall: traditional statistical methods and auto regression methods. Conventional statistical wisdom states that time series are reasonably delayable along trends and exhibit regularity. In order to solve the problems with retail sales forecasting. And used both the single and double exponential smoothing methods to forecast product sales at the XYZ retailer [7]. The autoregressive method is also utilized in supply chain development; for example, the ARIMA method for anticipating consumer demand [8]. When it comes to assessing nonlinear relations, time series-based parameter prediction algorithms fall short. They can only capture linear relations at most. For parameter prediction methods to work, stationary time series data is also required. A stationary time series is one in which the central tendency, dispersion, and correlation do not alter with passing time[9]. A stagnant time series is one that does not show signs of trending or periodic changes. A further complication with using parameter prediction methods is that the data utilized to forecast online sales is seasonal. Parameter prediction methods based on time series are usually only useful for single variable prediction, and the components involved in e-commerce sales scenarios are complex [10]. Various models for demand prediction and forecasting have been created and improved over the past few decades, each one designed to fulfill the specific requirements of its target audience. Although there has been a lot of attention paid to rapid time series, [11] claims that intermittent time series and intermittent demand forecasting have been underappreciated. When it comes to intermittent demand forecasting, the CR method is highly effective and widely used [12]. Many academics have taken an interest in the topic of obsolescence because it poses a significant challenge to reliable intermittent demand projections. The methods currently used for predicting intermittent demand are going to be discussed in this section. First, bootstrapping strategies exist that are independent of probability distribution [13]. Second, methods like the CR and SBA processes are examples of parametric approaches; they use historical data to forecast the values of key parameters. Thirdly, intermittent demand forecasting frequently employs neural networks and other machine learning technologies. [14] In quantitative forecasting methodology, prediction models are built using a variety of approaches, including mathematical statistical models, machine learning models, deep learning algorithms, and others. Machine learning models are foremost in the field of mapping and generalization. There are a plethora of machine learning models available, such as LSTM neural networks, extreme learning machines, and support vector machines. [15] The LSTM model is employed for commodity sales forecasting because of its robust mapping capabilities. An innovative method for predicting sales in the supply chain was proposed by [16] utilizing the LSTM model. This approach uses the temporal properties of sales data from supply networks to its advantage. For this reason, nickel price forecasts were made using the improved LSTM model. To accomplish this, [17] introduced an improved particle swarm optimization method (IPSO) to improve the LSTM's prediction performance by reducing the random parameter volatility. The data mining method improves performance and forecasts. [18] The combined model that accurately forecasted the sales of liquified natural gas (LNG) cylinders was created by integrating the time series model with the artificial neural network. This inventory forecasting technique uses current inventory data to produce the following inventory decisions. [19]

Usually, in practice, this problem is divided into two smaller processes: As an example, the first sub-process utilizes historical demand data to forecast future demand based on current inventory data. Using the demand forecast as an example, the second sub-process decides how much of a certain product to buy. [20] The difficulties of inventory forecasting are distinct from those of other forms of forecasting. Segmenting the process, predicting product demand, and using that information to update inventory forecasts is the most recent approach to fixing forecasting challenges so that inventory decisions can be made using that data. [21]states that single-learning and cross-learning are the two main categories of these approaches. Most statistical and machine learning forecasting models are taught series-by-series and use single-learning. Models' intrinsic features and performance records, data availability, and computational power developments are among the many factors at play here. Several sets of data are used by forecasting models that have been trained using cross-learning techniques. You could discover that some of these models are useful when dealing with inventory forecasting or any other issue involving several, frequently unconnected series.

III. Proposed System

The importance of e-commerce consumer behavior prediction is growing as more and more individuals forego traditional brick-and-mortar stores in favor of online marketplaces. The popularity and sales of products sold on online marketplaces such as Amazon and Flipkart have skyrocketed in the past few years. To stay relevant in the sector, several long-established merchants and wholesalers have set up shop online during this time.

