Forecasting the Impact of Raw Material Cost Variations on Finished Goods Pricing Using Random Forest and Naive Bayes Approach

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Abstract

Examining the effects of raw material price fluctuations on supply chain productivity is the driving force behind this study. In particular, the study aimed to investigate how the company dealt with unpredictable raw material prices, how these variations affected the company's productivity, and what role governments played in resolving this issue.The three main parts are feature selection, model training, and preprocessing. Among the three steps that make up preprocessing—outlier preprocessing, feature smoothing, and normalization—outlier preprocessing yields the best results with the least amount of effort investment. Feature selection, often called variable or attribute selection, is a method for improving performance by reducing the number of features to a manageable number by removing superfluous or unimportant information. We used the RELM framework to train the models. Conversely, it renders ELM and CNN unnecessary. According to the numbers, 95.61 percent of the time is successful.

Keywords: Raw Materials, Regularized Extreme Learning Machine(RELM), Cost Variations

I. Introduction

According to microeconomic principles, the extent to which consumers can withstand increases in raw material prices is determined by three microeconomic variables: market structure, firm competitiveness, and demand elasticity. The second option is dependent upon whether or not adequate alternatives are available and how crucial they are to household consumption. Raising prices for consumers as a result of passing on all increases in the cost of raw materials is highly unlikely to happen in most situations. Participation by businesses would boost their profits right away. Businesses may consider investing in IT upgrades as a long-term solution to their financial woes. Stock prices would be affected by a rise in the cost of raw materials since it would decrease profitability and make the future look less bright. Several other factors can contribute to decreased profitability, including high interest rates, poor technology, excessive overhead expenditures, and competitive pressure. Still, it's interesting to think about how a spike in raw material prices could affect stock prices.

A spike in raw material prices would affect the sector's overall outlook. One unit of raw material is changed into one unit of the final product during a zero-lead time process, which we will assume. Unfulfilled requests have built up a backlog. Given data on both historical and current costs, the only variable that can be used to forecast future raw material costs is the current cost, since the raw material cost process. If the corporation is solely permitted to deal in spot markets and not futures or any other forms of contracts, its operations will be much simplified. It would appear that this modelling feature has enough potential usage based on the data that is currently accessible. Assuming there is no set ordering cost, we will acquire raw materials. Every period, a steel mill would incur far smaller set accounting or order entering costs than the massive transaction quantities associated with contemporary steel factories. The correlation between volume and transportation or handling costs is another way of looking at it. Additionally, we do not consider any lead time for the supply of raw materials. Even when the price of one main raw material is completely out of our control, our model can nevertheless manage situations where the prices of other resources are somewhat stable. Keeping track of the money spent on Raw Materials (RM) is a crucial part of any manufacturing process. Numerous organizations have discovered that acquiring and selecting suppliers is a substantial difficulty. How does the procurement function impact company strategy and the formulation of strategic goals? Due to the "sensitivity" of decision-makers and the existence of tacit knowledge, companies have always supported RM purchases. Significant economic benefits or losses may occur as a result of unfulfilled RM needs or increased acquisition prices depending on the company's decision-making process for RM acquisitions. Decisions on the amount, timing, and price of RM can have strategic and operational ramifications, and this is particularly the case when RM costs constitute a significant portion of industrial product pricing and RM prices are very variable. It is common knowledge that companies dealing with raw materials, in particular, are vulnerable to market volatility. While examining two makers of steel products in the Southeast, we came upon this data. Companies face a huge hurdle when attempting to handle material procurement activities while also addressing pricing and inventory management problems all at once. The company risks paying more than needed for holding fees and missing out on future acquisitions that are less expensive if the purchase is done too early. However, if it's finished too late, the company may have to pay more for the backlog and lose out on the chance to purchase the raw material at a lower price. Finally, for the sake of argument, let's say the business's bank account actually earns interest that exceeds the rate of inflation, which causes all prices and costs to rise.

