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RESEARCH ARTICLE

Linear Regression Based Demand Forecast Model in Electric Vehicles -LRDF

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Abstract – Machine learning is an Artificial Intelligence (AI) software application that uses algorithms to analyze data, make inferences from that data, and then use what they've learned to create well-informed conclusions. Machine learning cannot process characters or strings; in order to process them, we must transform them to numerics. Otherwise, there will be exceptions or mistakes of some kind. After pre-processing, which removes the null or empty data from the original dataset, machine learning algorithms can predict or forecast future events using the provided dataset. Machine learning is now widely used in the software industry, and as a result, many software applications now offer predictions like weather forecast, impact of covid spread, future sales, etc. So, the problem of the demand of EVs in future is investigated using novel strategies for entirely eliminating problems with forecasting models, based on machine learning approach. The proposed LRDF model for Electric Vehicle's is based on machine learning that accepts a dataset as an input in the form of an CSV file containing electric vehicles data that are useful for predicting demand for electric vehicles. The accuracy of three distinct classification algorithms, including the SVM algorithm, the Random Forest system, and the Linear Regression algorithm, will be examined. The results demonstrate that the linear regression approach performs significantly better than the other two algorithms. The LRDF model for Electric Vehicle's when mounted on the public cloud server- which belongs to Infrastructure as a Service (IaaS), would increases the speed of dataset processing

Index Terms – Forecasting With Machine Learning, Forecasting of Electric Vehicles, Machine Learning, EV Dataset, IaaS Cloud, Supervised and Un-Supervised Algorithm

I. INTRODUCTION

Machine learning (ML) is incredibly quick at learning new things, performs well when generalizing, and can approximate anything. The use of machine learning in demand forecasting offers the potential to avoid common planning difficulties such as lengthy delivery lead times, expensive transportation,

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excessive inventory and waste levels, and incorrect decision-making as a result of inaccurate forecasts. The primary goal of both supervised and unsupervised machine learning algorithms is to open the planner's demand time in addition to improving the accuracy of demand forecasts. By concentrating on the majority of items and acquiring last-minute information that is recorded in the system to inform the predictions more precisely and accurately, planners may use their time considerably more effectively. By using Machine Learning (ML) approaches along with enough historical data on demand forecasts, product forecasts, and sales projections more accurate demand forecasts can be generated.

II. LITERATURE SURVEY

The goal of this research is to investigate how the proposed model would forecast the demand of electric vehicles in the next few years. The proposed system is evaluated for efficiency using three different machine learning classification algorithms, the Forecast Model using SVM[FM-SVM], the Forecast Model using Random Forest strategy[FM-RF], and the Forecast Model using Linear Regression algorithm[LRDF]. The proposed method's accuracy results will demonstrate that LRDF performs far better than the Forecast Model using SVM[FM-SVM], and the Forecast Model using the Random Forest strategy[FM-RF]. The LRDF model for Electric Vehicle when mounted on the public cloud server- which belongs to Infrastructure as a Service (IaaS), would increases the speed of dataset processing.

Table 1: Summary of literature survey

Ref. No.	Objective	Algorithm
1	Providing better and more efficient solutions for charging and discharging EVs at many power stations, leading to the proliferation of EV electricity and improved transportation.	Linear programming
2	Gain an understanding of the potential of machine learning in this field, such as the creation of smart electronics and the development of electric vehicle charging.	Random Forest algorithm and SVM
3	Gain insight into the potential use of multi-purpose algorithms in the configuration of electric vehicles and contribute to the development of efficient transportation systems.	Multi-objective Algorithm
4	Meet Smart Charging Planning for electric vehicles that can increase energy efficiency and reduce environmental impact.	Reinforcement Learning
5	It introduced to control the charging and discharging of electric vehicles, including the stochastic behavior of electric vehicles and their customers.	Reinforcement Learning

