INVENTORY MANAGEMENT USING BIG DATA AND INTERNET OF THINGS

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ABSTRACT

This review paper delves into the transformative potential of Internet of Things (IoT) and Big Data technologies in revolutionizing inventory management within the Food & Restaurant Industry. With consumption routines in this sector being notably high, the need for efficient inventory control is paramount. We examine the current landscape, revealing a disparity between small and medium-sized businesses and larger enterprises in inventory management practices. Drawing insights from extensive literature analysis, we explore the trends and opportunities for utilizing IoT and Big Data to address inventory challenges. Our research focuses on high-demand categories, analysing data from top-selling items in food outlets. Findings underscore the prevalence of ad-hoc inventory management methods, highlighting the necessity for real-time data analytics and forecasting techniques. We propose solutions that involve real-time data gathering, coupled with advanced forecasting algorithms such as Linear Regression and Random Forest. Despite promising outcomes, we also address the challenges and limitations inherent in implementing these solutions, offering insights for future research and industry adoption.

1. INTRODUCTION

Inventory management is the cornerstone for businesses dependent on physical goods, facilitating the effective management of raw materials and products. It serves to reduce supply chain stress by addressing demand fluctuations, supply uncertainties, and pricing stability concerns.

Transparency is paramount in inventory control, which bridges the gap between planned and actual operations while promoting supply chain visibility. Leveraging real-time data helps organizations optimize operations and increase supply chain efficiency, as well as benefit from relevant insights into demand forecasting. In today's dynamic market, customer demands change rapidly, requiring agile inventory strategies to maintain competitiveness. Stability in pricing depends on real-time data and prudent decision making by considering cost volatility and delivery timelines.

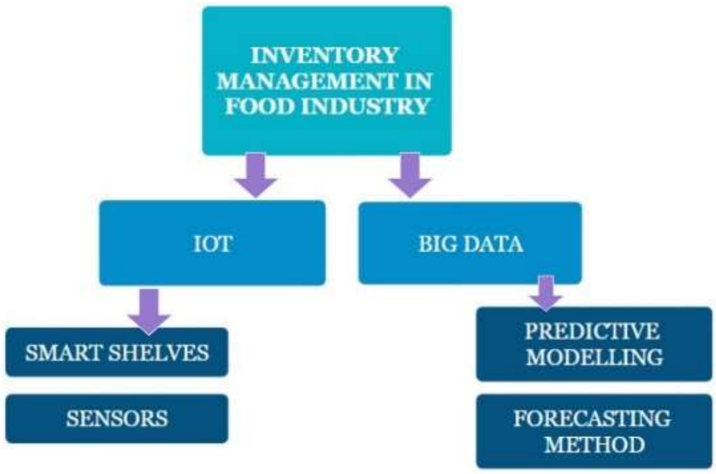
The Internet of Things (IoT) revolutionizes inventory management across industries by connecting physical objects to embedded technology, enabling interactions with their environment on a global scale. Big Data analytics plays a pivotal role in inventory management, addressing challenges like overstocking and understocking while optimizing costs and meeting demand through predictive analytics. In the food industry, IoT integration increases efficiency by providing real-time updates on product conditions, while consumer behaviour analytics informs responsive inventory adjustments.

In cloud kitchens, inventory management is revolutionized through the integration of IoT devices and sensors. These technologies enable real-time tracking of ingredient and supply levels, ensuring efficient operations and minimizing wastage. The key types of sensors and instruments used include RFID tags and readers, barcode scanners, weight scales, temperature sensors, and inventory management software. RFID tags and readers utilize electromagnetic fields to automatically identify and track tagged objects, while barcode scanners read unique barcodes on item packaging. Weight scales measure the weight of perishable goods, and temperature sensors monitor storage unit temperatures to prevent spoilage.

Inventory management software serves as the central platform for tracking and managing inventory levels, integrating data from various sensors. It provides real-time updates, alerts, and notifications to kitchen staff, facilitating timely restocking and preventing stockouts. When estimating costs for IoT-based inventory management systems, it's important to consider both software and hardware components. Software costs include licensing fees, customization, and ongoing support, while hardware costs encompass the purchase and installation of sensors, readers, and other IoT devices. Additionally, maintenance and operational expenses should be factored in for a comprehensive cost estimation.