II. LITERATURE SURVEY

Several methods for predicting the prices of raw materials have been considered by researchers. Others have sought methods to predict changes in the cost index or the price of construction supplies, while still others have focused on tactics for limiting the risk of price changes. [1] The targets of the present study's predictions—the characteristics of iron ore pricing and the factors that influence them—have been the subject of multiple previous studies. To reduce the impact of raw material price fluctuations, [2] proposed optimizing JIT procurement and storage capacity according to demand and price. The method of risk-hedging construction materials proposed should be taken into consideration by suppliers of building materials that use derivative goods. [3] investigated the relationship between derivative products and a company's financial health, and they suggested a methodology for risk-hedging based on these products. The impact of oil prices on exchange rates was investigated by [4] in their research of a small open economy. How price-sensitive construction components affected overall project expenses. Unfortunately, no one in the aforementioned studies proposed a method for predicting future raw material costs.Examining the interplay between CCI and other impact factors is essential for making predictions about construction-related indices like CCI. [5]Predicting an indicator associated with the construction industry was the aim of the present study, as it had been in previous studies. Previous studies had limitations, such as using elements that were already heavily included in the index to foretell how the index will evolve in the future. Product quality, production costs, administrative operations, and raw material damage can all be better managed with the use of the batching plant's inspection technique. [6] It is still not entirely clear how accurate product receipt projections are in relation to process expenditures. There have been cost overruns because of inaccurately estimated costs, which is the primary cause of the current vulnerability. [7] This is a common occurrence that leads to a loss of revenue due to unused bookings. Reduce the difference between ordered and received raw materials by optimizing the production process and controlling the selection of raw material providers through inspection and forecast of acceptance level[8]. The estimation process has not yet made use of a neural network technique, and there are still components that are not based on trends in booking cost and profit data. Cost estimating is the process of determining an approximate amount that will be required to complete a construction project. [9] For the most part, researchers in this field have relied on statistical approaches to deduce inferences from pricing data, generate projections, and evaluate financial and economic scenarios. As an example, consider the oil and petrochemical sector. At first, several unique intrinsic modes were identified by [10] from three different crude oil price series, each with its own unique time range and frequency. Afterwards, a fluctuating process, a component that gradually changed, and a trend based on fine-to-coarse reconstruction were constructed from the intrinsic modes. In their analysis of the crude oil markets price volatility, [11] considered the OPEC market structure, the elasticity's of demand, and the structures of steady and unstable demand. The degree to which petrol prices respond asymmetrically to shifts in oil prices is influenced by the volatility of oil prices, according to [12]. For this reason, a number of time series metrics were devised to quantify the asymmetry between the reactions of petrol prices to shifts in oil prices and movements in oil prices themselves. With regard to the problem of lag variable size, [13] discovered that larger sizes enhance forecast accuracy but reduce subsample heterogeneity representativeness. To add insult to injury, estimation accuracy will take a hit even though smaller samples can be more representative. Using lagged variables with 12,24, or 36-month durations, all of the aforementioned empirical research examined different possibilities. Nevertheless, the results demonstrate that the lags in the variable sizes were insignificant. [14] Despite the fact that the size significantly affects the lagged variable regression results, random selections are required because there are no good methods to find an appropriate size. Some authors argue that a lower lag variable is better because a larger one could lead to the loss of information on short-run predictability [15]. Transportation expenses in Thailand are driven higher by the high demand for roads compared to other, more affordable options like trains. Building railways is one technique to create inland commerce lines that try to lower transportation costs. They connect various industrial zones to major trading ports to ease access to distant markets and boost maritime freights [16]. This cost is the second most common in the industrial sector, behind inventory carrying cost, and it is caused by both over- and under-purchasing. The manufacturing sector relies on raw materials as the foundation for final products. [17] Crude oil, natural gas, gold, silver, aluminum, brass, copper, zinc, cotton, rubber, wheat, and so on are all commodities whose prices are directly affected by the prices of these raw materials. [18] They are subject to changes based on the law of demand. Consequently, commodity prices have a tendency to climb when demand is high and supply is scarce. Commodity prices decline when supply exceeds demand. An internal factor that has a major influence on a company's performance is the price of raw materials. [19] Discovering the impact of changes in raw material prices on stock prices is the main objective of the study. By observing how financial markets respond to changes in raw material prices, you can learn whether stock price swings are affected by these changes. [20] The effect of market mood and sectoral predictions is reduced. We demonstrated that raw material price fluctuations can affect sectoral predictions. Through the provision of a framework, we are able to conduct the inquiry by analyzing the duration of the affects and the degree of dependence. [21] We seek to ascertain if the effect of input costs on stock prices is transitory or has long-term ramifications. Our methodology can also be used to determine the time-varying link between sectoral expectations, market sentiment, and stock prices. In order to understand the time dependence, we break down the time series into its component pieces according to the week.

