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A Novel Machine Learning Technique towards Predicting the Sale of Washing Machines in a Small Organization

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Abstract--- *Machine learning has today become an important technical paradigm which is been used across all engineering disciplines to predict or convey some important information to the stakeholders involved in it. Several datasets gathered from several applications can be analyzed to arrive at conclusions. Earlier, machine learning was used only for large datasets due to the sample size but nowadays, machine learning algorithms are used even for small datasets. In this research work, we have taken a small dataset to analyze the sale of washing machines in a small organization using machine learning techniques.*

Keywords--- *Machine Learning, Prediction, ARIMA.*

I. INTRODUCTION

Business enterprises face lot of difficulties in selling their products due to the ever increasing competition in the market. This is the scenario throughout the world. There are many players in the market and always the fittest of those survive and others eventually close their shops. There are lots of resources that are deployed for manufacturing and sales by industries to meet designated targets. A forecast of the expected demand will help the industry in a great way in deploying resources intelligently and will further avoid wastage of money and materials. The accuracy of the forecast has a great role to play, as things have to be predicted well. Many traditional methods have been tried with reasonable accuracy. But the search for better techniques continues for improvement in the results. With this aim in mind, this paper makes an attempt to study a small dataset using machine learning algorithms. Machine Learning and its algorithms have gained profound influence due to their usage across all engineering disciplines.

II. RELATED WORK

Rasa Maria et al.[1] predicted the sale of chemicals through neural networks for a small dataset. They used a multilayer perceptron (MLP) model for sales forecasting. They found that the prediction error was 5% than the SMA method. They further suggested the use of Artificial Neural Networks (ANN) when the data is non-linear. Pongsak et al.[2] applied the concept of Artificial Neural Network (ANN) for demand forecasting in the supply chain of frozen chicken products. They also used an MLP model with the Quick Propogation training algorithm by using time series factor and casual factor for demand forecasting. The dataset they used was the current demand of cooked chicken products. After applying this model, waste reduction of cooked chicken came down from 16,500 kgs to 3800 kgs. They also suggested that other data mining tools such as support vector regression, recurrent neural network and ANFIS can be used to look at further predictions. Real Carbonneau et al.[3] applied machine learning techniques for

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supply chain demand forecasting. They used 3-layer back propogation neural network, recurrent neural network and support vector machines for demand forecasting. They compared their work with traditional methods like Naïve forecast, Average, Moving Average, Trend and multiple linear regression. This work was done using a foundry dataset wherein sample forecasts were made and compared with each other. They found the evidence of SVM and recurrent NN delivering the best accuracy in prediction. In their work, they used two datasets, one was the original real-time foundry dataset and the other was the simulated training set. In addition, they found that the real- time dataset gave better predictions and results when compared with the simulated dataset. They also suggested that further research can be done using internet and e-business inputs. Pablo et al.[4] investigated the application of machine learning algorithms on some dataset. They found that Fuzzy- ANN approaches showed excellent performance while dealing with imprecise data like weather forecasting variables. They also suggested that studies should be performed on data preprocessing techniques as they were offering significant advantages in terms of reducing the computational costs. Additionally they also advised as to when companies have to adopt novel forecasting techniques when compared with traditional methods. In a case study of a pressure container factory Yenradeea et al.[5] have used three forecasting models namely Winter's model, Decomposition model and ARIMA (Auto Regressive Integrated Moving Average) model to forecast certain product demands. They found that ARIMA models provide lower forecast errors in all the product groups. Prakash et al.[6] made an attempt to forecast the demand of automotive batteries. In addition they have used the concept of genetic algorithms to forecast the demand. Thomassey & Sebastien [7] propose different forecasting models which perform more accurate and more reliable sales forecasts. They used advanced models like fuzzy logic, neural networks and data mining algorithms.

III. DATASET USED

The dataset contains the data pertaining to the sale of washing machines from the year 2014 to 2019 for all the months in the corresponding year. In the year 2019, there was a requirement to predict the sale of washing machines from the month of September to December 2019.

