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An Efficient Medicine Demand Prediction System Using LTH-SES-Based Machine Learning Technique with Pharmacy Supply Chain

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ABSTRACT

The Pharmaceutical Industry (PI) is deemed as one amongst the most substantial industrial sectors. Therefore, for the healthcare system, effective management of the Pharmaceutical Supply Chain (PSC) is crucial. Thus, an efficient medicine demand prediction system is proposed in this paper by using the Logistic Tanh activation adapted Single Exponential Smoothing (LTH-SES)-based Machine Learning (ML) technique with PSC. The previous medication sales data from the PSC are collected from publicly available sources to predict future medication needs. Later, to reduce the vast amount of information present in the dataset, the MapReduce model is performed. Later, the features are extracted. After that, by using the Renyi Entropy Principal Component Analysis (REPCA) technique, the dimensionality is reduced. Later, by using Min-Max Distance Centroid Fuzzy C-Means (M^2DCFCM) clustering, the medications are grouped together. Lastly, for forecasting the future demand for medications, the LTH-SES technique is used. The proposed system's performance is further validated and the outcomes exhibited that the proposed methodology forecasts the demand more effectively than other prevailing techniques.

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1. INTRODUCTION

A set of strategies as well as decisions that enhance the supply chain performance is termed as supply chain management [1]. The process of managing material, information, capital flows, and cooperation amongst firms along the supply chain is named SCM [2]. It focuses on the flow of information, services, and goods from sources to customers by means of an entity chain as well as activities that are linked to one another [3]. Firms are concentrating more on predictive analytics techniques since competition is increasing every day among market retailers [4]. Thus, effective as well as efficient management of information, financial, and material flow amongst all constituents of the network are encompassed in SCM [5]. An amalgamation of processes, organizations, and operations encompassed in the growth, design, and production of beneficial pharmaceutical drugs is termed as PSC [6]. PSC extended broadly covering distributors, suppliers, retailers, manufacturers, health service providers, wholesalers, and doctors across multiple markets [7]. The supply chain operation will be a simple backward scheduling issue if the final demand of the customer is well-known with certainty well in advance [8].

The basis of all managerial decisions in SCM, namely demand planning and order fulfillment, is called Demand Forecasting [9], which is a source for all planning activities as well as execution processes [10]. The quantity of a product purchased by the customers is estimated by demand forecasting, which enhances customer satisfaction and guarantees suitable SCM by preventing inventory stock-out [12], [26]. To make major decisions, all major organizations truly rely on demand forecasting's efficiency [13]. Accurate demand forecasting can attain a lot regarding profit maximization, augmented sales, effectual production planning, etc. [14]. Since accurate demand forecasting plays a significant role in the healthcare system, it is crucial for pharmaceutical industries [15]. A group of activities and processes leading to the discovery as well as expansion of products (i.e. drugs and medicines) is the PI [16]. Any hazard that affects the PSC may impact on the health system's efficiency and disrupt the medicine supply [17], [24]-[25]. Thus, the basis for PSC management is the prediction of the necessity for drugs and the ordering of drugs to the required extent at the required time [18]. Therefore, in this paper, an efficient medicine demand prediction system using the LTH-SES-based ML technique with the pharmacy supply chain is proposed.

The subsequent sections of the paper are given as: the associated works are surveyed in Section2, the proposed framework is explained in Section 3, and the results and discussion based on performance metrics are illustrated in Section 4. Lastly, Section 5 concludes the paper with future work.