This research explores how the Internet of Things (IoT) can revolutionize warehouse management by offering real-time data on inventory through sensor networks. RFID tags and smart shelves are examples of IoT technology that can track and analyse inventory movement, enabling better organization, reduced labour costs, and improved fulfilment of customer demands. The authors propose an IoT framework that integrates machine learning for real-time data acquisition and prediction of inventory fluctuations, potentially optimizing warehouse operations and supply chain efficiency.

Traditional warehouse management often grapples with delays in information transfer, resulting in operational inefficiencies exacerbated by suboptimal location choices. Leveraging technologies like RFID tags within the Internet of Things (IoT) framework offers real-time inventory tracking capabilities, mitigating these challenges. Moreover, integrating machine perception techniques enhances the accuracy of demand and supply fluctuation predictions, aiding in proactive inventory optimization strategies. Additionally, addressing class imbalance issues in machine learning models, particularly for backorder prediction, ensures more robust and reliable forecasting, thereby optimizing inventory management practices and streamlining warehouse operations effectively.



2. METHODOLOGY

The solution employs ML algorithms to forecast perishable food demand for grocery delivery services, ensuring optimal inventory levels and preventing wastage or stockouts. It leverages ML's ability to learn patterns from noisy supply chain data, enabling accurate predictions and proactive decision-making. Robust tracing techniques are integrated for food safety compliance, enhancing supply chain resilience. By predicting demand well in advance, it facilitates efficient inventory management across warehouses, stores, and distribution centres. Effective communication between suppliers, warehouses, and clients is prioritized, minimizing disruptions and maximizing customer satisfaction.

2.1 Understanding Business Problem:

- Grocery delivery services need accurate daily and weekly forecasts for perishable items to prevent wastage and stockouts, ensuring customer satisfaction.
- Effective communication among suppliers, warehouses, and clients is crucial for a smooth supply chain.
- Implementing robust tracing techniques is necessary for food safety.
- Accurate forecasts aid in planning, decision-making, and minimizing inventory costs.
- Predicting demand for each product in advance ensures optimal inventory levels.
- Supply chain time series data is noisy; it's essential to extract true patterns and ignore noise.
- ML techniques offer the ability to learn complex patterns and control the learning process, aiding in supply chain forecasting.

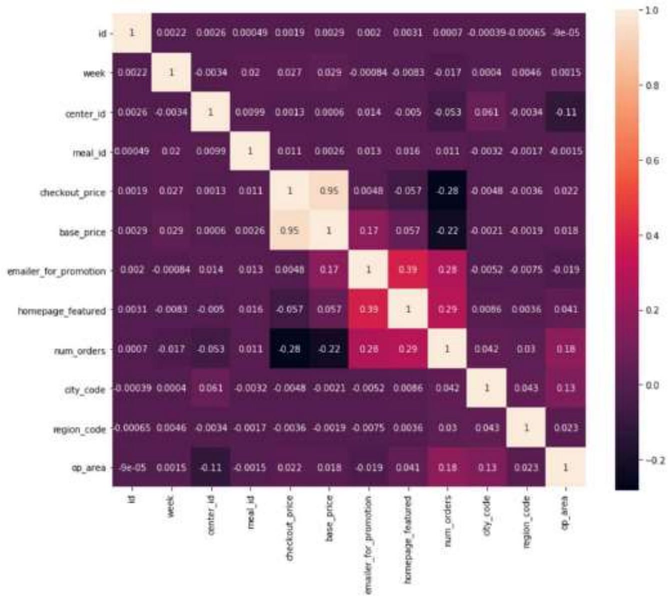
2.2 Data Collection and Preprocessing:

- Utilized Kaggle datasets for demand forecasting, including:
- Weekly demand data (train.csv): Historical demand with features like center ID, meal ID, prices, promotions, and orders count.
- Test data (test.csv): Similar structure to train.csv for model testing.
- Meal information (meal_info.csv): Details about meal types, categories, and cuisines.
- Fulfillment center information (fulfillment_center_info.csv): Data about centers, including city code, region code, center type, and operational area.
- Preprocessed data by merging all datasets into one, ensuring proper format for analysis.