IV. RESULTS AND CONCLUSIONS

The different analysis that were done results that were obtained are summarized as follows

a. Stationary Checking

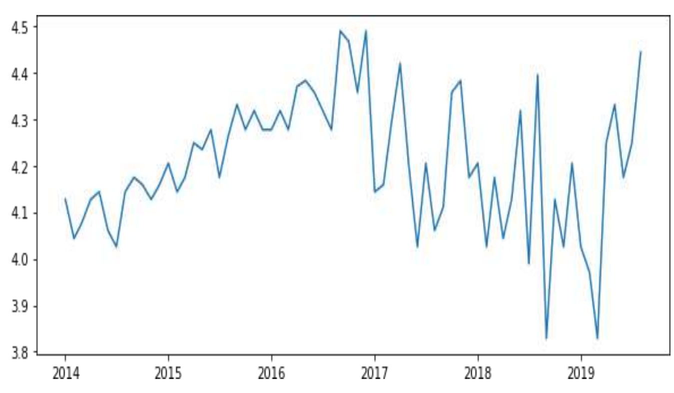

Figure 1: Checking for Stationarity in the Dataset

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A time series data can be called as stationary when its statistical properties mean and variance remain always constant over time. Generally time series models work on the assumption that time series data is stationary. Therefore, to check whether the data is stationary or not, the given data was converted to a stationary type to further the analysis.

The process of converting a non-stationarity dataset to a stationarity dataset can be done with two tests, one being the rolling statistics test and the other the Dickey-Fuller test. The results of rolling statistics can be found below in the Figure 2.

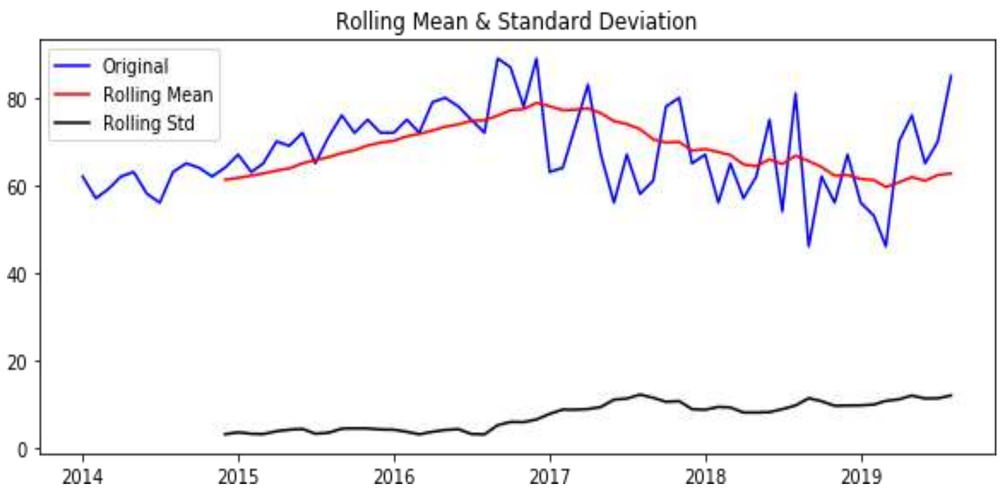

Figure 2: Rolling Statistics in the Dataset

It is evident from Fig 2 that both the rolling mean and rolling standard deviation are non-linear i.e. do not follow a linear trend. The results of the Dickey-Fuller test was as below.

Test Statistic	-3.435610
p-value	0.009803
#Lags Used	11.000000
Number of Observations Used	44.000000
Critical Value (1%)	-3.588573
Critical Value (5%)	-2.929886
Critical Value (10%)	-2.603185
dtype: float64	

When we tell that a dataset follows stationarity, the test statistic value should be lesser than the critical values at 1%, 5% or 10% accordingly. From the above results it is evident that there is a critical value at 1% i.e. -3.58 which is higher than the test statistic value of -3.43.

Later, to make the data follow stationarity, the logarithmic value of all the values in the dataset was taken. The time series trend was again plotted for the log value of the dataset. This is depicted in Figure 3.