A. Data Preprocessing:

The term "data preprocessing" refers to the steps used to remove any anomalies or noise from the chosen data. As a result, removing data with a great deal of extraneous significance is unnecessary and meaningless. For instance, since product reviews aren't relevant to sales forecast in this dataset, we may safely assume that they are the source of the noise and eliminate them. On top of that, we need to know how to deal with missing sales and price values in the dataset. This includes either averaging out the values or impinging them using the median or mean to ensure that the data is consistent. It may now also take into consideration the data's temporal sequence and the modifications that are known to have occurred.

1) Data Transformation:

Data transformation is the process of altering data's format to make it more versatile. This process is also known as "ETL" (which stands for "Extract, Transform, and Load"). Since the data amount has increased significantly, transformation has become an essential activity [22]. Users will have the ability to focus on data that is relevant to their business needs because of the strong data transformation. Similar to how the full dataset will be transformed for this project, only the most relevant facts will be combined. The researcher can then build a more precise prediction model by focusing on the most pertinent data. After going over all eight datasets, the researcher needs to pull out the important numbers and information before formatting the data. Research during the modeling stage will be much simplified by minimizing unnecessary data.

B. Feature Selection:

The quantity of big data in an e-commerce context is always growing as a result of the expansion of internet technology. The variety of information forms and sources used to compile big data is one of its defining features. This includes, but is not limited to, tweets, internet, text, click-stream, video, audio, and log files. Features selection, which involves removing irrelevant variables, and feature extraction, which involves transforming existing variables to obtain new ones, have been discussed extensively as ways to reduce the dimensionality of data by eliminating redundant and irrelevant information from various types of data. The two methods mentioned are wrapper feature selection and filter-based [16]. By predicting the validity of feature subsets using an in-learning algorithm subroutine statistical resampling approach (such as cross-validation), wrapper feature selection is a better choice for different algorithms modeling the different data series. Several algorithms should utilize filter-based feature selection when modeling the same data series.

This method suggests using standard deviation (SD), Pearson correlation coefficient (PCC), coefficient of variation (CV), and feature importance scores (FIS) as metrics to streamline multidimensional data by eliminating irrelevant qualities using forecasting and grouping algorithms. The standard deviation (SD) symbolizes the extent to which the data collection is dispersed; it is calculated as σ, where Z is the sample size and μ is the sample mean value (m_g).

$$\sigma = \sqrt{\frac{1}{Z}\sum_{g=1}^{Z}\left(m_g - \mu\right)^2} \tag{1}$$

The degree of variation in the observed values in the data can be measured by calculating the statistic CV, which is written as h_d:

$$h_d = \frac{\sigma}{\mu} \tag{2}$$

As an indicator of the degree to which two variables are related linearly, the Pearson correlation coefficient (PCC) can be expressed as n:

$$n = \frac{1}{r-1}\sum_{g=1}^{r}\left(\frac{M_g - \bar{M}}{\sigma_M}\right)\left(\frac{Q_g - \bar{Q}}{\sigma_Q}\right) \tag{3}$$

The variables $\left(\left(M_g - \bar{M}\right)/\sigma_M\right)$, $\bar{M}$ and σ_M reflect the standard deviation, mean value, and standard score of M_g, respectively. When developing the model's enhanced decision trees, FIS gives each feature a score that represents its usefulness. Decision trees base the relative worth of an attribute on how frequently it is used to make critical judgments. The relevance is determined for each node in a single decision tree by adding the weighted performance measure at each attribute split point to the total number of observations. One possible performance metric is the data purity as assessed by the Gini Index or another more specific error function. The next step in determining the feature importance is to average the model's decision trees.

