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Time Series Forecasting and Modelling of Food Demand Supply Chain Based on Regressors Analysis

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Abstract:

Accurate demand forecasting plays a crucial role in managing the food supply chain, particularly for perishable products with a short shelf life. This paper investigates the application of machine learning and deep learning models for forecasting meal orders in a meal delivery service to optimize procurement planning and minimize waste. We compare seven different forecasting models, including traditional methods such as Random Forest Regressor, and advanced boosting algorithms like Gradient Boosting Regressor (GBR), Light Gradient Boosting Machine (Light GBM), Extreme Gradient Boosting (XGBoost), and Cat Boost Regressor. Additionally, Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) models, which are known for handling sequential data, are examined for their performance in time series forecasting. The models are evaluated based on several metrics, including Root Mean Squared Log Error (RMSLE), Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE), and Mean-Average Error (MAE). The results demonstrate the superiority of deep learning models, particularly LSTM, over traditional machine learning approaches in forecasting food demand. The paper also explores the significance of lag features and Exponentially Weighted Moving Averages (EWMA) in enhancing the prediction accuracy. This study offers valuable insights into the effectiveness of various forecasting techniques in improving demand-supply chain management for the food industry.

Keywords: Machine Learning, Deep Learning, Random Forest Regressor, Gradient Boosting Regressor, Light GBM, XGBoost, CatBoost, Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Time Series Forecasting, Exponentially Weighted Moving Average (EWMA), Lag Features, Perishable Products, Meal Delivery Service, Procurement Planning, Inventory Management, Forecast Accuracy, Root Mean Squared Log Error (RMSLE), Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE).

1.INTRODUCTION

Accurate demand forecasting is crucial in the food industry, especially for businesses dealing with perishable products where improper inventory management can lead to significant waste and financial losses. In particular, meal delivery services must adjust their production and stock levels to minimize the loss of raw materials, which are often short-lived and need to be replenished regularly. Demand forecasting is an essential tool for companies to predict future food orders and optimize their procurement planning, ensuring that sufficient raw materials are stocked while avoiding overstocking that could lead to wastage. In this context, demand forecasting not only impacts the operational side of the business but also helps in financial planning, marketing strategies, and optimizing staffing levels across different fulfillment centers.

Recent advancements in machine learning and deep learning have significantly improved the accuracy of demand forecasting, particularly when dealing with time-dependent and sequential data. While traditional models like Linear Regression and Random Forest Regressor have been used for demand prediction, more advanced algorithms such as Gradient Boosting Regressor (GBR), Light Gradient Boosting Machine (Light GBM), XGBoost, and CatBoost offer better performance, particularly with datasets containing both numerical and categorical features. Furthermore, deep learning models like Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) excel at capturing long-term dependencies in sequential data, making them ideal for time series forecasting. This paper aims to compare the performance of these models in predicting meal demand, focusing on the use of lag features and Exponentially Weighted Moving Averages (EWMA) to enhance the forecasting accuracy and improve overall demand-supply chain management.

2. LITERATURE SURVEY

[1]. "Comparison and Financial Assessment of Demand Forecasting Methodologies for Seasonal CPGs" Forecast accuracy is an ongoing challenge for made-to-stock companies. For highly seasonal fast-moving consumer packaged goods (CPGs) companies like King's Hawaiian, an improved forecast accuracy can have significant financial benefits. Traditional time series forecasting methods are quick to build and simple to run, but with the proliferation of available data and decreasing cost of computational power, time series' position as the most cost-effective demand forecasting method is now in question. Machine learning demand forecasting is increasingly offered as an improved alternative to traditional statistical techniques, but can this advanced analytical approach deliver more value than the cost to implement and maintain? To answer this question, we created a three-dimensional evaluation (cube search) across five unique models with varying pairs of hyper-parameters and eight different data sets with different features to identify the most accurate model. The selected model was then compared to the current statistical approach used at King's Hawaiian to determine not just the impact on forecast accuracy but the change in required safety stock. Our approach identified a machine learning model, trained on data that included features beyond the traditional data set, that resulted in a nearly 4% improvement in the annual forecast accuracy over the current statistical approach. The decrease in the value of the safety stock as a result of the lower forecast variation offsets the incremental costs of data and personnel required to run the more advanced model. The research demonstrates that a machine learning model can outperform traditional approaches for highly seasonal CPGs with sufficient cost savings to justify the implementation. Our research helps frame the financial implications associated with adopting advanced analytic techniques like machine learning. The benefits of this research extend beyond King's Hawaiian to companies with similar characteristics that are facing this decision.