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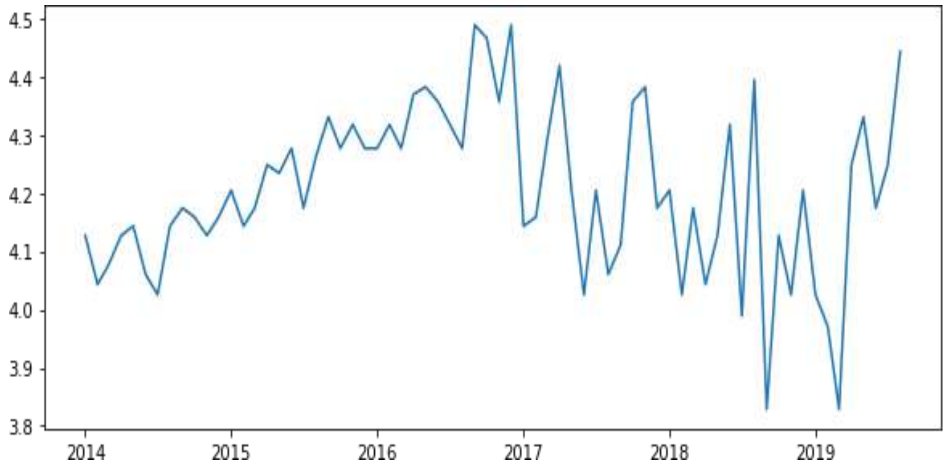

Figure 3: Checking for Stationarity – Logarithmic Value of all Data Values in the Dataset

b. Smoothing

In this technique, the mean of the dataset values after applying a logarithmic function was plotted. The results of this can be seen in Figure 4.

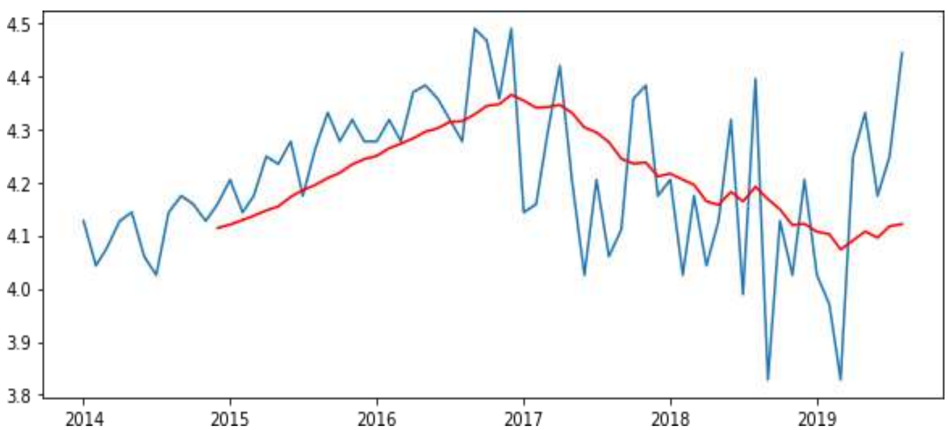

Figure 4: Rolling Mean and Moving Average after Smoothing

Later, the moving average difference was calculated by subtracting the overall moving average with the dataset (after applying the logarithmic function). The stationarity in the dataset was tested by finding the rolling mean and standard deviation which is depicted in Figure 5. The dickey-fuller test was again done and the results were as follows

Test Statistic -5.699522e+00

p-value 7.733700e-07

#Lags Used 0.000000e+00 Number of Observations Used 5.600000e+01 Critical Value (1%) -3.552928e+00

Critical Value (5%) -2.914731e+00

Critical Value (10%) -2.595137e+00 dtype: float64

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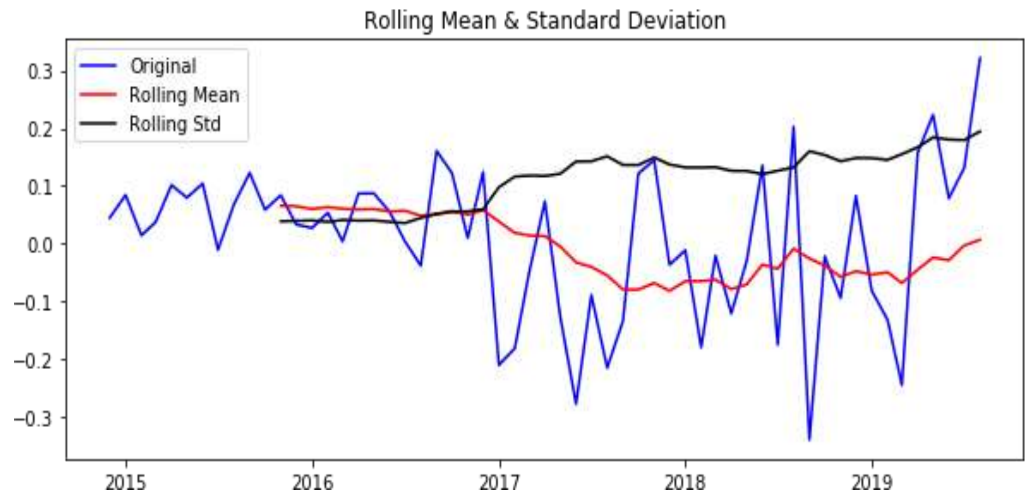