2. LITERATURE SURVEY

Shancheng Jiang et.al [19] established a hybrid model for forecasting the patients' demand for diverse key resources in the Outpatient Department (OPD). In this, for the feature selection, a modified version of the Genetic Algorithm (GA) was introduced. A feed-forward Deep Neural Network (DNN) was presented as the forecast methodology. Furthermore, the presented method's outcomes exhibited its effectiveness and performed superior to other prevailing models. Nevertheless, the loss of neighbourhood information might be caused by the use of a feed-forward DNN, and it was helpful for future forecasting. Husein et.al [20] introduced Adaptive Neuro-Fuzzy Inference System (ANFIS) methodology to predict medication necessities. Primarily, ANFIS was implemented as a data source. Then, for prediction, the clustering process from the K-Means algorithm was applied. Based on the evaluation analysis, the presented methodology attained superior prediction rates from the testing outcome. In contrast, the computing time utilized in the k-means algorithm was still higher. Therefore, further research was required to calculate time optimization. Bahareh Fanoodi et. al [21] aimed to detect the blood platelet demands centered on Artificial Neural Networks (ANNs) as well as Auto-Regressive Integrated Moving Average (ARIMA) methodologies. For 8 sorts of blood platelets, daily demands were employed in the current study. As per the study outcomes, when compared with the baseline models, ANNs and ARIMA methodologies were more precise in predicting the uncertainties that were in demand. This approach had a disadvantage that the ARIMA model employed in forecasting was unable to predict the demands for long-term forecasts. Huai Su et. al [22] presented a robust hybrid hours-ahead gas consumption methodology by merging Recurrent Neural Network (RNN)-structured deep learning, wavelet transform, and GA. To diminish the forecasting task's difficulty, the Wavelet Transform was employed. By linking a multi-layer Bi-LSTM and an LSTM methodology, the RNN was constructed. When analogized with prevailing methodologies, the outcomes illustrated the superior performance of the established technique. However, the entire forecasting methodology's performance might be diminished by the higher dimensionality of the features. João N.C. Gonçalves et. al [23] presented a multivariate framework for detecting manufacturer's demand in the assembly industry from an automotive supply chain. Firstly, to generate a set of training instances, a sliding time window was adopted. After that, to collect multiple forecasting errors, a rolling origin forecasting scheme was designed. The experiments showed that when compared with traditional models, the presented method provided superior performance. In contrast, this work didn't comprise a wider range of components for statistical and ML-centric forecasting methodologies.

3. PROPOSED FRAMEWORK

The PSC is a process by which pharmaceutical products with appropriate quality are disseminated at the proper place as well as time for reaching final customers. For this, demand forecasting plays a crucial role, where the future demand for a certain medicine is predicted centered on the data flow created by the consumers. Numerous forecasting methodologies have been developed. However, these methods' estimation accuracy is insufficient. In addition, for PSC, only a limited amount of forecasting techniques is available. Therefore, an efficient time-series medicine demand forecasting system using the LTH-SES-based ML technique with the PSC is proposed in this work. Figure 1 illustrates the proposed model's architecture.

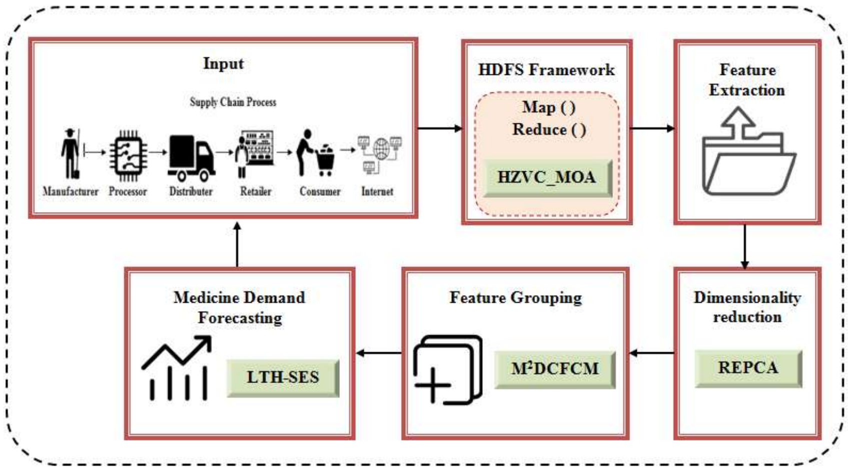


Figure 1. Block diagram of the proposed framework.