[2]. "Greedy function approximation: A gradient boosting machine." Function estimation/approximation is viewed from the perspective of numerical optimization in function space, rather than parameter space. A connection is made between stagewise additive expansions and steepest-descent minimization. A general gradient descent "boosting" paradigm is developed for additive expansions based on any fitting criterion. Specific algorithms are presented for least-squares, least absolute 3 deviation, and Huber-M loss functions for regression, and multiclass logistic likelihood for classification. Special enhancements are derived for the particular case where the individual additive components are regression trees, and tools for interpreting such "Tree Boost" models are presented. Gradient boosting of regression trees produces competitive, highly robust, interpretable procedures for both regression and classification, especially appropriate for mining less than clean data. Connections between this approach and the boosting methods of Freund and Shapira and Friedman, Hastie and Tulshiram are discussed.

[3]. "XG Boost: A Scalable Tree Boosting System" Tree boosting is a highly effective and widely used machine learning method. In this paper, we describe a scalable end-to-end tree boosting system called XG Boost, which is used widely by data scientists to achieve state-of-the-art results on many machine learning challenges. We propose a novel sparsity-aware algorithm for sparse data and weighted quantile sketch for approximate tree learning. More importantly, we provide insights on cache access patterns, data compression and sharding to build a scalable tree boosting system. By combining these insights, XG Boost scales beyond billions of examples using far fewer resources than existing systems.

[4]. "Cat Boost: gradient boosting with categorical features support" In this paper we present Cat Boost, a new open-sourced gradient boosting library that successfully handles categorical features and outperforms existing publicly available implementations of gradient boosting in terms of quality on a set of popular publicly available datasets. The library has a GPU implementation of learning algorithm and a CPU implementation of scoring algorithm, which are significantly faster than other gradient boosting libraries on ensembles of similar sizes.

[5]. "Long term memory" Learning to store information over extended time intervals via recurrent backpropagation takes a very long time, mostly due to insouciant, decaying error back ow. We brie y review Hochreiter's 1991 analysis of this problem, then address it by introducing a novel, scient, gradient-based method called \Long Short-Term Memory" (LSTM). Truncating the gradient where this does not do harm, LSTM can learn to bridge minimal time lags in excess of 1000 discrete time steps by enforcing constant error ow through \constant error carrousels" within special units. Multiplicative gate units learn to open and close access to the constant error ow. LSTM is local in space and time; its computational complexity per time step and weight is O(1). Our experiments with arterial data involve local, distributed, real-valued, and noisy pattern representations.

[6]. "Using Internet of Things (IoT) in Agri-Food Supply Chains: A Research Framework for Social Good with Network Clustering Analysis" Agri-food supply chains (AFSCs) are critical in our society. Proper management of AFSCs is crucial for improving social welfare. Over the past years, digitization in AFSCs has emerged as a new paradigm. In this context, the Internet of Things (IoT) is a growing approach, providing a huge amount of information to manage AFSCs. Thus, the purpose of this article is to examine extensive studies on IoT-based AFSC. Our research starts with the identification of 346 articles in the relevant field from the Web of Science (Woos) database by applying rigorous filtration. Using the VOS viewer software, a network analysis has been performed. With seven identified clusters, this article recognizes the role of IoT technologies as Cluster 1: agri-food safety, traceability and sustainability; Cluster 2: AFSC sustainability; Cluster 3: AFSC performance measurement; Cluster 4: AFSC resilience in disruption; Cluster 5: AFSC integration and traceability; Cluster 6: AFSC transparency and coordination, and finally Cluster 7 identifies the barriers in IoT adoption. Thus, findings of this study offer robust guidance to link IoT technologies and AFSCs together. Based on these findings, propositions are proposed and a research framework is established. We believe the findings would help engineering managers, researchers, and government regulating bodies better plan and manage AFSCs for social good.

