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Original Article

Leveraging Economic Factors for Volume Forecasting in Manufacturing Industries

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***Abstract -** In this study, we investigate the output of the sector. The success of a manufacturer is contingent on the management team's capacity to forecast future sales volumes precisely. Businesses can learn about customer demand, manufacturing capability, and resource allocation based on economic variables through sales volume forecasting. This study examines the impact of production volume and economic forecasts on business decision-making. As an illustration, we use the DataRobot tool to create a regression model based on sample data to forecast vehicle sales in a particular industry in the United States. Total Vehicle Sales (TOTALSA) are a key economic indicator for predicting future automobile demand. Using this information to make decisions regarding manufacturing capacity, marketing strategies, and supply chain management will better enable the industry to compete in the fiercely competitive auto industry. Incorporating economic factors into predictive models can yield substantial benefits for businesses.*

***Keywords -** DataRobot, Manufacturing, Prediction, Regression, Volume.*

1. Introduction

Products are manufactured when basic materials or components are transformed into finished items. Industries as diverse as automobile manufacturing, aircraft engineering, electrical components manufacturing, textile production, and more may be involved. Production in the manufacturing sector is essential to the development and prosperity of many countries worldwide. The industrial sector as a whole has changed considerably over the past few decades. Manufacturing in the early 20th century was centred on mass production methods, such as the assembly line creation of large quantities of identical goods. Henry Ford is credited with popularizing this method with the invention of the car production line [4]. Industry 4.0, characterized by incorporating cutting-edge technologies like AI, the IoT, and big data analytics into the production process, is one of the most exciting trends in manufacturing today. The goal of Industry 4.0 is to link and automate workplaces so that they are "smart" and can improve efficiency, output, and adaptability [7]. Despite these improvements, industrial output has been hampered in recent years by the worldwide COVID-19 pandemic, which wreaked havoc on supply networks and significantly slowed down production. Some activities typically done by humans are now being automated, raising concerns about the effect on employment in the manufacturing sector due to the rise of automation and artificial intelligence. The industrial sector is essential to international trade, supplying everything from everyday basics to cutting-edge technologies. Economic development and new job creation are two of the sector's most important contributions, making it a vital engine of progress for many nations [9]. The term "manufacturing" refers to the process through which tangible items are created through activities like assembly, fabrication, and machining. It is used across many different sectors, including but not limited to the automotive, aerospace, electronics, and healthcare sectors. Changes in production methods, supply chains, and the dynamics of the market have all occurred as a result of significant transformations that have taken place in the manufacturing sector over the past few decades. Technological developments and globalization have fuelled these shifts. The integration of digital technologies has enabled real-time monitoring and optimization of production processes, resulting in increased manufacturing efficiency and productivity as a result of the adoption of automation and artificial intelligence, both of which have resulted in increased manufacturing efficiency and productivity. Many businesses have relocated their production facilities to take advantage of lower labour costs and other benefits that have emerged due to new manufacturing hubs in Asia, particularly in China. This has had a deep influence on the manufacturing sector globally. The determinants of manufacturing industries are:

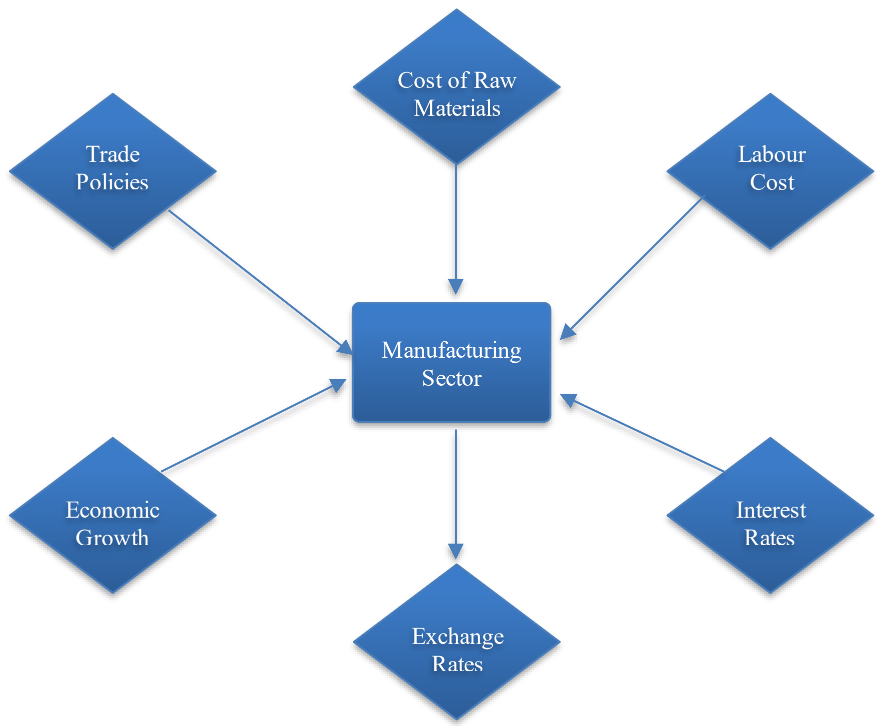

Fig. 1 Factors that affect the manufacturing sector

1.1. Cost of Raw Materials

Among the numerous economic determinants that influence the industrial sector is the cost of raw materials. Price volatility in major inputs such as metals, energy, and agricultural products can significantly influence manufacturing firms' bottom lines.

1.2. Labour Costs

The cost of labor is a significant economic factor that can influence the production sector. In comparison with countries with lower labour costs, the latter have a higher cost of output and lower profits.

1.3. Interest Rate

The price of borrowing money for investment or to expand output is determined by interest rates, which impact the manufacturing industry. Low rates stimulate investment and growth, whereas high rates increase the expense for industrialists to expand their plants.

1.4. Exchange Rate

Manufacturing is responsive to fluctuations in exchange rates since they determine the price of foreign raw materials and finished products. If the domestic currency is strong, imports are low-cost, and exports are high-cost, and the opposite is true if the domestic currency is weak.

1.5. Economic Growth

Manufacturing is dependent on economic growth as it spurs demand. An improving economy means more spending by consumers on products and services, Which could benefit both manufacturing and service industries. Prosperous economic times usually encourage consumers to fuel their spending, but in times of financial woe, the spirit to splurge might instead turn to a spirit of thrift. This, in turn, may mean fewer planned and impulse purchases, the result being that fewer products are sold.

If an estimated one percent of the population consumes nothing beyond what it strictly needs to survive. Eighty percent of the population can afford little or nothing beyond the barest necessities; this roughly corresponds to what can be considered a crisis in demand for means of production.

1.6. Trade Policies

Trade policies can affect the cost and availability of inputs and outputs, which can affect production. Free trade agreements can make inputs cheaper and more accessible, while restrictions such as tariffs and quotas can make them more expensive. Despite these fluctuations, the manufacturing industry is a major driver of the majority of economies and produces a high percentage of exports and overall GDP.

The industry, though, faces a host of challenges ranging from competition from newly industrialized markets, erratic demand and supply fluctuations, and adapting to shifting tastes among consumers and shifting environmental regulations. Research and development in every sector are important parameters that must be considered before implementing an investment. This results in the most effective supply chain management in manufacturing industries. The manufacturing unit of every industry plays a vital role in increasing the GDP of the country and the world. Hence, this sector always keeps pace with innovation, novel technologies and shifts in customer product demand. To remain competitive, manufacturers have to observe the statistical data and be ready to adapt to these shifts [19].

2. Production Volume of Manufacturing Industries

The term "manufacturing or production volume" is defined based on the number of product items manufactured by a manufacturer in a specific time period. To supply the customer products based on demand, there is a need for an effective and significant manufacturing process for effective and efficient product manufacturing volume. To identify and recognize the customer demand based on product preference, the machine learning technique is used for forecasting and predicting production with accuracy. It reduces the efforts of the manufacturer and helps in proper supply chain management. Since every manufacturer in the world is connected with global supply chain management, this has made business complex and competitive for manufacturers. It is very difficult to judge the requirements of a product in the global market.