This work focuses solely on using ML techniques to forecast the demand of electric vehicle rather than describing all of the varied load forecast model techniques. The operating cost of the PV-based charging station is reduced by 167.71% when compared to the EV charging scheduling algorithm, according to Hojun Jin et al. [1] presentation of the power management scheme of interdependent microgrids and EV fleets. Compared to the outcomes of the typical EV charging/discharge scheduling algorithm, the operating cost is reduced by 28.85%. In order to increase energy efficiency and cut costs, this document outlines the creation of charge/discharge programs for numerous EV (electric vehicle) charging stations. The program successfully balances the charging and discharging of electric vehicles to save energy and lower operating costs. These elements include user needs, grid limits, and battery aging. Using well-known machine learning methods like Random Forest and SVM, Sakib Shahriar et al. [2] proposed using previous payment data along with weather and traffic data to forecast EV session duration and energy consumption. The 2019 ACN dataset's payment sites were all chosen. 20% goes towards evaluation, and 80% goes into training. utilizing local event data is really beneficial. It gives an introduction to various machine-learning techniques for simulating and forecasting the behavior of electric vehicles (EVs). Authors Sakib Shahriar and A.R. Al-Ali, IEEE Life Senior Fellows, examine various studies that employ machine learning to recognize and forecast electric car models using techniques like neural networks, support vector machines, and decision trees. This article addresses the advantages and disadvantages of these various strategies as well as the difficulties in gathering and processing the data required to develop machine learning models for EV driving behavior. The authors also emphasize the advantages of utilizing machine learning to enhance grid efficiency generally and EV charging infrastructure specifically. Using multipurpose algorithms, Xuefeng Jiang [3] concentrated on creating a charging plan for electric vehicles (EVs).

This study intends to address issues with EV charging, including insufficient charge, prolonged charging times, and high electricity use. The study's multi-purpose system took into account a number of goals, including decreasing the charge, cutting down on charging time, and conserving energy. The algorithm optimizes EV charging times while accounting for the accessibility of charging stations, the capacity of EV batteries, and the preferred charging schedules of EV owners. This article offers comprehensive details on the charging procedure, including optimization mathematical models, algorithm implementation, and simulation results. The simulation outcomes demonstrate the proposed strategy's good balance between charge rate and charge time and maximum power consumption. In-depth information on support learning methods for intelligent programming, such as Q-learning and deep Q-network (DQN) algorithms, is provided by Marian Remus Baltariu et al. in their paper [4]. An artificial neural network that calculates the price of billing a function is trained using the DQN technique. An intelligent programming technique for electric vehicles (EVs) based on support learning is suggested in this research. By taking into account parameters like charging stations, the energy requirements of the grid, and user preferences for payment time, the algorithm seeks to optimize the charging time for a group of electric vehicles. The simulations from the EV charging dataset are used by the authors to evaluate the proposed system. The simulation findings demonstrate that the smart distribution algorithm lowers the grid's peak power demand and enhances the charging of electric vehicles.

When planning the charging and discharging of electric vehicles, complications can arise. Naram Mhaisen et al.[5] explore these issues and the benefits of utilizing extra learning techniques in this situation. The authors suggest a strategy that involves education officials making decisions based on environmental feedback through support learning. Utilizing simulations, the plan was assessed and contrasted with other accessible planning techniques. According to the findings, the support learning-based approach performs better than other approaches in terms of cost savings, energy efficiency, and maximum demand. The plan can be efficient and effective for planning the charging and discharging of electric vehicles, according to the document's conclusion. According to the authors, future research might examine how the concept is put into practice in actual settings and how it is combined with other clever ideas.

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Table. 2: Summary of Literature Survey

Sl. No	Published Year	Title and Author	Methodology	Advantages	Disadvantages
1	2022	"Development of Charging/Discharging Scheduling Algorithm for Economical and Energy-Efficient Operation of Multi-EV Charging Station", Hojun Jin et .al	mixed-integer linear programming (MILP) algorithm	Efficient and Economical, Real-time control, Scalable	Complexity, Data Requirements
2	2021	"Machine Learning Approaches for EV Charging Behavior: A Review", SAKIB SHAHRIAR et .al	regression-based methods, classification-based methods, and clustering-based methods.	provide a critical evaluation of the existing literature in this field, which can help researchers in identifying the research gaps and future directions	do not provide any experimental results to demonstrate the effectiveness of the different approaches.
3	2022	"Research on Electric Vehicle Charging Scheduling Strategy Based on the Multiobjective Algorithm", Xuefeng Jiang	Multiobjective algorithm, NSGA-II algorithm	Multiobjective optimization, Real-world data, NSGA-II algorithm, Flexibility	Limited scope, Simulation-based evaluation
4	2022	"Smart Scheduling of Electric Vehicles Based on Reinforcement Learning", Marian Remus Baltariu	Reinforcement learning (RL) techniques	Efficient charging and discharging of electric vehicles, Flexibility, Environmentally friendly, Scalable	Computational complexity, Data requirements.
5	2022	"Real-Time Scheduling for Electric Vehicles Charging/Discharging Using Reinforcement Learning", Naram Mhaisen	Q-learning with adaptive learning rate (QALR).	Real-time scheduling, Load balancing	May not reflect current state, Require large amount of data
6	2022	"A Modified Rainbow-Based Deep Reinforcement Learning Method for Optimal Scheduling of Charging Station", Tian Zhang	Modified version of Rainbow Algorithm	Efficient charging station scheduling, Improved charging experience, Use of Rainbow-based DRL	Complexity, Lack of Real world validation