[7]. "Solving stochastic online food delivery problem via iterated greedy algorithm with decomposition-based strategy" Online food delivery (OFD) service has developed rapidly due to its great convenience for customers, the enormous markets for restaurants and the abundant job openings for riders. However, OFD platforms are encountering enormous challenges, such as massive demand, inevitable uncertainty and short delivery time. This article addresses an OFD problem with stochastic food preparation time. It is a complex NP-hard problem with uncertainty, large search space, strongly coupled subproblems, and high timeliness requirements. To solve the problem, we design an iterated greedy algorithm with a decomposition-based strategy. Concretely speaking, to cope with the large search space due to massive demands, a filtration mechanism is designed by preliminarily selecting suitable riders. To reduce the risk affected by the uncertainty, we introduce a risk-measuring criterion into the objective function and employ a scenario sampling method. For timeliness requirements caused by short delivery time, we design two time-saving strategies via mathematical analysis, i.e., an adaptive selection mechanism to choose the method with less computational effort and a fast evaluation mechanism based on the small-scale sampling and machine learning model to speed up evaluation.

3. PROPOSED METHODOLOGY

In propose Time series data is extracted from entire dataset for 10 week periods and then forecasting will happen for next 10 weeks. Extracted lag data will get trained with various ML and DL algorithms such as Random Forest, Gradient Boosting, XGBOOST, CATBOOST, LIGHT GBM, LSTM and BI-LSTM. Each algorithm performance is evaluated in terms of RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error) and RMSLE. All this metrics refers to difference between original values and predicted values so the lower the difference the better is the algorithm. Among all algorithms LSTM is giving less MAE and RMSE error rate.

For better understanding various exploration graphs have been generated from the dataset and then extracted new features such as Mean of Base Price, Max, Min, sales from each centre, sales or orders for each meal etc.

Advantages:

1.High Accuracy.

2. A comparative study of seven regressors to forecast the number of orders

4. EXPERIMENTAL ANALYSIS

Importing required python classes and packages and reading, displaying meals and its sales dataset. Reading and displaying dataset of different centers which are handling sales and now we will merge both datasets to find sales from different Centers.

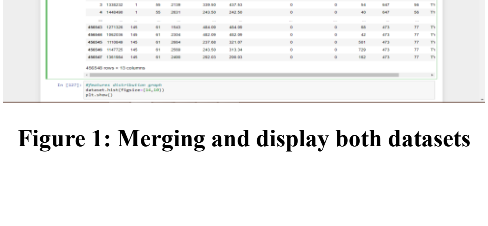


Figure 1: Merging and display both datasets

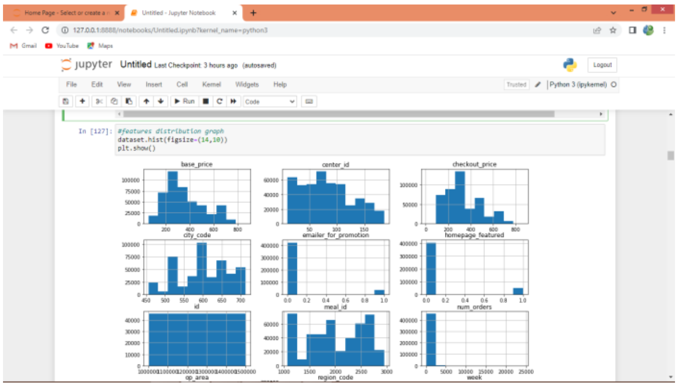


Figure 2: Finding distribution of values in each column in the dataset and in graph you can see the high low values of each column in the graph

Collected data is categorized and plotted on graph like max and min range of each column values, center type vs order in each week, no. of orders from each centre, center_id vs orders, centre type vs no.of centers working under that type. Similar to below graphs.