The machine learning techniques have a variety of algorithms that help in predicting production volume, basic material requirements of products, and other important key variables, based on statistical data for forecasting the product manufacturing and current manufacturing status. To avoid the losses, they can also decide to select the right employee, raw material requirements for production and other demands for maintaining the global supply chain management.

This results in efficient product manufacturing and leads to an increase in their product quality and efficiency level. The manufacturer can also seek support to understand the current market trends and patterns in the manufacturing sector to improve their product and processes. This helps them make proper and accurate decisions for their industry to meet sufficient quantity and reduce the barrier in supply chain management. It helps them reduce the inflation rate of the product, providing an opportunity for manufacturing quality products and fulfilling the demand of customers [12].

Based on past experience and customers' demands, machine learning techniques help the manufacturer achieve its goals. The exact statistical data of the manufacturing volume helps in projections, the project level of output, and the requirements for the manufactured product. This can help in a pandemic as well as in a crisis in a volatile market. This leads to projecting future predictions for product development by making appropriate strategies for the development of industry operations. It helps in particular volume projections, from which the industry can take benefits like:-

- Avoiding extra production during a recession and a slack market. It can be done easily by the manufacturer's forecasting technique. It is most beneficial for manufacturing volume projection used by producers, from which producers can plan production and understand their own manufacturing capacity.
- It also helps monitor inventory and supply chain management during recessions. It avoids the risk of overstock production or unavailability of production by observing the forecasting trend in the market.
- Forecasting technique using a machine learning algorithm helps to monitor the supply chain of manufacturer strategies and transportation arrangements based on supply and demand. This results in saving costs and effective operation of manufacturing during a recession.
- It also helps in attracting investors to the market. From this, the relation between manufacturer and investor improves, which results in gaining a huge volume of orders during demand. It also acts as a supportive member in the strategic planning of the manufacturing of a large volume of products and in providing the required resources for the future.

2.1. Use of Machine Learning in the Automobile Industry

During the pandemic, people accepted cars as vehicles. The car required different spare parts, such as pistons, crank, gearbox, car-body, a variety of wheels and mechatronic-based equipment like speedometer, lights, radiators, etc, since it has the ability to carry 4 to 6 passengers and products.

The automobile industry plays an important role in the GDP of most nations. This gives a chance to rise in employment. The components of the engines are welded and properly manufactured. This required more time to develop the single car, which goes through rigorous inspection and measurements. There are various vehicle types like trucks, buses, cars, bikes, mopeds, etc. Western countries and a few countries from Asia have dominated the automobile industry and its associated production industry. The industry is faced with numerous challenges and pressures, including alterations in customer demand, regulatory requirements, and technical innovation.

In the last few years, the industry has placed a great deal of emphasis on the production of electric and autonomous vehicles, which have the capability to revolutionize the way people travel and influence the broader transport sector. The car industry is undergoing a revolutionary phase due to the introduction of machine learning and AI, which are helping firms work more effectively, reduce costs, and provide better service to consumers. Companies can make choices and automate much of what they do based on information. It helps firms streamline numerous activities by using machine learning algorithms, which can analyze humongous amounts of data collected from sensors, client interactions, manufacturing processes, etc. Since AI allows self-driving cars to execute calculations on sensor and other data in real-time, it plays a central role in the development of the technology. The automobile industry is tapping artificial intelligence to enhance predictive maintenance, quality monitoring, supply chain management, and the customer experience [8].

In order to maximize their manufacturing, sales, and marketing efforts, automakers must forecast the number of vehicles they will produce. To forecast car volumes, automakers typically combine machine learning methods with economic considerations. The economy is a most significant indicator in the automobile sector. It always varies based on the trends of supply and demand made by customers. The regression techniques implemented using the ML algorithms offer insights into industry financial health.

The annual turnover of the automobile sector is calculated using significant variable parameters like feedback, inputs, supply, demand, prices, manufacturing cost, infrastructure and techniques, as well as labour and employee finances, etc. They correlate with each other by examining the link between sales and profit variables of the relevant automobile industry. To forecast trends and public demand for products, as well as improve sales and profit, the industry's R&D department carries out its research to satisfy the public's requirements regarding products. There are various automakers that use machine learning algorithms for predicting and forecasting the volume projection of vehicle production. This helps producers make appropriate decisions to satisfy customer demand and streamline operations using technology.