7	2021	"L. Reinforcement Learning Based EV Charging Management Systems–A Review", Abdullah H.M	Reinforcement learning (RL) techniques	Flexibility, Environmentally friendly, Scalable, autonomous, adaptability	Training time, Complexity, Generalization, Sensitivity to hyperparameters
8	2022	"Preemptive scheduling of EV charging for providing demand response services", Shiping Shao	Preemptive scheduling, mixed-integer linear programming (MILP)	Demand response services, Cost savings, Reduced emissions	Limited adoption, Complexity, Incentives.
9	2021	"A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand", Zongfei Wang	Problem Formulation, Stochastic Optimization	Consideration of Uncertainties, Scenario-based Approach, Optimization Algorithm	Computational Complexity, Limited Scope
10	2022	"A novel intelligent transport system charging scheduling for electric vehicles using Grey Wolf Optimizer and Sail Fish Optimization algorithms", Rajasekaran R	Grey Wolf Optimizer (GWO) and Sail Fish Optimization (SFO) algorithms	Intelligent Transport System (ITS), Optimization Algorithms, Real-Time Decision-Making	Lack of Comparison, Data Requirements, Complexity

III. PROPOSED SYSTEM

Computational numbers, another area of artificial intelligence (AI) that focuses on forecasting using computers, are closely related to machine learning. It has strong linkages to mathematical optimization, which help the area by dispersing methodologies, theory, & application domains. The latter sub-field, known as unsupervised machine learning, focuses additionally on experimental data analysis whereas ML is usually combined with data-mining approaches. Unsupervised machine learning (ML) can also be used to construct baseline behavioral profiles for different entities by learning from the features that are given, followed by the use of these profiles to find relevant forecasts. ML was first described by its precursor, Arthur-Samuel, as a "field of learning that gives computers the capacity to learn without being obviously programmed." ML primarily focuses on classification and regression using previously learned known structures.

The most common electric car datasets available online for download contain the flaws of an old dataset, redundant data, and an unbalanced number of groups. Despite the fact that the data can be enhanced after processing, the volume of data is poorly behaved or insufficient. Therefore, a primary objective in the field of demand forecasting for the future is to build electric vehicle forecasting datasets with huge volumes of data, wide types of coverage, and balanced sample numbers of car/battery categories. Our proposed regression system will be based on a machine-learning model or approach and will use data inputs like electric vehicle purchases, which are useful for predicting future electric vehicle demand. The accuracy of three different classification algorithms, including SVM, Random Forest, and Linear Regression, will be compared. The results will demonstrate that our proposed Linear Regression model has significantly higher accuracy than the other two machine learning algorithms. We are predicting the demand for electric vehicles and the sale of future electric vehicle types and battery modes/models based only on the linear regression algorithm/model.