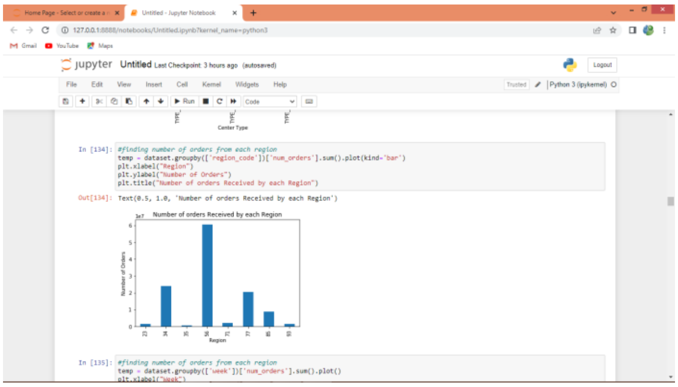


Figure 3: x-axis represents region code and y-axis represents orders

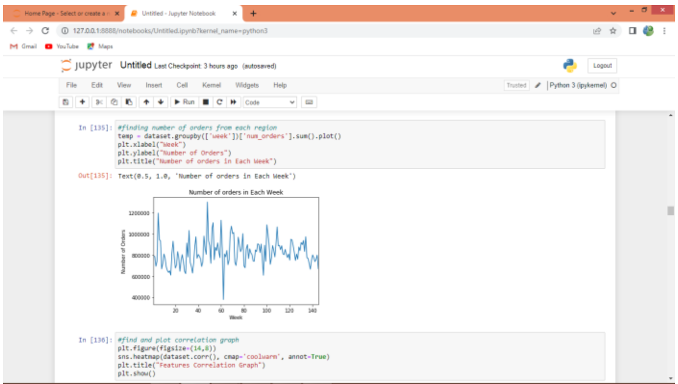


Figure 4: x-axis represents week and y-axis represents number of orders

We also use graph to display Features correlations, extracted New features. After this datasets is displaced by using 0.5 alpha value on Y target when LAG features are extracted.

Normalization is done then dataset is split into train and test.