3. Literature Survey

The research is evaluated on the basis of external financial parameters for predictive forecasting, as well as the different disadvantages and advantages of the most important aspects of the research findings of many researchers. According to S.Bingol (2020) et.al. in [3], elaborate on the various elements that affect and control the market value of gold based on the quantity and quality of gold. The primitive goals were to:-

(i) Identifying the communication trade-off based on the supply and demand of gold awards, and (ii) the working principle of the regression model used to forecast the gold rates. Ching-Fong (2020) et al. [5] discussed grey analysis and its implementation to find the derived predictor from economic variables. The inputs to the Deep Neural Networks (DNN) and Least-Squares Support Vector Regression (LSSVR) are the specified characteristics, plus Google Index, an exogenous variable utilized extensively in research. The experimental findings show that the grey DNN model, a cutting-edge AI technology, can provide reliable forecasts of future sales quantities using non-parametric statistical testing. Guefano (2020) et.al. in [6] elaborate that demand for electricity in Cameroon is growing due to the country's rapidly expanding population. The purpose of this work is to construct a VAR model that can anticipate the demand for electricity. In order to achieve this, the research focuses on six different macroeconomic measures, namely (i) Gross domestic product, (ii) Gross domestic product per capita, (iii) Electricity consumption, (iv) Population, and (v) Number of subscribers and households. This model can assist in monitoring the consumption of electricity and provide information regarding the rate at which the hydroelectric and thermal grids are expanding. Jiang et.al. (2021) in [10] elaborate on the study investigating the viability of using standard time series models, hybrid models that combine time series models with machine learning models, and machine learning models alone to forecast sales at Walmart. The Prophet model breaks down data based on trend, season, and holiday, and the machine learning model, the lightGBM model, are utilized in training and testing data about grocery sales at Walmart. Lee et.al. (2021) in paper [11] expand upon previous work that used ARIMA, SARIMA, and Regression to forecast container volumes in Busan.

The paper elaborates on the shortcomings of the standard approach, which does not provide information regarding data fluctuations caused by external variables in the forecast. The author utilized the deep learning LSTM approach to dissect the time series and explain the data's variability due to events like the financial crisis and the economy's reaction to it. The LSTM method of deep learning was used to achieve this goal. The accuracy of predictions was much improved over the standard approach. Mehmet et.al. (2022) in [13] focus on a study that provides additional information on the demand forecasting of one of the components of e-retails using deep learning and machine learning techniques with sales-impacting variables.

Monterio de Almeida et.al. (2022), in paper [14], describes the future outlook and how machine learning algorithms assist in anticipating the retail sales of superstores. Sen et.al. (2019) in [16] describe how multiple regression models may be used to anticipate Turkey's natural gas consumption based on socioeconomic factors. Natural gas use is highly correlated with GDP and the inflation rate. Vasilios Plakandaras et.al. (2019) say that the paper [17] aims to use econometric and machine learning techniques to predict the domestic demand for air, road, and rail transportation in the United States. The transportation demand forecasts extend up to 18 months into the future. By using Support Vector Regression (SVR) from machine learning, Least Absolute Shrinkage and Selection Operator (LASSO), and Ordinary Least Squares (OLS) regression from econometrics. Results are achieved by following the existing research and factoring in the possible impact of certain factors as regressors in the forecasts. Velappam Shalini et.al. (2017), in paper [18], evaluate Neural Network and Vector Auto Regression models. It also analyses the impact of predictors controlling for total industry volume. Machine learning algorithms can be used instead of econometrics based on data characteristics like non-stationarity, non-linearity, and non-normality.

4. Data Used

The study in this paper focuses on how economic factors impact the manufacturing volume. GoodCarBadCar.com is a resource for information on the North American car market. The website is a popular resource for consumers, industry professionals, and investors because it provides information about the sales success of various automobile manufacturers and models. The monthly sales data on the FORD Company is taken as a sample from the website.