2.3 Exploratory Data Analysis (EDA):

- Examined data for quality issues and insights.
- Analysed categorical variables, such as center type, food category, and cuisine type.
- Visualized correlations among variables.
- Conducted analysis of orders count (num_orders) with categorical variables, including center type, food category, and cuisine type.

- **Visualizing correlation among variables:**



3. RESULTS AND DISCUSSION

In the predictive modelling phase, various machine learning models are employed to analyse data and make predictions. The models discussed include:

I. Linear Regression: A model used for predicting continuous outputs by fitting a linear curve to the data based on feature weights.

II. K Nearest Neighbours (KNN): A non-parametric method for classification and regression that predicts values based on the similarity of neighbouring data points.

III. Decision Tree regressor: A tree-based algorithm used for regression and classification, where decision nodes are based on conditions over features.

IV. Random Forest Regressor: An ensemble model that combines multiple decision trees to create a robust and accurate model, which outperforms individual trees.

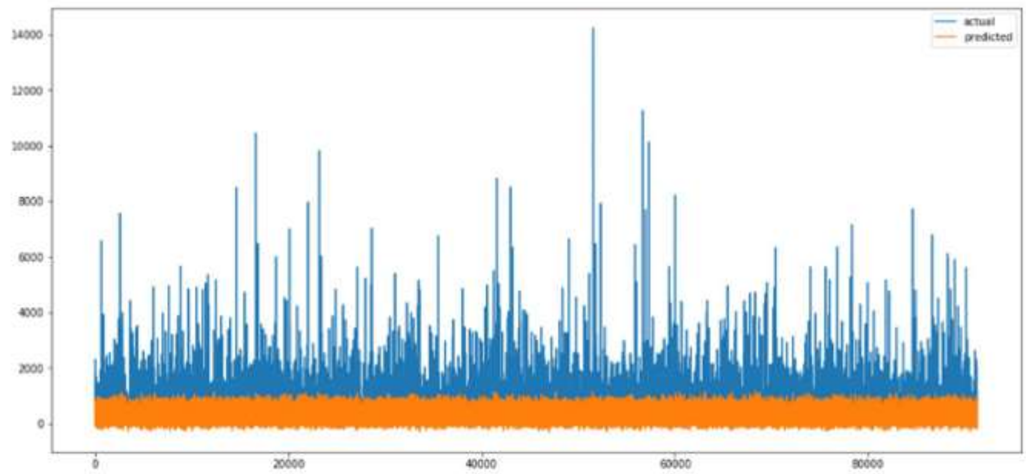
V. XGBoost: A gradient boosting method that sequentially adds decision trees to the ensemble to minimize the loss function, resulting in high model performance and computational efficiency.

Each model has its own characteristics and is suitable for different types of data and prediction tasks. The choice of model depends on factors such as the nature of the data, the problem at hand, and the desired performance metrics.