III. PROPOSED SYSTEM

Every manufacturing process has the same overarching goal: to increase profits while minimizing production expenses. Cuts to product quality are an unintended consequence of trying to save money. Thus, the goal is to lower production costs without sacrificing quality. This study aims to provide the best practices for manufacturing in a system where the inputs are raw materials that can change. The objective is to minimize production costs while preserving a particular degree of raw material quality, with specific constraints on the end-product quality.Figure 1 shows that the processes of the proposed system.

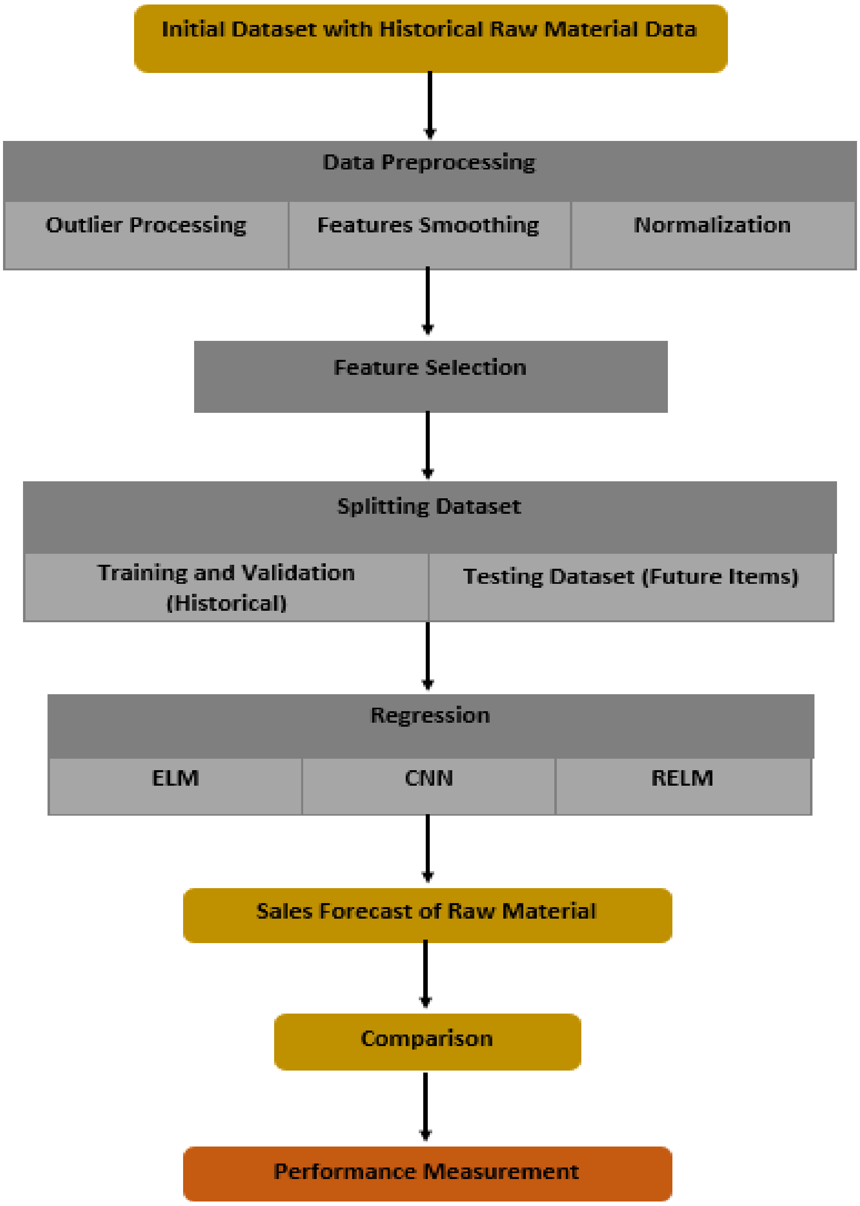

Fig. 1. An Illustration showing the Processes that were employed

A. Preprocessing:

1) Outlier Preprocessing:

Outlier samples encompass a substantial portion of the feature space, despite their diminutive size. They are able to affect the outcomes of the following normalization processes by modifying the cumulative distribution of the healthy, non-outlier samples. Several novel methods exist for detecting outliers, reducing their effect, and, finally, improving classification accuracy. We utilized Grubb's method to separate the outlying samples from the rest of the samples. To make the identified outliers stand out even more from the rest of the data set, which is free of outliers, we multiply their values by 1.1 times the maximum value in the remaining set[22]. It is one anomaly at a time that Grubbs discovers. Each iteration ends with rerunning the test to remove any remaining outliers from the dataset. This test is based on the premise that all data points are normally distributed. Here is how the two-sided Grubbs' test statistic is defined:

$$D = \frac{\max_{b=1,\ldots,P} |R_b - \bar{R}|}{\tau} \quad (1)$$

Where τ is the standard deviation and $\bar{R}$ is the sample mean. The null hypothesis of no outliers at the significance level β may only be rejected if the following inequality is satisfied:

$$D > \frac{P-1}{\sqrt{P}} \sqrt{\frac{c^e_{\beta/(2P)-2}}{P-2+c^e_{\beta/(2P)-2}}} \quad (2)$$

Given $P-2$ degrees of freedom and a significance level of $\beta/(2P)-2$, where $c^e_{\beta/(2P)-2}$ is the upper critical value of the t-distribution.

2) Features' Smoothing:

Total signal power levels that are either increased or decreased clearly indicate the level of dominance. Not only does feature smoothing make them less defiant, but it also makes them easier to see or computationally classify. After 13 consecutive 6-second epochs, a moving average window of 1 minute length smooths out each feature " ".

$$\bar{f_h} = \frac{1}{y+1} \sum_{l=1}^{y} f_{h-l} \quad (3)$$

3) Normalization:

The most basic kind of preprocessing is to normalize the input space vectors. The statistical and signal processing contest uses feature scaling to normalize the sets of independent variables or data features due to the significant range in data values. [23]Support vector machines (SVMs) and other big margin classifiers are among the machine learning methods that become more vulnerable as data sizes increase. Data points or the classifier's kernel can be normalized to improve its classification performance. Consequently, nonlinear kernels are left with no choice but to normalize their data. In this study, normalization is used as a preprocessor for the support vector machine (SVM) classifier. There are three different ways that feature normalization is achieved.

After dividing by the highest feature value:

$$r_{norm} = \frac{r - \min(r)}{\max(r) - \min(r)} \quad (4)$$

The feature's average absolute value is divided by this:

$$r_{norm} = \frac{r - mean(r)}{mean(abs(r))} \quad (5)$$

Considering the standard deviation of the feature.

$$r_{norm} = \frac{r - mean(r)}{std(r)} \quad (6)$$

Here, r represents the feature sequence that is being normalized and r_{norm} stands for its normalized form.

B. Feature Selection:

Feature selection (FS), sometimes known as variables or attributes selection, is a data mining technique that aims to enhance performance by eliminating non-informative qualities and retaining just the most informative ones. By selecting a subset M features from the complete set of N features, feature selection aims to improve the performance of the learning algorithm. Feature selection is a method for improving prediction accuracy by reducing the influence of unnecessary or noisy variables while keeping a subset of input variables that can characterize the data effectively. The filter method and the wrapper method are the two most common approaches to feature selection[24]. The use of filter approaches, which do not depend on any specific machine learning algorithm, is widespread at the pre-processing step. Additionally, wrapper strategies leverage the prediction model's accuracy in identifying important features from the training data by using the selected feature subset. This proposed approach made use of the wrapper method as its feature selection technique. The wrapper technique incorporates the supervised learning algorithm to validate the feature subsets that are produced using one of the search strategies. To choose the subset, the learning algorithm examines the training data and evaluates the variable subset based on the performance of the current subset, which serves as the objective function. Three main parts make up wrapper-based feature selection: a search technique, an inductive implementation, and evaluation measurement. Procedures such as forward feature selection, backward elimination, and recursive feature removal frequently employ wrapper approaches.