C. Model Training:

1) CNN:

All two methods rely on CNNs for environmental object recognition. With R CNN, object recognition is accomplished. Use of a convolutional neural network trained on RPNs allows for comparisons without regard to value in this method. Network areas can be set by dragging the item suggestions window across convolutional feature maps. Layers that follow use this mapping window to collect low-dimensional data. Data is analyzed using regression and categorization. With careful placement, the anchors can showcase the region's most promising bids. It will change the window size for each anchor so that detailed data inquiries are easier to do. To put it another way, the anchors have five windows. For instance, the overall number of windows used grows in tandem with the size of the feature map. A visual inventory is essentially what comes out of it. There are a number of methods to use this list to create an item list that can be used to find the scene's focus points.

Three hidden unit layers, an output layer, and an input layer make up S-CNN's five layers. The ability of convolution layers to pool and filter data is initially activated by a number of hidden layers. With the help of convolutional filtering and pooling, characteristics that remain unchanged when scaled or translated are extracted after the input. Last but not least, the classification process is completed by the output and hidden layers [23]. Key point discriminator (KPD) analysis using convolutional layer filtering and pooling capabilities. At the S-input CNN level, data is received in a 2D array that depicts the scene's numerous objects, together with KPD produced by feature extraction, picture color density, background object concentration, and regional information. The outcomes of the visual filters used to input the data are displayed below. Some types of data are removed by these systems. The third hidden layer is activated in a linear fashion by the parameters of the second hidden layer. Last but not least, we used linear addition to aggregate the second hidden layer's predictions. Activated neural circuits were utilized to develop predictive classifications. Using S-CNN for environmental feature classification can do this. After considering FLIM and R CNN data, we will arrive at a classification for vehicle speed detection. When training, a large number of labeled, similar samples are utilized. This impartial connection is subjected to a battery of analytical and performance tests.

2) Fuzzy LIM:

Classical K-Means clustering relied on vector quantization in its day. It is common practice to use a recursive procedure that modifies the distance calculation method to randomly determine the cluster center. Using the average from the previous cycle, it can find the center of the cluster. At each iteration, this computation is carried out. The cluster will continue to recalculate indefinitely until convergence is reached. Full convergence causes the K centers to shift. Everything that is happening is causing this. In the traditional K-Means approach, the cluster bin, convergence function, and recalculation of cluster centers are the three main parts.

$$V_c = \sum_{a=1}^{xv} (V_v a - XV_v a^2) \tag{4}$$

$$XV_v a = \frac{1}{xkv_a} \sum_{g=1}^{xkv_a} Vtgr_a \tag{5}$$

$$Vtgr_a = Vtgr_a | U_z a \tag{6}$$

$$U_z a = pgx_{g=1\ to\ xu}\, u_g\ if\ dist\ of\ u_g\ is \min to\ V_v a \tag{7}$$

$$dist = q_g - V_v a^2 \begin{Bmatrix} g = 1\ to\ xu \\ a = 1\ to\ xv \end{Bmatrix} \tag{8}$$

The function calculates the distance between cluster centers. Both the stopping criteria and the repeated stage regulation require accuracy. These clusters are the ones that the user has selected or is freely accessible. This part contrasts the existing cluster nodes with the ones that are planned. Inserting the previously defined cluster bin into the formula, where and are equivalent, allows us to find the total number of cluster bins. Clusters should be proportional to bins. When two points are at least the minimal distance apart, then say that one of them is accessible. Maybe the K-means algorithm will converge to the local minimum instead of the global minimum. The global minimum influences the last cluster, but the initial random selection continues to impact it. More and more iterations make it harder to maintain the cluster centers from wandering around too much. It will now put FLIM into action, which stands for fuzzy local information means.

$$pgr_{ga} = \frac{1}{kag} (Max(q) - V_v a)^c \tag{9}$$

Information unique to each cluster is shown in Equation (9). In mathematics, this is calculated as the inverse of the distance between the centers of the two clusters. The optimal solution is found by directing the cluster centers to the convergence rate with the smallest possible, which is located via this function. If this were to hold, FLIM would increase the push-in cluster center selection parameter as per equation (10) because its membership function is identical to K-mean's.