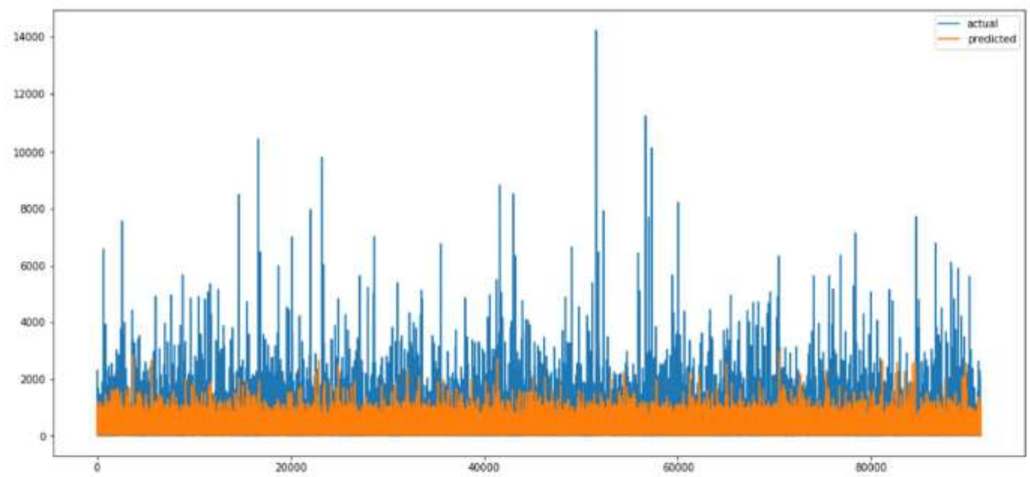
In the modelling phase, various machine learning models are employed after thorough research and evaluation. Linear Regression utilizes features to predict continuous outputs by fitting a linear curve to minimize mean squared error through gradient descent. K Nearest Neighbours utilizes feature similarity among neighbouring data points for prediction, employing distance metrics like Euclidean, Manhattan, and Hamming. Decision Tree Regressor constructs a tree-based model by recursively splitting data based on feature conditions, using the Gini index for node selection. Random Forest Regressor combines multiple decision trees through bootstrapping and majority voting to create a robust ensemble model. XGBoost, a gradient boosting technique, sequentially adds decision trees to minimize loss, offering computational efficiency and high performance through its objective function and regularization.

The model performance is assessed by plotting actual versus predicted values and evaluating using the R2 score, indicating predictive capability where 1.0 signifies perfect prediction. Scores for each model are as follows: Linear Regression (0.24), K Nearest Neighbours (0.075), Decision Tree Regressor (0.70), Random Forest Regressor (0.85), and XGBoost Regression (0.83).

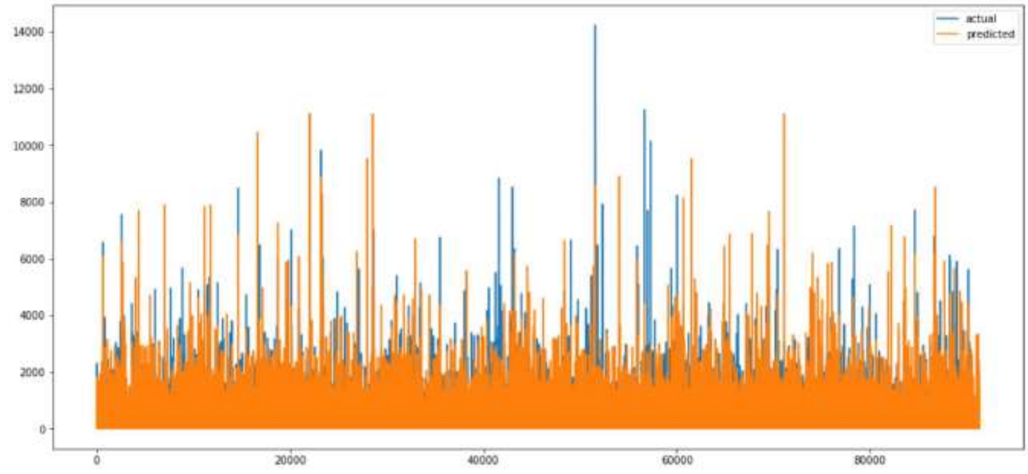
- **Linear regression:** R^2 Score for Linear Regression was 0.24