C. Training the Model:

1) RELM:

The purpose of this research is to examine RELM and determine how changes in the cost of raw materials affect the final product pricing. Using the recovered 2D-CNN features of changes in raw material cost, a RELM classifier is employed to make predictions among five emotion classes. Being an SLFN (single hidden layer feedforward neural network), ELM trains fast and does well when introduced to novel scenarios. The issue is that it often results in overfitting because it is based on the ERM principle. Rooted on structural risk minimization (SRM), RELM was introduced as a solution to this issue. For the ERM to work, the data samples' squared errors must be added together. In overfitting, the training errors on observed data are fewer than the testing mistakes on unseen data since there aren't enough data samples to make reliable inferences. Therefore, the SRM principle and RELM's ability to operate are both grounded on statistical learning theory. It demonstrates the relationship between empirical risk and real risk and serves as a metric for the limit of generalizability. In this situation, the empirical risk is represented as $\|\varepsilon\|^2$, and structural risk can be represented as $\|\alpha\|^2$.To be more precise, the activation function is $d(r)$, and there are p unique training samples$(r_b, c_b)\varepsilon\mathbb{R}^h * \mathbb{R}^y$. The model for the b th samples is the RELM with hidden nodes P.

$$\sum_{b=1}^{\tilde{P}} \alpha_b d_b(r_b) = \sum_{b=1}^{\tilde{P}} \alpha_b d_b(u_b.r_b + i_b) \qquad (7)$$

while $u = \left[u_{b1}, u_{b2}, \ldots, u_y\right]^T$The weighted vector T represents the relationship between input nodes and hidden ones. The set $\alpha = [\alpha_{b1}, \alpha_{b2}, \ldots, \alpha_b]^T$is defined as α_bThe weighted output (T) indicates the link between hidden nodes and the output nodes, the bias of the hidden layer nodes is i_b, the inner product is represented by the value $u_b.r_b$, and $Q = \left[q_{b1}, q_{b2}, \ldots, q_{lp}\right]$ is the network output. T is the symbol for the output vector, which is $y \times 1$. Standard SLFNs with $\tilde{P}$ hidden nodes can usually approximate p different training samples with zero error, meaning

$$\sum_{b=1}^{P} \|q_o - c_o\| = 0 \qquad (8)$$

α_b, i_b, and u_b must be present in order for the function to be satisfied.

$$\sum_{b=1}^{\tilde{P}} \alpha_b d_b(r_b) = \sum_{b=1}^{\tilde{P}} \alpha_b d_b(u_b.r_b + i_b) = c_l \qquad (9)$$

Another way to express the previous equation is as

$$K\alpha = C \qquad (10)$$

$$K(u_1, u_2, \ldots, u_b, i_1, i_2, \ldots, i_b, r_1, r_2, \ldots, r_b) = \begin{bmatrix} d(u_1.r_1 + i_1) & \cdots & d\left(u_p.r_1 + i_P\right) \\ \cdots & \cdots & \cdots \\ d(u_1.r_P + i_1) & \cdots & d\left(u_p.r_P + i_P\right) \end{bmatrix} \qquad (11)$$

the network's hidden layer output matrix is represented by K. In order to find the best minima, hidden node properties are typically tweaked iteratively. In contrast, the output weights can be determined analytically and hidden node parameters can have any nonzero activation function when training an SLFN. Therefore, the estimation of α can be expressed as follows in order to get the output matrix according to the theory of least squares:

$$\hat{\alpha} = K^{\dagger}C \qquad (12)$$

$K^{\dagger}$ is the notation for the generalized inverse of K, which is also called the Moore-Penrose generalized inverse. To solve this particular equation, the RELM algorithm seeks the best possible solution o.