Figure 5: Rolling mean and moving average after smoothing and applying dicky-fuller test

The dickey-fuller test reveals that a good p-value of 7.0 has been obtained but the test statistic value is higher than the critical values at 1%, 5% and 10% level of significance. Since the data was not following stationarity, an exponential weighted moving average technique was adopted to make it stationarity data.

c. Exponential Weighted Moving Average

The exponential weighted moving average was also found for twelve months and the graph was plotted. Later, the exponential weighted average was subtracted from the log value of the dataset and mean value of the graph was plotted as shown in Figure 6.

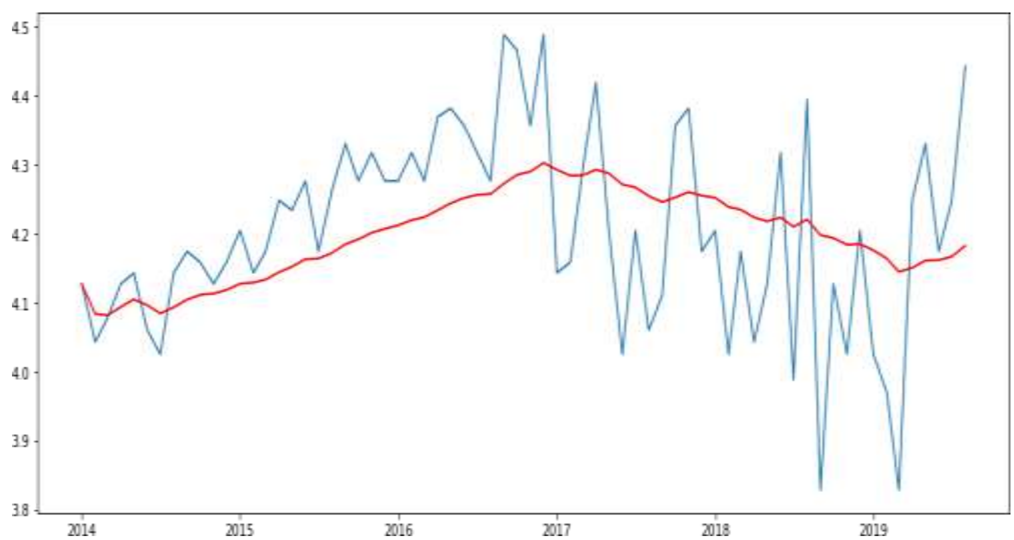

Figure 6: Exponential Weighted Moving Average

The rolling mean and standard deviation after applying exponential weighed moving average can be seen in Figure 7.