3. 1 Map Reduce Framework

The previous historical medicine sales data from the PSC are collected from publicly available sources to begin the process of medicine demand prediction. It encompasses daily sales details of medicines from the manufacturer, distributor, retailer, and consumers. Therefore, the MapReduce framework is adapted to make the prediction system more efficient with less processing time. A programming model for processing large datasets is termed MapReduce, which contains 3 fundamental operations, namely mapping, shuffling, and reducing. The mapping phase obtains a set of data and converts it into other sets in the form of a key/value pair. The shuffle phase arranges and then passes the outputs that come from mapping to the final phase (reducing) in a similar format (key/value). The outputs as of shuffling are amassed in the reducing phase, and the reducing phase's output is the final output. Figure 2 depicts the basic structure of the MapReduce system.

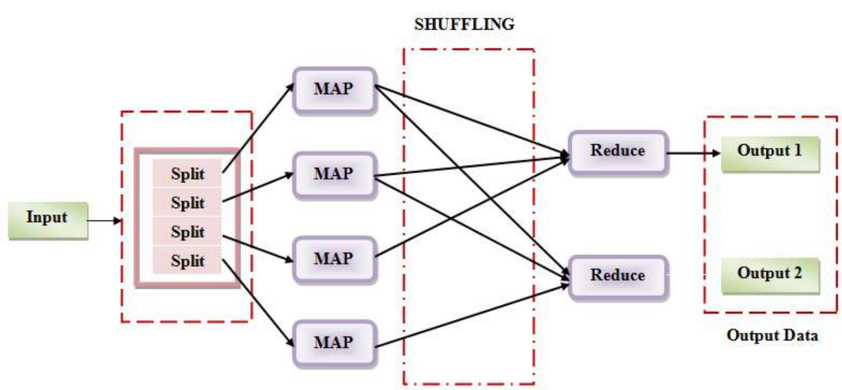


Figure 2. General structure of HDFS MapReduce model.

The split data chunks $(f_{(i)})$by the mapping function are given by (1). In (1), the number of the split data group is represented as F . After that, the HZVC_MOA technique is utilized as a reducing function. Generally, a newly emerged population-based optimization technique, which is stimulated by the flighting behavior and mating process of mayflies, is called the Mayfly Optimization Algorithm (MOA). This optimization approach has a drawback that some stages in mating may cause premature convergence and also has the possibility of falling into a locally optimal solution. Thus, the proposed work uses Horizontal and Vertical Crossover (HZVC) search mechanisms to recover MOA from these limitations. The proposed technique is named Horizontal and Vertical Crossover Mayfly Optimization Algorithm (HZVC_MOA) owing to the made in the baseline MOA. The optimization process of HZVC_MOA is explained further by the bellow steps.

$$f_{(i)} = f_{(1),}f_{(2)},\ldots\ldots,f_{(F)} \tag{1}$$

Step 1: Primarily, the initial mayflies' population in $D-$dimensional search space is signified as $f_{(i)} = f_{(1)}, f_{(2)}, \ldots\ldots, f_{(F)}$ (mapped data). These mayflies' velocities during flying and changing in position are $\vartheta_{(i)} = \vartheta_{(1)}, \vartheta_{(2)}, \ldots\ldots, \vartheta_{(F)}$. After that, based on the cosine similarity, the fitness of each mayfly is computed to identify the best one. The cosine similarity betwixt mayflies $C\left(f_{(i)}\right)$is computed as (2). In (2), the neighboring fly in the initial population is notated as $f'(t)$.

$$C\left(f_{(i)}\right) = \min \frac{\sum_{i=1}^{F} f_{(i)} * f'_{(i)}}{\left\| f_{(i)} \right\| * \left\| f'_{(i)} \right\|} \tag{2}$$

Step 2: After that, the vertical crossover is used by the position and velocity updation process of male flies to prevent them from falling into a locally optimal solution. It can be arithmetically represented as (3)

$$f_{(i)}(t+1) = \alpha \cdot f_{(i)}(t) + (1-\alpha) \cdot \vartheta_{(i)}(t+1) \tag{3}$$

In (3), the updated position at the time$(t+1)$is determined as $f_{(t)}(t+1)$, the mayflies' current position at the time$(t)$is notated as $f_{(i)}(t)$, α is a random number [0, 1], and the updated velocity at the time $(t+1)$ is signified as $\vartheta_{(i)}(t+1)$.