$$XV_v a = \frac{1}{xkv_a} \sum_{g=1}^{xkv_a} L^c a + pgr_{ga} \tag{10}$$

$$L^a p = U_z p \forall Q_p \tag{11}$$

Here, simply uses the user-requested cluster size, represented by X and xv. A weight, or " g," is assigned to each component in each cluster group to denote its significance. Two of the many functions that $V_v a$ performs are computing $V_v a$ and storing the clusters that have resulted from $XV_v a$ (11). The function additionally considers the clusters $U_z a$ from the previous calculation. Unique features that set FLIM apart from other methods. The regular K-means computing approach would not have included the fuzzy feature denoted by $L^a p$. People may be physically located in distinct clusters even though they appear to be part of the same cluster in a cluster group.

$$U_z p = pgx_{g=1\ to\ xq}\ Q_g if\ k_{ag} of\ U_g is\ \min to\ V_v p \quad (12)$$

$$k_{ag} = Q_a - V_v a^2 \begin{Bmatrix} g = 1\ to\ xu \\ a = 1\ to\ xv \end{Bmatrix} \quad (13)$$

The data items' distance from the group is measured by equation (13), whereas equation (12) gives the chosen data for each cluster. How well the data points fit within the cluster was assessed in this way. Cluster significance is increased for data points containing humans and decreased for quasi-data sets as a result of this choice.

$$Obj\ C_{Iter} = \sum_{a=1}^{xv} \sum_{g}^{xu} R^c\, uf_{ag} + pgr_{ga} \quad (14)$$

Determining the degree of convergence, the decision-making goal function is also found using the recursive approach. In optimization scenarios, membership factors and data-specific knowledge parameters work together to detect convergence. Consequently, fuzzy k-means was effectively applied to the business.

IV. Result and Discussion

Verifiable sales forecasts are of the utmost importance to internet retailers. Most of the most recent algorithms are univariate, which means they only consider the sales history of a single product when making predictions. It might be useful to use the past actions of similar, related time series to condition the prediction of one time series if there are plenty of them.

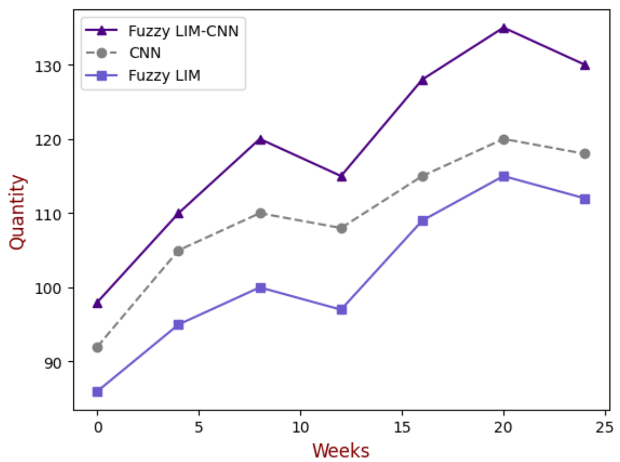

Fig. 1. Prediction Comparison of Proposed Model

Figure 1 shows a combined graph of the line graphs for the Fuzzy LIM, CNN, and Fuzzy LIM-CNN models. Outperforming all other models is the Fuzzy LIM-CNN model, according to the graph lines.