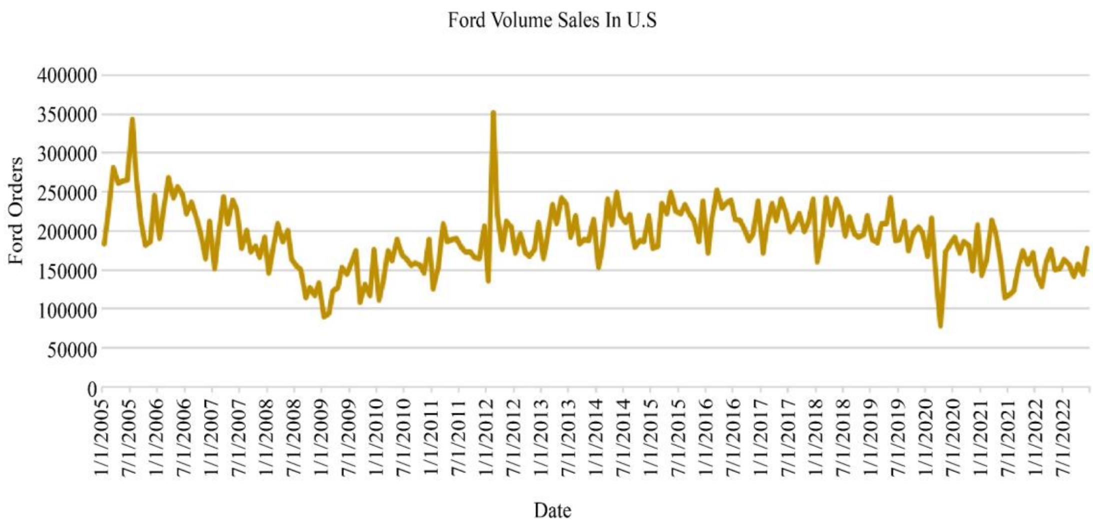

Fig 2. Ford monthly orders from (2005-2022)

Ford is among the largest and most well-known U.S. automakers, recognized for its durable and popular automobiles. Thus, industry experts, investors, and customers constantly monitor the company's monthly sales volume statistics. The data contains sales figures from January 2005 to December 2022. The Economic data was taken from Fred; the Federal Reserve Bank of St. Louis compiles and maintains a massive database of economic data known as FRED. In order to analyze and investigate economic patterns, the database is often used by economists, politicians, academics, and researchers. Total Vehicle Sales (TOTALSA) is an economic factor. The term "Total Vehicle Sales" is used to describe the sum of all automobiles sold by a car company or dealership within a given time frame. Automobiles, trucks, vans, and sport utility vehicles are all included. The total number of vehicles sold is a useful measure of the automotive industry and the economy's health. Monthly data of (TOTALSA) from Jan 2005 to Dec 2022 is pulled from FRED through an API [1].