Step 3: Distinct from male flies, female flies are attracted towards the males, and their change in position is updated as (4). In equation (4), the female mayfly's current position at the time(t) is notated as $E_{(i)}(t)$ the updated position at the time$(t+1)$ is specified as $E_{(i)}(t+1)$ and the velocity of a female mayfly added during its movement is notated as $\vartheta_{(i)}(t+1)$.

$$E_{(i)}(t+1) = E_{(i)}(t) + \vartheta_{(i)}(t+1) \tag{4}$$

Step 4: Lastly, by using a horizontal crossover mechanism, the mating of mayflies occurs. A pair of male and female mayflies is chosen in the mating process, and it undergoes a horizontal crossover mechanism and generates 2 offspring. This enhances the exploration ability of mayflies and then augments the convergence speed. Horizontal crossover is assessed by (5) and (6).

$$O_{(1)} = \eta \cdot f_{(i)} + (1-\eta) \cdot E_{(i)} + \kappa\left(f_{(i)} - E_{(i)}\right) \tag{5}$$

$$O_{(2)} = \eta \cdot E_{(i)} + (1-\eta) \cdot f_{(i)} + \kappa \cdot \left(E_{(i)} - f_{(i)}\right) \tag{6}$$

In (5) and (6), the random number between [0, 1] is illustrated as η, a random distribution in the range [-1, 1] is notated as κ, and $O_{(1)}, O_{(2)}$ mentions the offsprings of $E_{(i)} \& f_{(i)}$. Therefore, after executing the MapReduce framework, the $\mathrm{M}-$amount of data in the reduced dataset is signified as$(R_{(i)})(i = 1,2, \ldots \ldots, M)$. Later, for further processing, features are extracted from this reduced dataset.

3. 2 Feature Extraction

The process of extracting the most significant features required for predicting future demands is termed feature extraction. For analysis, some of the features like product name, product ID, brand name, brand popularity, price, number of products sold, product code, product description, product status, Sales per customer, etc. are extracted. These extracted features are in the higher dimensional feature space. The higher dimensional features are reduced to lower dimensional space utilizing the REPCA-based dimensionality reduction technique to make the process more reliable.

3. 3 Dimensionality Reduction via REPCA

One of the most widely used dimensionality reduction techniques, which maps large dimensional data into a smaller dimensional feature space without losing valuable information, is Principal Component Analysis (PCA). Nevertheless, the relationship between each feature is determined only by the covariance matrix computation in PCA analysis, and the strength between features is not measured. Therefore, covariance calculation is replaced with Renyi

Entropy (RE) in the proposed work. This alteration of covariance formulation with RE is termed as REPCA. The REPCA dimensionality reduction is detailed as follows.

Step 1: Let the input to the REPCA dimensionality reduction technique is $x_{(j)}$(extracted features in a $d-$dimensional vector space). Initially, the mean $(\tilde{\mu}_{(j)})$and variance $(\tilde{\sigma}_{(j)})$ of the feature vector $x_{(j)}$ are computed as (7).

$$\tilde{\mu}_{(j)} = \frac{\sum_{j=1}^{N} x_{(j)}}{N} \tag{7}$$

$$\tilde{\sigma}_{(j)} = \frac{1}{N-1}\sum_{j=1}^{N}\left(x_{(j)} - \tilde{\mu}_{(j)}\right)^2 \tag{8}$$

Step 2: Later, the RE (R_E) is evaluated and signified in matrix form (9).

$$R_E = (\lambda - 1)^{-1} * \log\left(\sum_{i=1}^{N}\frac{\left(x_{(j)}\right)^{\lambda}}{\left(\tilde{\sigma}_{(j)}\right)^{\lambda-1}}\right) \tag{9}$$

$$\Delta = \frac{\mathrm{A}^T \mathrm{A}}{N-1} \tag{10}$$

In the equation (10), the RE divergence in the range [0, 1] is mentioned as λ, and the feature matrix composed of entropy of features is notated as A.