$$\|K\tilde{\alpha} - C\|_A^2 = min_{\alpha}(\|K\alpha - C\|_A^2) \qquad (13)$$

The Frobenius norm is where $\|.\|_A$is located. Notable regularization methods include minimax concave, ridge regression, and nonconvex term, among others. Linear systems have made use of these terms to lower the total variance. Overfitting occurs, however, when ELM's hidden node count surpasses 4800. It employ the Frobenius norm as a regularization measure, capitalizing on the fact that the output of these SLFNs can be quantitatively determined as a linear system.
Here is another way to express Equation (13):

$$\|K\tilde{\alpha} - C\|_A^2 = min_{\alpha}(\|K\alpha - C\|_A^2) + \mu\|\alpha\|_A^2 \qquad (14)$$

$$\tilde{\alpha} = (K^T K + \mu\beta)^{-1} K^T T \qquad (15)$$

Equation (15) shows the calculation of $\tilde{\alpha}$ for regularized ELM, where μ is the regularization factor. When the constant term μ is positive, greater than 0, the optimal solution to equation (14), given by equation (15) is obtained[25]. By controlling μ, there is the ability to modify the quantity of empirical risk and structural risk. By determining the best compromise between these two risks, a more generalized model can be created.

IV. Result and Discussion

It is essential for industrial process control experts to understand how raw materials, process parameters, and the end product interact with one another. There are many instances where the basic materials are complex and difficult to change methodically. Because of this, using systematic variable fluctuation and other traditional methods of experimental design becomes more difficult. One possible answer is to measure the available raw resources; however, there is the problem of knowing what to measure.

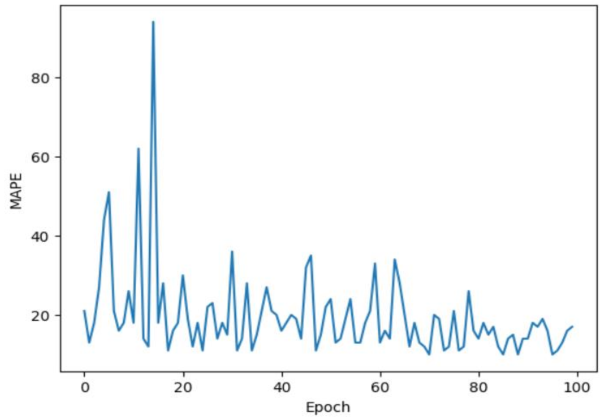

Fig. 2. MAPE for Proposed Methods

Figure 2 shows that there is almost no difference between the actual and estimated raw steel cost figures. The values for the model's performance evaluation are shown by the average absolute percentage error (MAPE) in the RELM study.

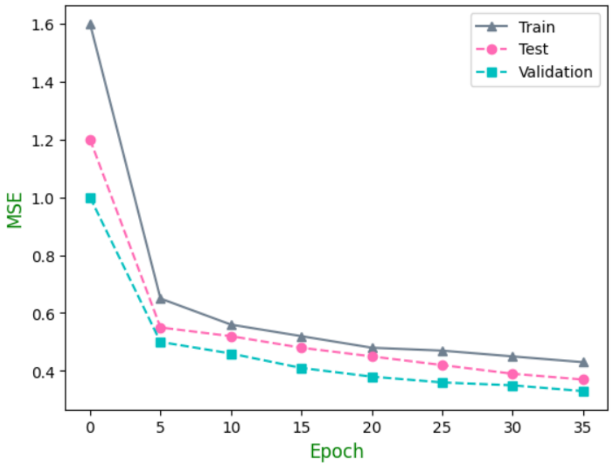

Fig. 3. Training Accuracy of the Proposed Model(how the Standard Error Changes Depending on the Training Iteration)

The training accuracy is displayed in Figure 3 as the mean square error's reliance on the training iteration. Additional information is provided regarding the mistakes made in the "Training," "Validation," and "Testing" data sets. Training ends when the "Validation" set error rate does not decrease. The results of the "Test" show that the network can generalize.