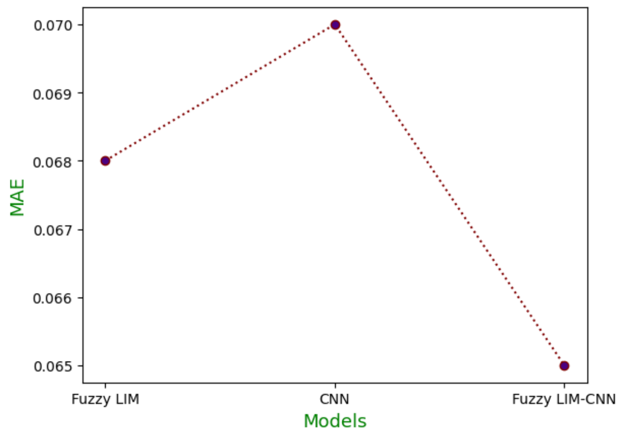

Fig. 2. Evaluation Index Of Different Models

A lower MAE value indicates that Fuzzy LIM-CNN is more accurate in its prediction. Our approach seems to be more accurate than the others in estimating e-commerce sales, which means that corporations can get more precise estimates. This is illustrated graphically in Figure 2.

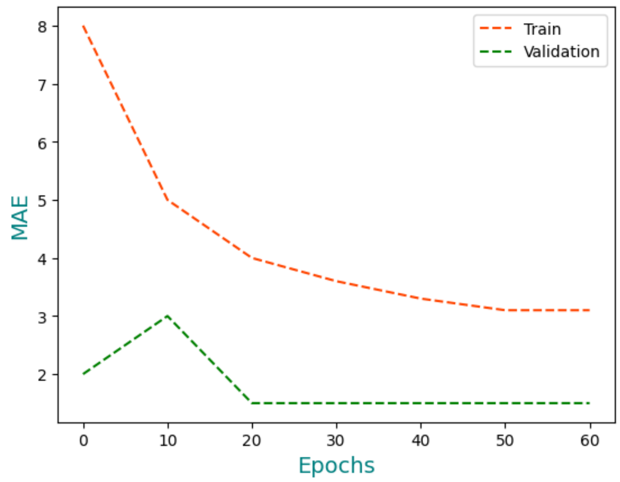

Fig. 3. Graph Showing Changes in Training Model Loss

Figure 3 shows that when the number of training sessions increases, the regression loss graphs stay the same. Minimal loss fluctuation is seen, with a mean absolute error (MAE) of 3.1 for unary regression and 1.5 for binary regression. The training effect seems to be the better option based on these results.

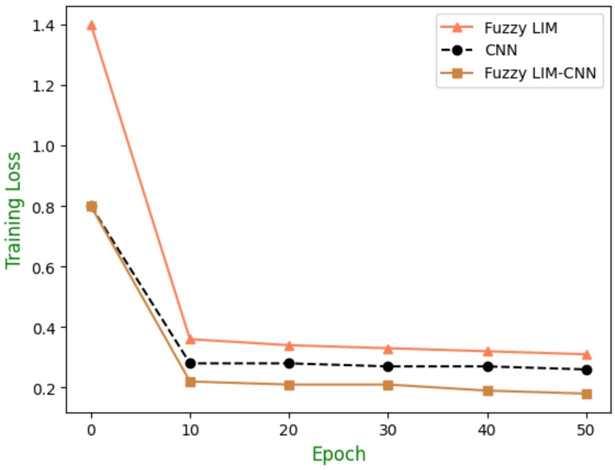

Fig. 4. Performance Summary of the Model

Figure 4 shows that all three models' loss functions decrease throughout training. Losses for the training set for all three models approach zero as the number of iterations increases. The Fuzzy LIM-CNN model has a small loss value right from the bat; it falls sharply and remains there. The results show that the Fuzzy LIM-CNN model outperforms the other two models on the training set.

V. Conclusion

Enterprise resource planning (ERP) software for cross-border e-commerce is in charge of managing and optimizing global supply chain warehousing in light of the increasing operational costs of overseas warehousing and the ongoing expansion of cross-border business activities of e-commerce enterprises. In order to make the selected data free of errors and noise, a technique known as "data preprocessing" is employed. It is possible to filter through various datasets and remove the extraneous and irrelevant data using feature selection. The Fuzzy LIM-CNN model was utilized during the entire training procedure. Compared to CNN and Fuzzy LIM, the proposed technique has a better average accuracy of 91.67 percent.

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