Step 3: Then, to attain the dimensionality of reduced principal components, the corresponding Eigenvalues as well as Eigenvectors of Δ are computed. The principal components (ς) can be given as (11).

$$\varsigma = e_{ji}\mathrm{A}_1 + e_{j2}\mathrm{A}_2 + \ldots\ldots + e_{Nk}\mathrm{A}_N \tag{11}$$

In (11), the Eigenvalues of the feature matrix are notated as e_{jk}, $k = 1,2,\ldots k$ defines the new feature vector in the lower dimensional space. Therefore, the n number of dimensionalities reduced feature set $(y^{(i)})$ is articulated as (12).

$$y^{(i)} = y^{(1)}, y^{(2)}, \ldots\ldots, y^{(n)} \tag{12}$$

3. 4 Feature Grouping with M^{2}DCFCM

Feature grouping is done in this phase by using the M^{2}DCFCM technique. An effective clustering technique, which partitions the data object into a few clusters by calculating the Euclidean distance between data, is called Fuzzy C-Means (FCM) clustering. After that, the cluster centroids are initialized randomly, which makes the algorithm flow many iterations and may fall into local optimum easily. Therefore, by using the minimum and maximum distance between data points, the centroid points are estimated to alleviate this issue. Such adjustment made in the convention FCM is the so-called M^{2}DCFCM clustering. The M^{2}DCFCM technique for feature grouping is detailed below.

- Let $y^{(i)} = y^{(1)}, y^{(2)}, \ldots\ldots, y^{(n)}$ and ζ be the data points and the number of clusters, respectively. After that, the initial cluster centroids (ψ_C) are assessed in equation (13),

$$\psi_c = \tau^{\min} + \left(1/\zeta + 1/2\zeta \right) * \left(\tau^{\max} - \tau^{\min}\right) \tag{13}$$

In (13), the number of cluster centroids is illustrated as $c = 1,2, \ldots\ldots,$ m and the minimum and maximum distance between data points in the feature set $y^{(i)}$ is given as τ^{min}The M^{2}DCFCM's objective is to diminish the criterion function, $\left(\varpi^{ic}\right)$,which is given as (14).

$$\varpi^{ic} = \sum_{i=1}^{n}\sum_{c=1}^{m} \nu^{ic}(\rho)\cdot\tau\left(y^{(i)},\psi_c\right) \tag{14}$$

In (14), the fuzzy membership function is denoted as $\upsilon^{iC}(\rho)$ the degree of fuzziness is notated as ρ, and the Euclidean distance between data points and cluster centroids is illustrated as $\tau(\bullet)$ which is estimated as (15).

$$\tau\left(y^{(i)},\psi_c\right) = \sqrt{\sum_{i=1}^{n}\left(y^{(i)}-\psi_c\right)^2} \tag{15}$$

- The fuzzy membership function $\upsilon^{iC}(\rho)$ is defined as (16).

$$\nu^{ic}(\rho) = \frac{\left\|y^{(i)}-\psi_c\right\|^{-(\rho-1)^{-1}}}{\sum_{c=1}^{m}\left\|\psi_c - y^{(i)}\right\|^{-(\rho-1)^{-1}}} \tag{16}$$

- The above process continues by recalculating the cluster centroids, computes the Euclidean distance, and stops when the cluster centroids remain unaltered. Finally, the obtained M-number of feature groups z^k is notated in (17).