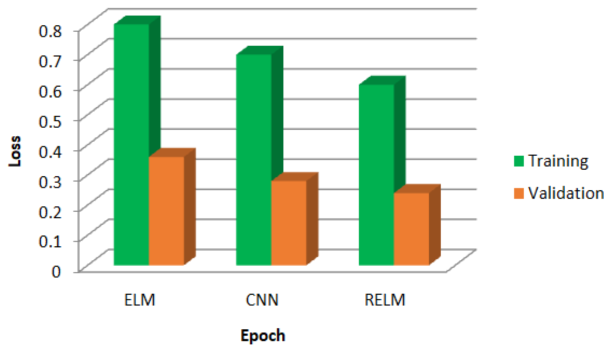

Fig. 4. Training and Validation Loss of RELM

In Figure 4, we can see the training and validation loss of RELM. The graphic above shows a comparison of the losses of the ELM, CNN, and RELM models.

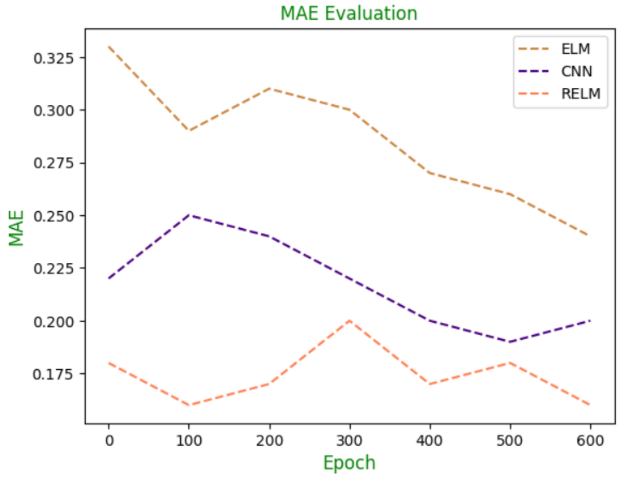

Fig. 5. Mean Absolute Error Evaluation

Figure 5 illustrates that we made good use of machine learning with a 100-item learned dataset; RELM trained with still classifying and achieved a production accuracy of about 95%, significantly better than the competing classifiers. We discover that, when data is processed manually, an ideal dataset size of 500 to 600 records is known, and we also demonstrate that RELM can increase datasets to reach this target.

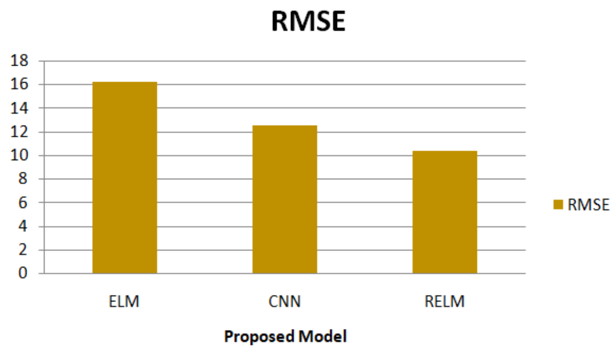

Fig. 6. RMSE of the Proposed Model

Figure 6 shows the results of comparing the root-mean-square (RMSE) values of the three models. With an RMSE of 10.41, the RELM model outperforms the other two models.

V. Conclusion

The business that has in mind is one that buys raw materials in bulk, keeps them in inventory, and then processes orders for completed goods. Changing raw material costs are described by the model, and the demand process is determined by a mix of this model and the firm's sales pricing. Both the acquisition of raw materials and their sale price are overseen by the corporation for each assigned time period. Policies of the base-stock-list-price type, which account for raw-cost dependence, are optimal will proved.Feature smoothing, normalization, and outlier preprocessing are the three components of preprocessing; outlier preprocessing produces the best outcomes with the least amount of work. To improve efficiency, feature selection (also known as variable or attribute selection) eliminates irrelevant or unnecessary characteristics, bringing the total number of features down to a more manageable level. For model training, the RELM method is employed. With a consistency rate of 95.61%, the proposed method outperforms the CNN and ELM models.

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