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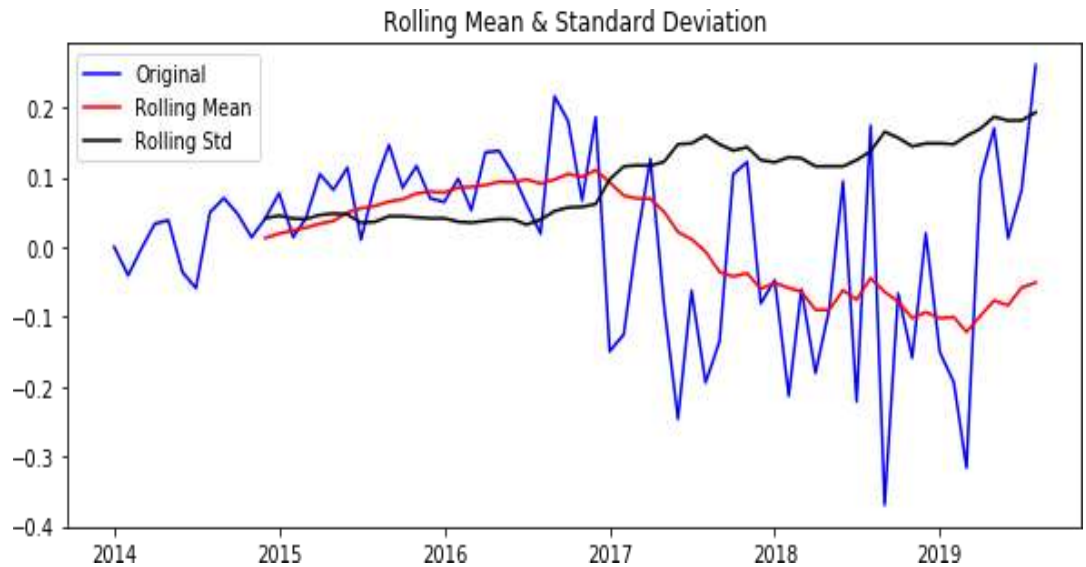

Figure 7: Rolling Mean and Standard Deviation after Applying Exponential Weighted Moving Average

Further, the trend and seasonality in the time series dataset was removed. This is one more method to ensure that data follows stationarity. Decomposition techniques was also applied on the dataset and the rolling mean and standard deviation was calculated. This is shown in Figure 8.

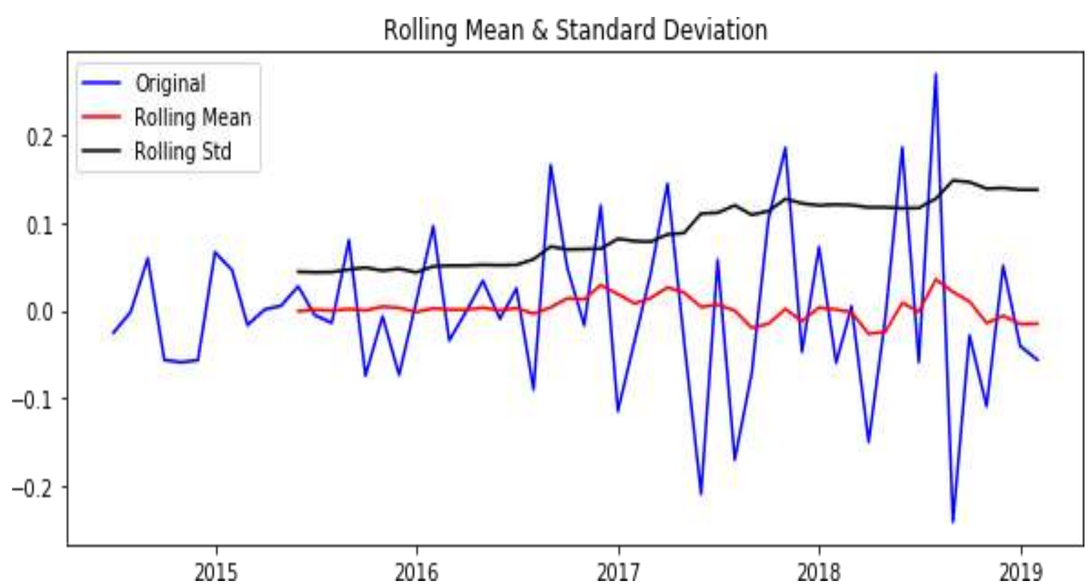

Figure 8: Rolling Mean and Standard Deviation after Applying Decomposition Technique

d. ARIMA Model

The ARIMA model has been found to be the best time series model that makes futuristic predictions. The ARIMA model has three components i.e. AR stands for Auto Regressive, I stands for Integrated and MA stands for Moving Average. The results of the ARIMA model are shown in Figure 9.