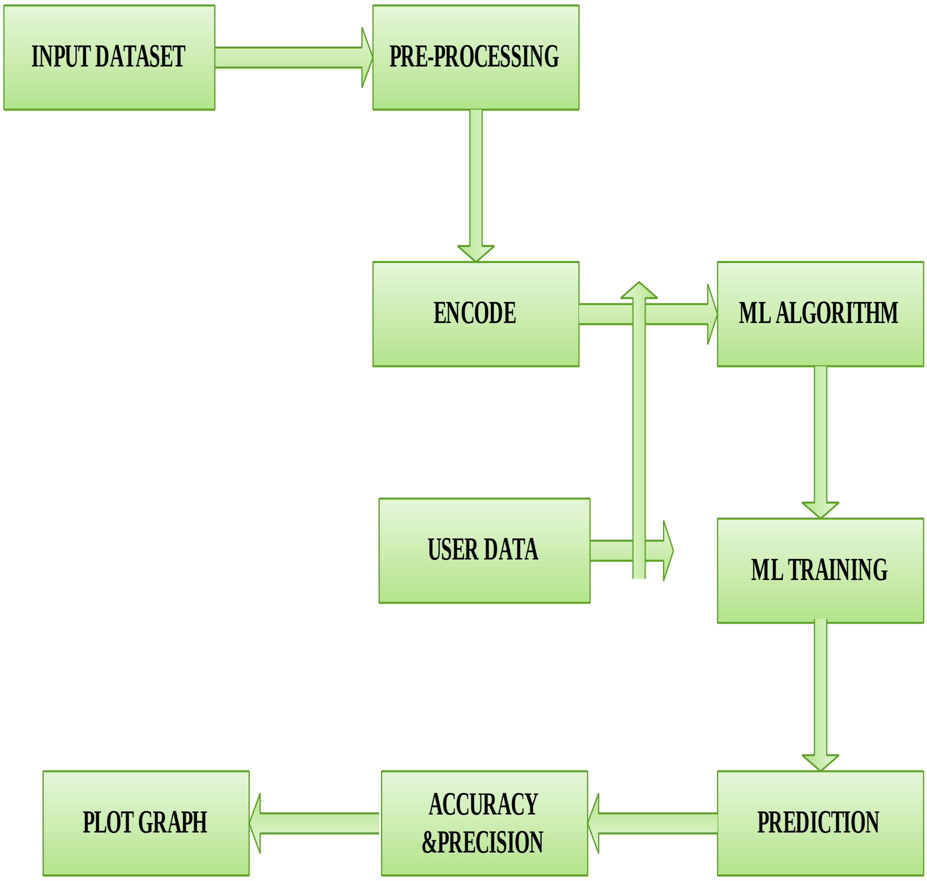

Fig 1: Forecasting Model Architecture Diagram

Forecast Model using SVM Classifier Algorithm [FM – SVM]

The SVM classifier model is a fascinating technique, and the ideas are quite straightforward. The classifier uses a hyperplane with the largest amount of margin to divide data points. An SVM classifier model is therefore also recognized as a judicial classifier. SVM classifier finds the best hyper-plane to help categorize cutting-edge data points. Similar high accuracy is provided by the SVM classifier in comparison to other classifiers like decision trees and logistic regression. It's known for having a kernel rick that can grasp nonlinear input spaces. It is discarded in many software applications, including handwriting recognition, intrusion detection, categorization of emails, news articles, and web pages, classification of genes, and face and intrusion detection models. We will test the SVM classifier today to estimate and anticipate the demand for electricity vehicles in the future and to display the accuracy parameter as a bar graph.