$$z^k = z^1, z^2, \ldots\ldots, z^M \tag{17}$$

3. 5 Demand forecasting using LTH-SES

By employing the LTH-SES technique, the demand for medicines is predicted and forecasted after feature grouping. The prediction is made regarding the historical data obtained from the pharmacy supply chain. A time series forecasting model, which uses the previous forecast data for analysis, is the Single Exponential Smoothing (SES). Nevertheless, complex patterns for forecasting cannot be handled by the SES. Thus, in the proposed work, the Logistic Tanh activation function is used that triggers the function of SES and helps the model for learning complex patterns in the data. Finally, the modified form of SES is renamed as LTH-SES. The LTH-SES formula for computing medicine demand forecasting is articulated below (18).

$$\Gamma(t+1) = \hbar\left(\iota\cdot z^k + (1-\iota)\cdot\Gamma(t-1)\right) \tag{18}$$

In (18), the forecasting value of the future period is notated as $\Gamma(t+1)$, the random number between [0, 1] is signified as ι, the actual grouped data is represented as z^k, the forecasting value of the previous period is mentioned as $\Gamma(t-1)$ and $\hbar(\bullet)$ specifies the logistic tanh activation function utilized to trigger the forecasting methodology and is formulated as (19).

$$h(z) = {e^{-z}-1}\big/{e^{-z}+1} \tag{19}$$

Later, by measuring the deviation between the actual and forecasted value of the given period, the forecasting error is computed. The formula for computing MSE is (20).

$$MSE = {\sum\left(A^t - F^t\right)^2}\big/{N-1} \tag{20}$$

In equation (20), the actual demand for time $(t)$is mentioned as A^t, the forecasted demand is signified as F^t, and the number of time periods is notated as N. Lastly, for the effective production of required medicines, the predicted medicine demands are transferred to the manufacturer, thereby enhancing the supply chain process in the PI.

4. RESULTS AND DISCUSSION

Here, by comparing the proposed technique with a few prevailing techniques, the proposed Medicine demand prediction system's effectiveness is verified. Regarding the performance metrics, the comparison is made. The dataset utilized in the proposed framework is taken from publicly available sources, and the work is implemented in the PYTHON platform.

4. 1 Supremacy assessment of proposed M^{2}DCFCM

In this part, regarding clustering accuracy, precision, and recall, the efficiency of the proposed M^{2}DCFCM clustering technique used to group the features is analysed by comparing it with some of the prevailing techniques, namely FCM, K-Means Algorithm (KMA), K-Medoids (KM), and Mean Shift (MS). Figure 3 represents the graphical evaluation of the model.

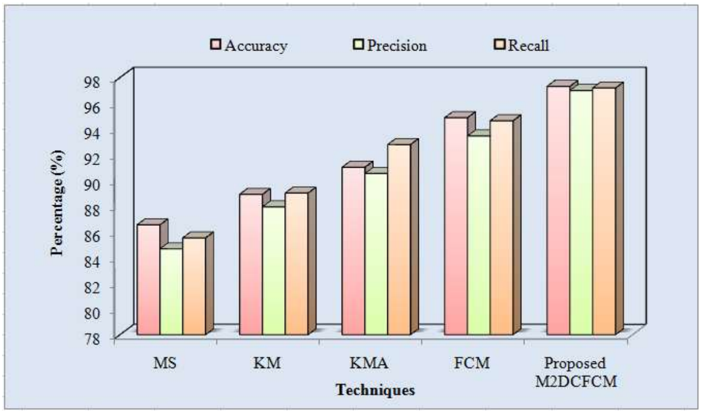
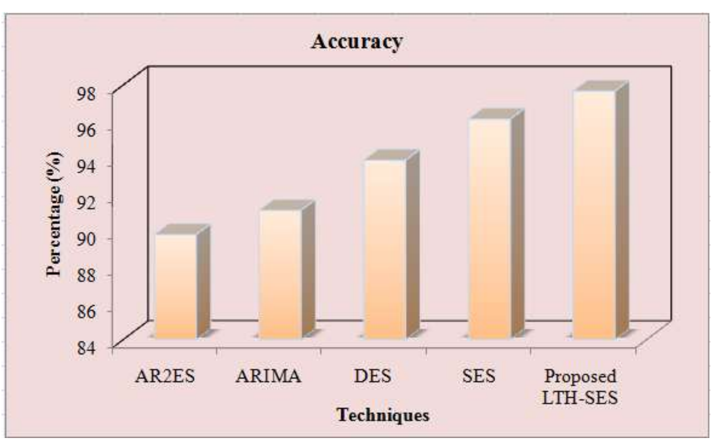


Figure 3. Accuracy, precision, and recall analysis of M^{2}DCFCM.