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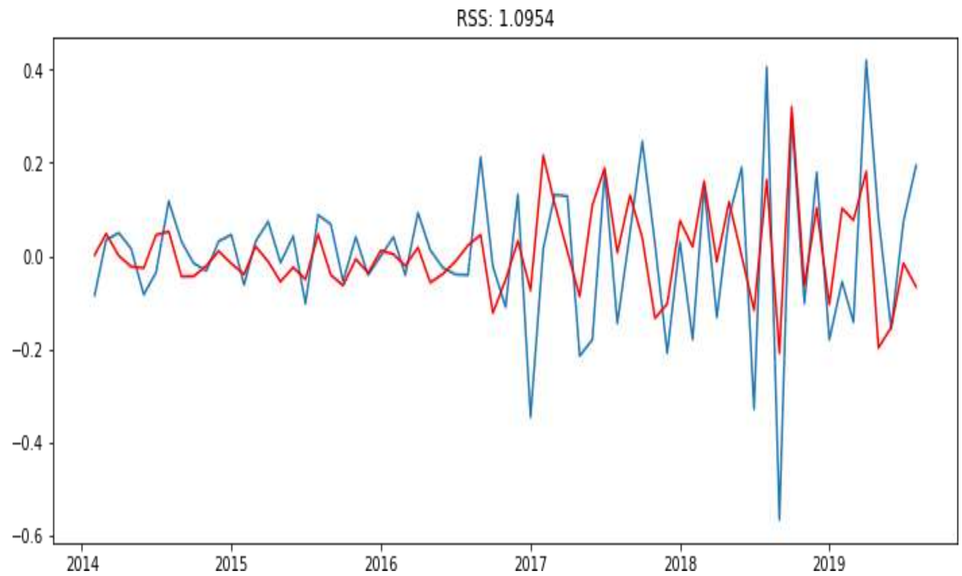

Figure 9: ARIMA Model after Converting Dataset to Logarithmic Form

Since the dataset was converted to the logarithmic form earlier, the dataset values have to be converted back to their original form. After performing this conversion, the final ARIMA model was derived. The final model is depicted in Figure 10.

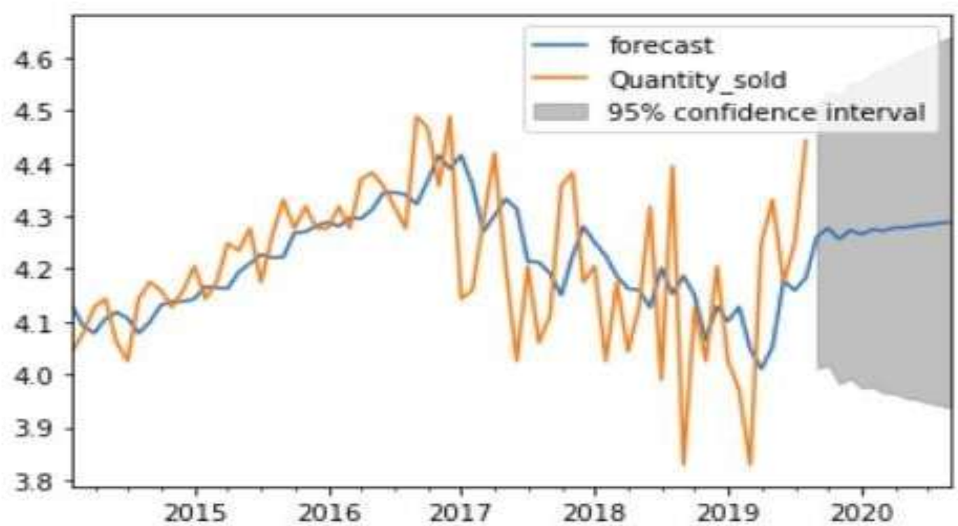

Figure 10: Final ARIMA Model after Converting Dataset from Logarithmic Form to Original Form

As presented earlier, the three models of ARIMA namely AutoRegressive model, Integrated model and Moving Average model were found independently and the three models were integrated further to depict the results.

V. Conclusion

This research has highlighted the fact that machine learning could be used even for small datasets across several engineering disciplines. Earlier, it was advised that machine learning models only for large datasets. Currently, we are seeing that machine learning algorithms are producing better results for small datasets also. This will help small companies to utilize the benefit of machine learning and make predictive decisions on the production and

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manufacture of goods, sales forecasting etc… This also shows that using machine learning algorithms are effective in prediction and forecasting when compared with traditional algorithms and techniques.

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