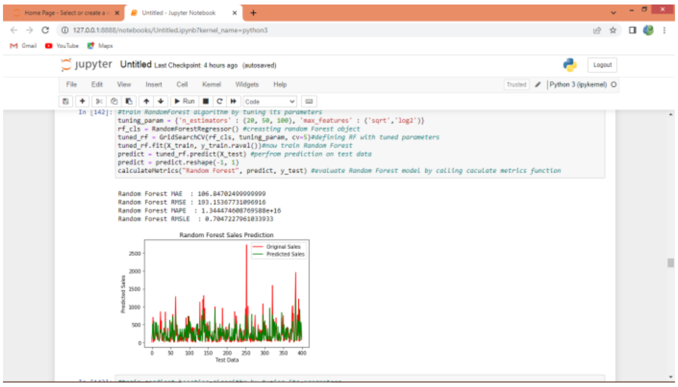


Figure 5: Random Forest

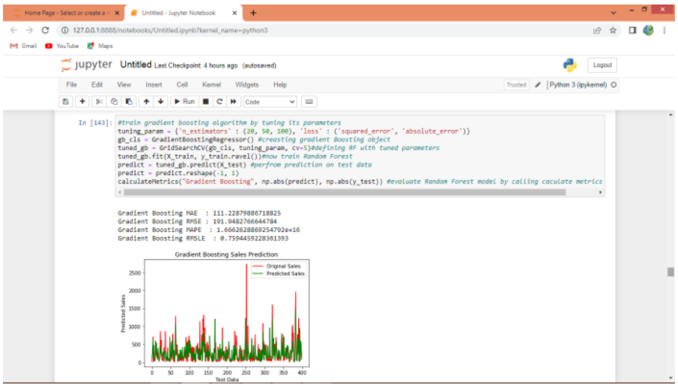


Figure 6: Gradient Boost

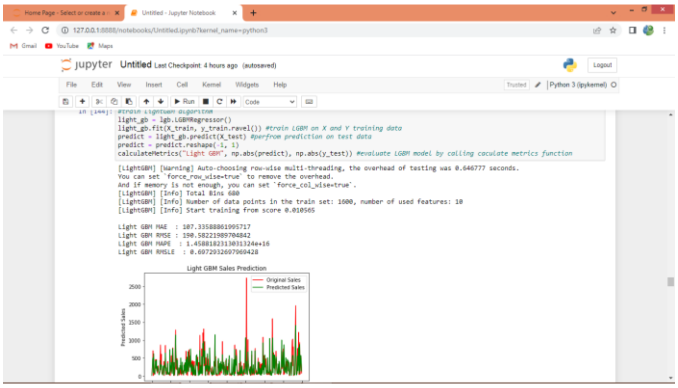


Figure 7: LIGHT GBM

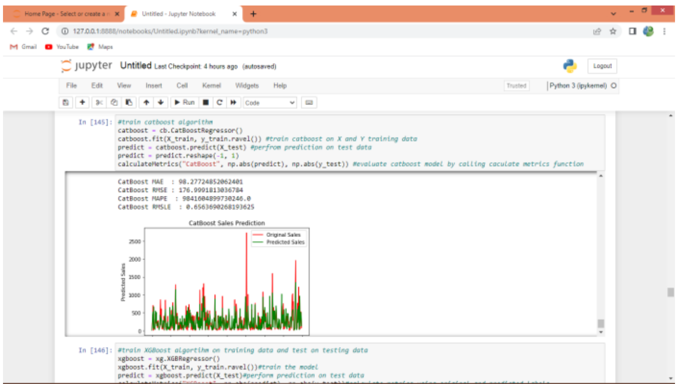


Figure 8: CAT BOOST

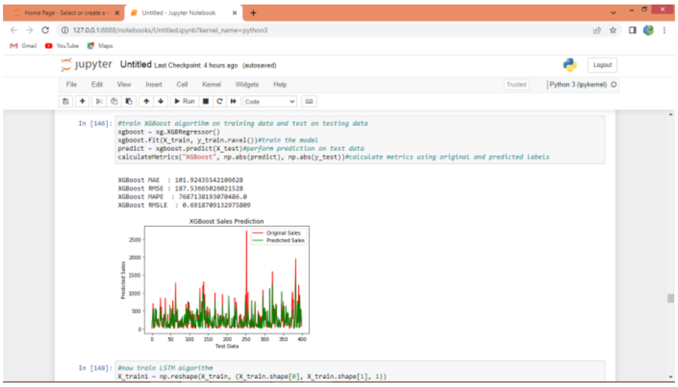


Figure 9: XG BOOST

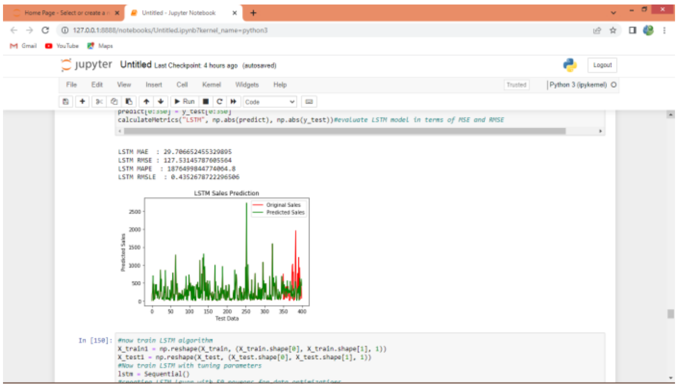


Figure 10: LSTM

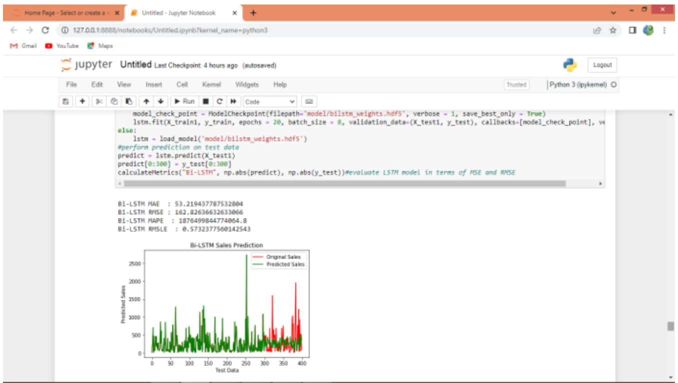


Figure 11: BI-LSTM

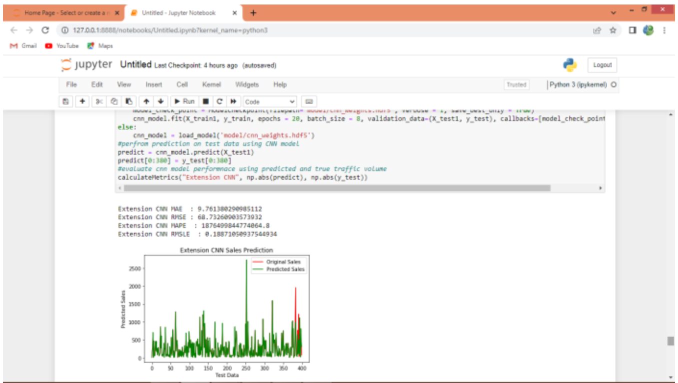


Figure 12: CNN2d

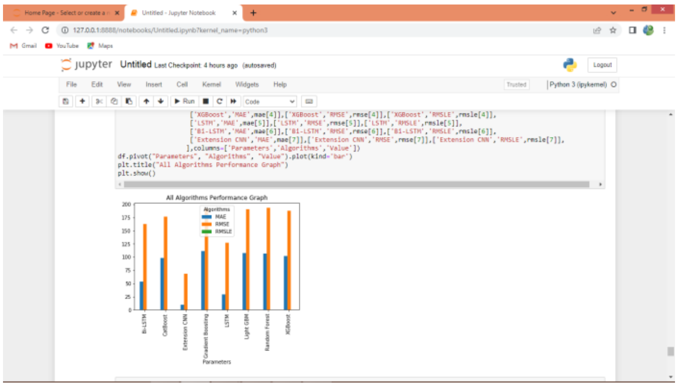
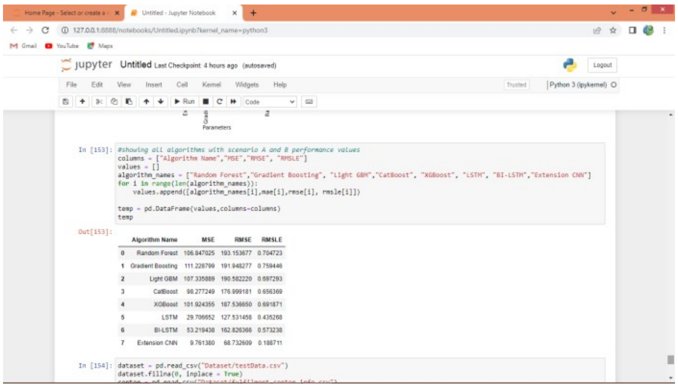


Figure 13: x-axis represents algorithm names and y-axis represents MAE and RMSE values



	Algorithm Name	MSE	RMSE	RMSLE
0	Random Forest	106.847025	193.153677	0.704723
1	Gradient Boosting	111.228799	191.948277	0.759446
2	Light GBM	107.335889	190.582220	0.697293
3	CatBoost	98.277249	176.999181	0.656369
4	XGBoost	101.924355	187.536650	0.691871
5	LSTM	29.706652	127.531458	0.435268
6	BI-LSTM	53.219438	162.826366	0.573238
7	Extension CNN	9.761380	68.732609	0.188711

Figure 14: Performance Table

5. CONCLUSION

The management of raw materials for a meal delivery service is significantly impacted by demand forecasting. Accurately forecasting the number of orders provides pertinent information to the concerned authority about the expected situation so that the inventory can be managed effectively without any waste. This study demonstrates the efficacy of deep learning and machine learning techniques for forecasting the volume of orders. In essence, these deep learning models are capable of identifying the time-variant characteristics and significant trends of historical data as well as predicting the future tendency of the given time-series data. On the basis of 135 weeks' worth of historical data, forecasts for the next 10 weeks are given. Each model's performance has been validated in terms of RMSLE, RMSE, MAPE, and MAE. Results and the statistical tests show that LSTM outperformed all other models in terms of forecasting performance. The dataset used in this study was restricted as it did not account for the date, month or any holidays. Without these factors, it was difficult to infer any trend or seasonality. Also, there was no mention of any event (like special discount or occasion) which may be able to explain sudden spikes of the target variable. The concept of applying transfer learning to time-series can also be explored as it may hold the key to improve the performance on smaller dataset. In future, these variables must be considered along with the limitations of the studied models to perform in depth analysis and propose a robust model.

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