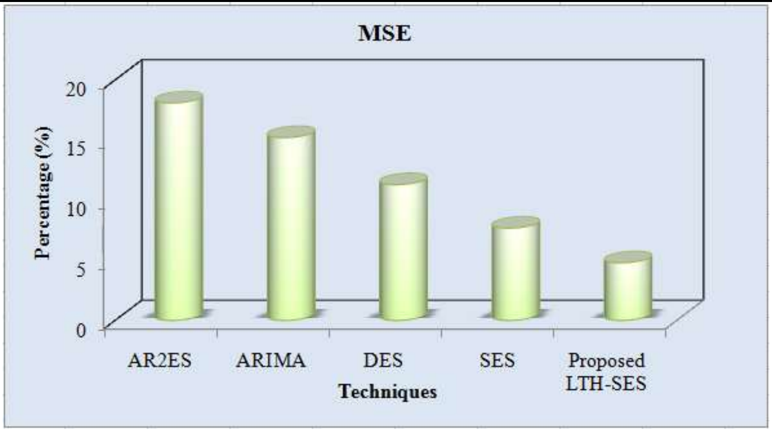
In Figure 3, the clustering accuracy attained by the proposed M^{2}DCFCM technique is 97.31%, whereas the prevailing clustering techniques exhibited lower accuracy of 94.87% (FCM), 91.02% (KMA), 88.91% (KM), and 86.54% (MS). Similarly, when compared with the existing techniques, the proposed system's precision and recall are higher at a rate of 96.99% and 97.18%, respectively. Thus, it is certain that when contrasted with the existent clustering methods, the proposed M^{2}DCFCM clustering performs well. Therefore, the proposed system is more effective than other top-notch models.

4. 2 Performance Evaluation of Proposed LTH-SES

In this section, the proposed LTH-SES demand forecasting technique's performance is analogized with prevailing SES, Double Exponential Smoothing (DES), Adaptive Response Rate Exponential Smoothing (AR^{2}ES), and ARIMA. Forecasting accuracy and Mean Squared Error (MSE) are the performance metrics used for comparison. The comparative investigation of the proposed LTH-SES and the prevailing frameworks like SES, DES, ARIMA, and AR^{2}ES regarding (a) forecasting accuracy and (b) MSE is displayed in Figure 4. The higher accuracy and lower value of MSE determine the effectiveness of the model. That statement stated that 97.67% accuracy and 4.789% MSE were attained by the proposed model, whereas the prevailing works obtained the lowest accuracy and highest MSE. Thus, it is concluded from the graphical analysis that the proposed method processes the data in a more proficient way and renders more accurate forecasts in less time.



(a)



(b)

Figure 4. Performance assessment of proposed LTH-SES by (a) accuracy, and (b) MSE.

5. CONCLUSIONS

An efficient medicine demand prediction system using the LTH-SES-based ML technique with the pharmacy supply chain has been proposed in this work. The proposed framework underwent MapReduce model, feature extraction, dimensionality reduction, clustering, and demand forecasting. The future demands of medicines from the past sales history were efficiently identified by the forecasting phase. After that, the experimentation analysis occurred, and the proposed methodology attained the highest metrics rate, such as 97.31% clustering accuracy, 96.99% precision, 97.18% recall, 97.67% forecasting accuracy, and 4.789% MSE. Overall, the proposed approach performed better than the prevailing top-notch methods and remained to be more reliable as well as robust. The study can be extended in the future by using advanced techniques with limited computing resources for real-time applications.

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