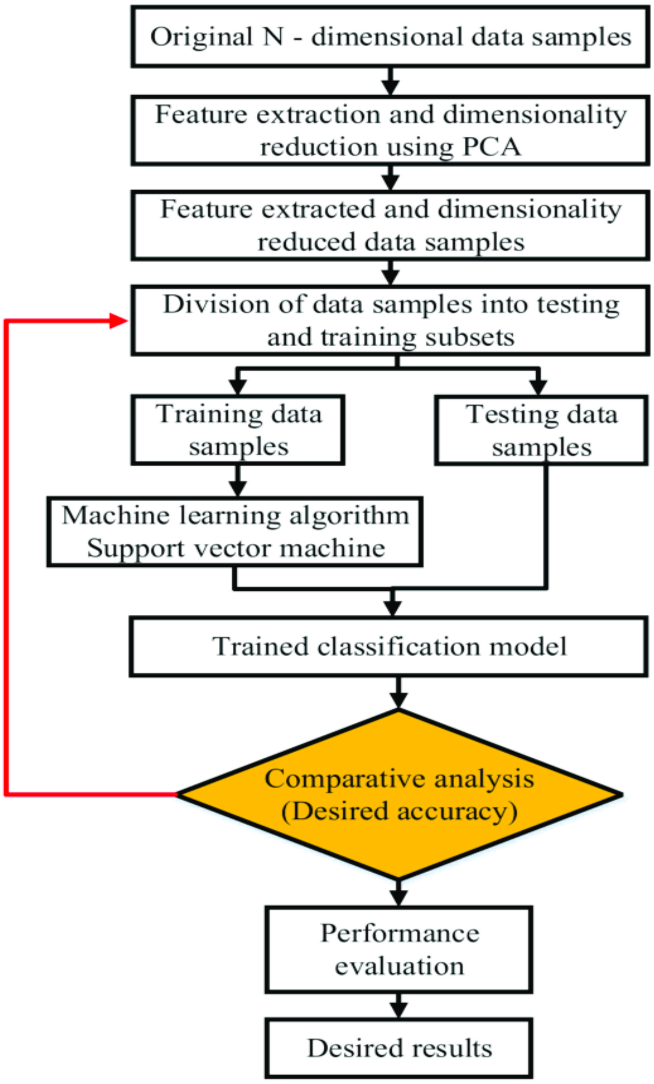

Fig 2: Flow chart of FM-SVM

Forecast Model using Random Forest Classifier Algorithm[FM-RF]

A supervised learning and regression algorithm is Random Forest. For both regression and classification, it can be passed down. It follows that this method is the most flexible and easy to use. Trees make up a forest, and each tree represents a distinct category of data. Other data is kept in nodes on the right and left sides of the root node (tree). It is believed that a forest is more active the more trees it has. An electric vehicle purchase data sample decision tree generated by Random Forest receives predictions from each tree and votes for the top option. It also offers a desirable, accurate indicator of the significance of the characteristic. Applications for Random Forest include feature selection, picture classification, and recommendation engines. It can be used to categories dependable loan applicants, uncover fraud, and forecast diseases. The "Boruta" model/algorithm, which chooses significant features in a dataset, is based on dishonesty. We will use the Random Forest classifier today to forecast and predict the demand for electrical vehicles in the future, and to display the accuracy parameter in a bar graph.

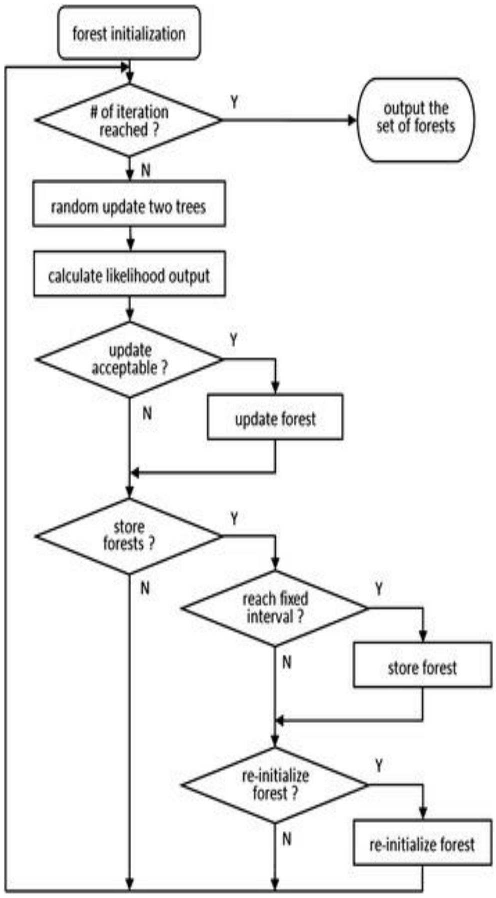

Fig 3. Flowchart of FM-RF

A good feature selection indicator is also provided by the random forest classifier. An additional variable that Scikit Learn includes with the model illustrates the relative importance or contribution of each feature to the prediction. Each feature's significant score is automatically calculated during the training phase. The bearing is then scaled downward until all scores equal 1. The above score will help you select the more relevant characteristics and eliminate the least significant ones for model creation. To determine each feature's reputation, Random-forest applies "Gini-Importance" or mean decrease in impurity (MDI). A further definition of "Gini-importance" is the overall decline in node impurity. This is how much dropping a variable affects the model's accuracy or fit. The variable is more relevant the more pronounced the decline. In this case, a notable parameter for variable selection is the mean decrease. The variables' full capacity for explanation can be determined using the Gini index.

