|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **S.NO** | **TITLE** | **YEAR OF**  **PUBLISHING** | **AUTHORS** | **THEME** | **INFERENCE** |
| 1. | Demand Forecasting for production planning in a food company. | Jan-2015 | * Nathalia Barbosa * Kelly Alonso Costa | Food demand in beverage industry. | The food products have a factor that limits the maintenance of stocks, the short perishability. These products have a period in which they keep their characteristics and should be consumed before being considered unsuitable for consuming. Thus, it is suggested for future works that the short perishability of products must be taken into account when evaluating the results obtained by the quantitative methods. To make possible not only plan the production to satisfy the forecasted demand, but also contribute to minimize the loss of products due to its short perishability and consequently, improving the profitability of the company. |
| 2. | Demand forecasting in food retail: Comparison between Holt-Winters and ARIMA | Jan-2014 | * Veiga | Machine learning based demand forecasting using HW and ARIMA models. | Veiga compared the performances of ARIMA and Holt-Winters models for predicting a time series formed by a group of perishable dairy products. They used sales data of 8 years. They used MAPE and U-Theil as evaluation metric. They concluded that Holt-Winters model obtained better results on the comparison |
| 3. | Support Vector Regression to predict carcass weight in advance of slaughter | Jan-2013 | * Alonso | Food demand forecasting by predicting carcass weight in beef cattle | Alonso developed an SVM model to forecast cattle weight with one or few weights. They noted that the level of error metrics of MAPE for their model were between 3.9 and 9.3 for varying datasets. Then he developed SVR to estimate the beef cattle carcass weight 150 days before slaughter. They used MAPE to test accuracy of their model and reported that the average MAPE of their model was 4.27%. Research has used advanced machine learning tools to predict agricultural and livestock production, the focus of the research has been on specific product or livestock, and developed models are not designed to forecast different production at macro level of a country. |
| 4. | Demand forecasting in supply chains. | Jan-2007 | * Rustam Vahidov * Kevin Laframboise | Machine learning based demand forecasting. | From the results we can see that one  of the ML approaches, the SVM under the super wide modeling approach is at the top  of all three data sets by providing consistently better performance.  If we ignore the  super wide models, we find that the results of previous research and the very large M3 competition were essentially reproduced, that is, simple techniques outperform the  more complicated and sophisticated approaches. |

Team ID : PNT2022TMID15280