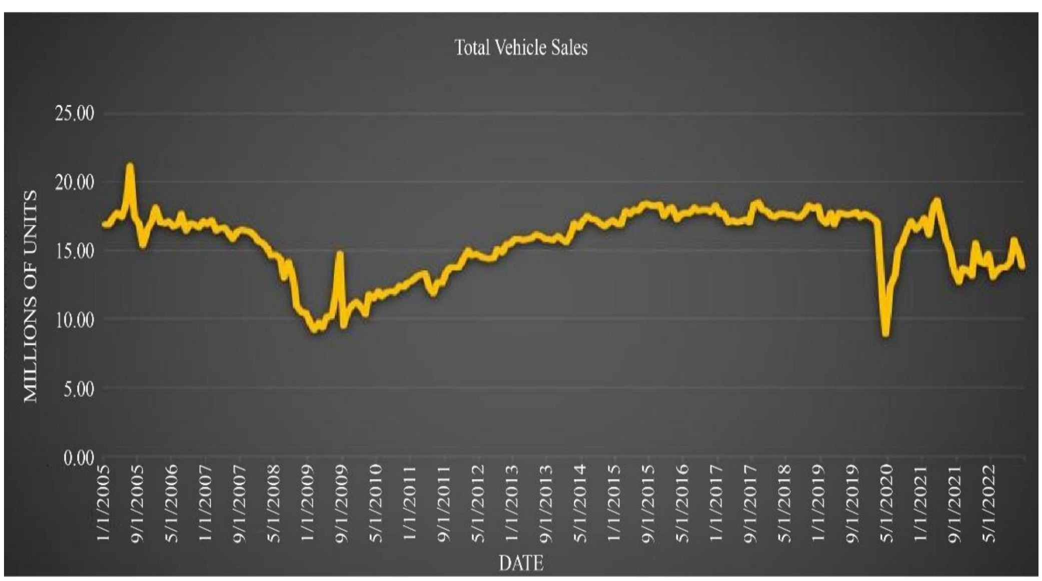

Fig. 3 Total Vehicle Sales (TOTALSA) monthly from (2005-2022)

5. Materials & Methods

Predicting production volumes is the primary emphasis of this research. For that purpose, Ford's volume sales in the U.S. are considered as sample data. Economically speaking, the TOTALSA is a feature that can be correlated with vehicle sales volume. The relationship between the two factors was determined using a Pearson correlation. The variables were correlated monthly at a 68% clip. Due to the substantial nature of a car's purchase, the total number of vehicles sold is sometimes used as a proxy for discretionary expenditure. Because of the information they give on consumer confidence, spending habits, and economic growth, total car sales are frequently cited as a crucial economic indicator. The industry as a whole may be evaluated by looking at each manufacturer's and brand's share of total vehicle sales. Manufacturers and retailers of automobiles pay great attention to sales data in order to spot patterns, form strategies, and alter their practices accordingly. From January 2005 through December 2022, monthly sales data for Ford and total vehicle sales were compiled and then divided into a training set consisting of data from January 2005 through December 2021 and a testing set consisting of data from all other months. (January 2022 - December 2022). The dataset went through some preliminary processing to ensure the data were accurate and consistent. With the help of Datarobot, a regression model was chosen and optimized, with the target variable set as the volume of sales for Ford vehicles and the predictor variable set as TOTALSA. DataRobot is a platform for automated machine learning that facilitates the rapid development and deployment of predictive models. It has an intuitive interface and automates several model development, testing, and optimization steps. Models for tasks are as diverse as record or instance of data in the table, and each column in the forecasting, fraud detection, and customer segmentation can all be created with the help of DataRobot. The platform can process both structured and unstructured data, and it is compatible with a wide range of algorithms (such as regression, time-series forecasting, and deep learning). DataRobot employs cutting-edge automation and machine learning methods to probe a variety of algorithms and zero in on the most suitable model for a dataset. Hyperparameter tweaking can also increase the model's precision. In addition, it predicts the outcome based on evaluation parameters and chooses the most appropriate algorithm for the problem.