IV. PERFORMANCE VALIDATION

Result analysis section

In this section, the Support Vector Machine (SVM), Random Forest Classifier, and Linear Regression Classifier algorithms' accuracy is compared. The tables and graphs that follow compare the current Support Vector Machine (SVM) and Random Forest algorithms with the linear regression classifier algorithm. In comparison to the other two algorithms, which are able to predict many qualities, the Linear Regression Classifier method will always perform far better.

Implementation setup

30% of the dataset is divided up for testing and the remaining 70% is for training using the electric vehicle purchase dataset that is offered. The technique is the same for all three of the algorithms shown below. According to Table 3, the accuracy of the Random Forest and SVM Classifier algorithms is 76% and 75% respectively, while the accuracy of the Linear Regression Classifier algorithm is 92 percent at the 500th iteration.

Table 3: Comparison of Forecast Models for accuracy

Model	500 Iterations	500+ Iterations
FM- SVM	75	78
FM-RF	76	82
LRDF	92	97

Table 3 shows the precision using the Linear Regression Classifier algorithm is 91% at the 500th iteration whereas the accuracy the of Random Forest Classifier and SVM Classifier algorithm is 73% and 70%.

Table 4.2 Comparison of Forecast Models for precision

Model	500 Iterations	500+ Iterations
FM- SVM	70	72
FM-RF	73	85
LRDF	91	96

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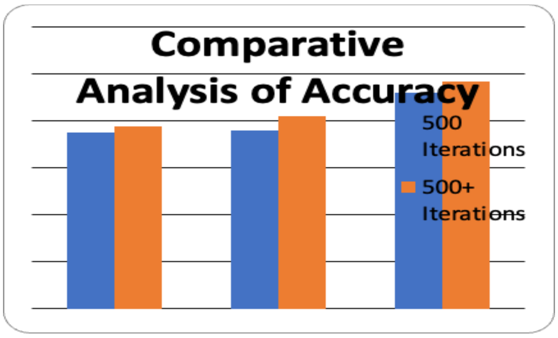

Fig 4: Comparative Analysis of Accuracy.

Analysis of results in Precision

Figure. 4 Provides a detailed comparison of the Precision of different programs methods and Linear Regression Classifier algorithms. This figure shows that Linear Regression Classifier gives better results than comparable planning algorithms. Keep in mind that the SVM Classifier and Random Forest Classifier algorithms require a maximum Precision of 75% and 76%, respectively, when measuring the results of very large dataset. On the other hand, the Random Forest algorithm requires a competitive precision of 73%. However, the proposed Linear Regression Classifier algorithm is providing maximum of 91% precision.

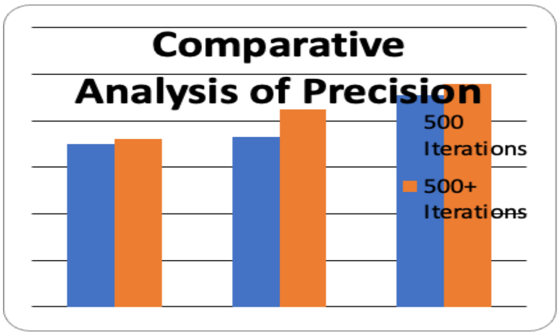

Fig 5: Comparative Analysis of Precision

V. CONCLUSION

The effectiveness of the proposed framework is tested through experiments by applying it to a case study. The findings of these experiments are encouraging since they demonstrate that electric vehicle forecasting may be loaded with a 92% accuracy rate and completed in less time. The linear regression classifier approach performs effectively when the length of the tree traversal requires a prolonged amount of time. because as the length of the journey increases, the degree of traversal standard automatically climbs. The suggested work will continue to be improved in the future with an emphasis on changing the Linear Regression Classifier algorithm settings to make them appropriate for public, private, and hybrid cloud systems. The linear regression classifier approach performs better in terms of accuracy & precision when estimating the output demand when managing the classification process on cloud servers. The linear regression classifier can also be enhanced to look at the success and failure rates of the categorizing process. In order to ensure high levels of effectiveness and accuracy when used in cloud systems, future classification methodologies should be investigated. In order to increase accuracy and effectiveness in cloud environments, characteristics of the linear regression classifier technique can be investigated in the future along with classification level.

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