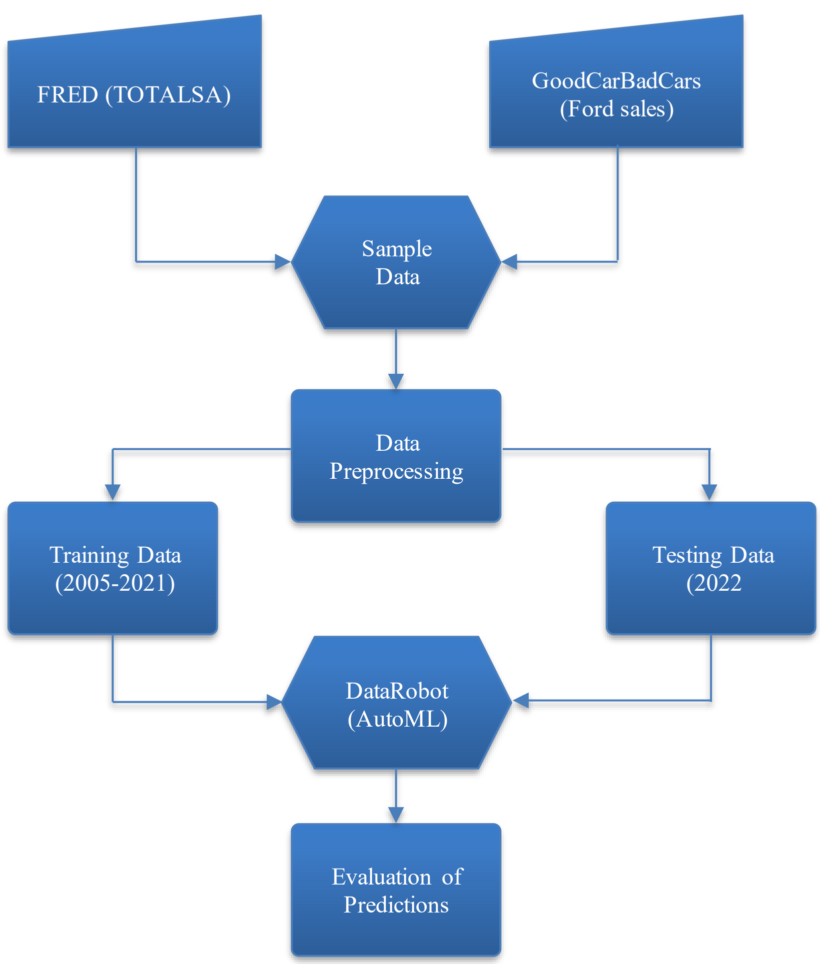

Fig. 4 Overall process

Furthermore, to showcase the result, we have used Power BI, a business analytics tool that delivers interactive visualizations and business information with an interface allowing end-users to generate reports and dashboards without IT assistance. It is a web, desktop, and mobile cloud service. Power BI connects to many data sources, from Excel spreadsheets to business databases. Power Query lets users effortlessly alter and clean data. DAX, a mathematical language, lets Power BI users calculate and customize data metrics. All of the information in a flat-file database resides in a singular table, with no cross-references to any other tables. Each row represents one table represents one feature or characteristic of the data.

6. Result & Discussion

DataRobot picks the forecast programme that performs best. It performs an exploratory study of the data and takes care of the preliminary processing steps, such as the imputation of missing values. It suggested two algorithms for our research, and we used them to hone our retrieved training data. Which are (i) the Rule-Fit algorithm and (ii) the XGBoost algorithm.

6.1. Rule-Fit

In the first step of the RuleFit method for regression, the input characteristics and the outcome variable are used to construct a decision tree. The tree is expanded until a stopping condition is reached by recursively splitting the data into smaller groups based on the feature values. When finished, a linear regression model takes the tree's nodes as input characteristics. Finding coefficients for each leaf node such that the linear mixture of their values accurately predicts the target variable is the objective of the linear regression phase. The coefficients can be optimized by calculating the total squared errors between the expected and real goal values. By fusing decision trees with linear regression, the RuleFit method produces a model that is easy to understand and highly reliable.

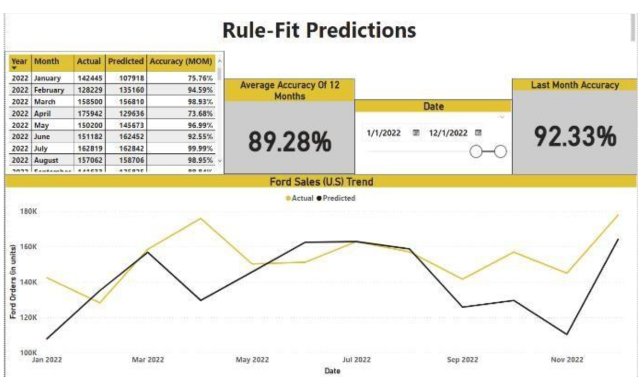

Fig. 5 Rule-fit predictions summary

6.2. Extreme Gradient Boosting (Poisson Loss)

In recent years, Extreme Gradient Boosting (XGBoost) has become more renowned as a stable machine learning algorithm because it can handle large amounts of data and provide accurate predictions. For count data regression problems, the Poisson loss is a widely used selection of a loss function. It is presumed that the answer variable obeys the Poisson distribution, a discrete probability distribution that accounts for the number of events occurring within a particular amount of time or space. The variance and expected value of the answer variable are equal, so the mean is the only measure in the Poisson distribution. Gradient boosting is applied iteratively to fit decision trees to the data in XGBoost with Poisson loss. The Poisson loss is minimized during training for every decision tree. XGBoost with Poisson loss utilizes the Poisson loss function to calculate the gradient and the Hessian of the loss function for every sample when it is in the training process. At the same time, the Hessian represents the curvature of the loss function, and the gradient points towards the direction of the steepest ascent. In every iteration, the weights of the nodes in the decision tree are updated by using these numbers.

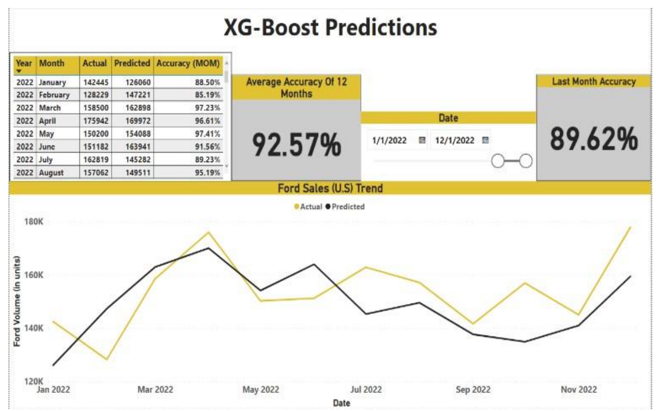

Fig. 6 XG-Boost (poisson loss) predictions summary

The result was calculated on the testing data i.e. (2022), and a Power BI dashboard was created using the summary of the testing data. Figures 5 and 6 show the summary of the results.

An average accuracy of the 12 months was calculated, and the average accuracy for X.G. Boost is 97.57%, which is better than the Rule-fit, which is 89.28%. The comparison of the evaluation metrics on the testing data of the two algorithms is shown in Table 1.

Table 1. Comparison of algorithms

Evaluating Parameters	Rule-Fit	XG Boost
RMSE	22203	13180
RMSLE	0.16	0.09
MAPE	8%	7%
SMAPE	12%	8%

According to the findings, XGBoost generates more accurate, specific, and consistent projections than those generated by RuleFit. It is possible to attribute XGBoost's effectiveness to its capacity to handle complicated non-linear relationships between variables, as well as to its ability to handle missing data.

7. Conclusion

Predicting the manufacturing volume is essential work in the manufacturing industry because it enables businesses to improve the effectiveness of their production processes, lower their expenses, and improve their general competitiveness. Therefore, the study explains how we may utilize economic indicators to foretell the future volumes of associated sectors, giving us valuable insight into the economy's ups and downs. It can tell us how many sales the industry can handle in the event of a potential recession. Our research into DataRobot's capacity for volume forecasting in the Ford car sector has focused on TOTALSA as a predictor. TotalSA turned out to be an excellent addition to building the models of predictive performance in a very up-to-the-minute manner, and the exactness level. The conclusion of this study clarifies the point that TOTALSA is a critical variable when volume forecasting is done, with the XG-Boost (Poisson loss) strategy being advantageous. The remaining part of the description should contain a couple of sentences to show the relationship between the model and the feature, and also, the impact that the addition of TOTALSA has resulted in a significant improvement of the existing DataRobot volume forecasting models for Ford vehicles. In support of this argument, the current investigation signals that the use of TOTALSA as a surrogate for total demand can lead to manufacturers making better-informed decisions about their production schedules and resources. It is most significant for a manufacturing business person to remember that there are a number of factors, such as maintaining the quantity and quality of product based on available data, strategies and hyper-parameter techniques setting. As a result, the research work was performed in the Ford car industry. A few variable parameters, such as TOTALSA, monitor the complete supply chain management from manufacturing to product delivery in the market. It helps to determine the resource requirement and its allocation at the appropriate time in the market volume of various types of vehicles. The market always has volatility, uncertainty, consistency, and ambiguity. This leads as a prompt for doing more research to give better predictive analysis.

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