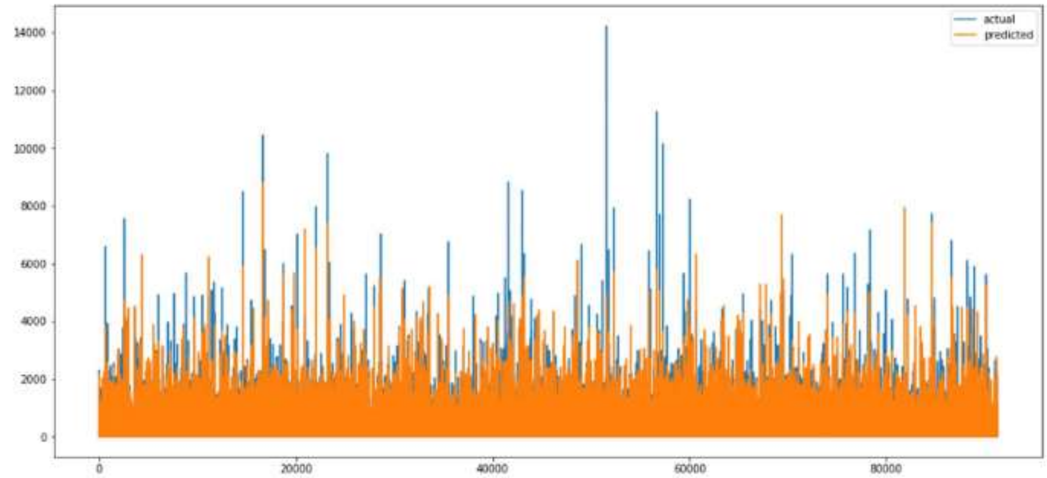
- **K Nearest Neighbors**: R^2 Score for Linear Regression was 0.075



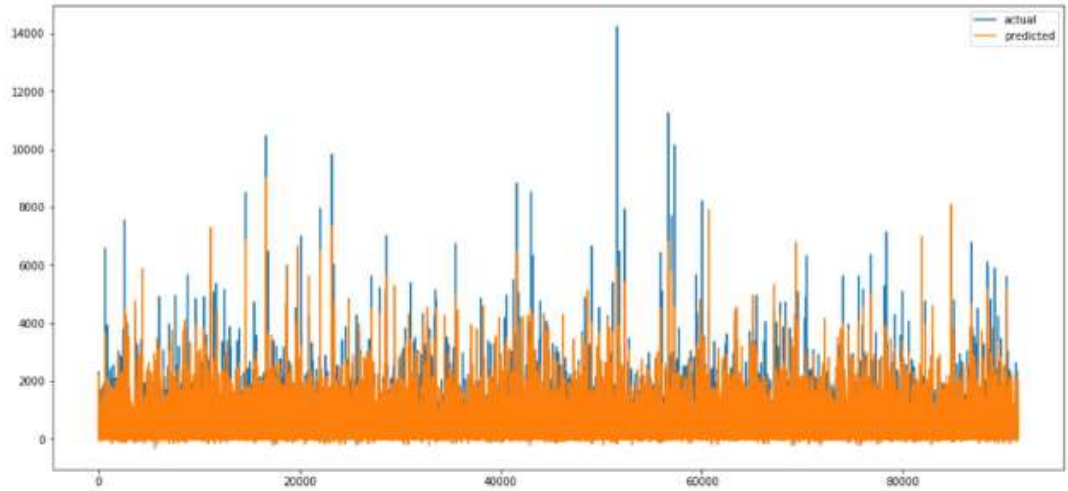
- **Decision Tree Regressor**: R^2 Score for Linear Regression was 0.70



- **Random Forest Regressor**: R^2 Score for Linear Regression was 0.85



- **XGBoost Regression**: R^2 Score for Linear Regression was 0.83



4. CONCLUSION

Random Forest outperformed other models due to its ensemble nature, which reduces bias and moderates variance, effectively handling overfitting. It also conducts implicit feature selection, performs well on medium-sized datasets, handles outliers adeptly, and is suitable for non-linear data. In contrast, Linear Regression assumes linearity and independence among features, while KNN struggles with outliers and is more suited for classification tasks. Decision Trees can lose information in time series data and are prone to overfitting, especially with many categorical variables. XGBoost, although comparable to Random Forest, is sensitive to outliers and performs better on smaller datasets. Overall, leveraging IoT and Big Data for inventory management fosters proactive decision-making, efficiency, and cost savings, crucial in navigating dynamic market demands and competition.

REFERENCES

[1] S. Yerpude and T. Singhal, “Augmentation of Effectiveness of Vendor Managed Inventory (VMI) Operations with IoT Data A Research Perspective”, International Journal of Applied Business and Economic Research, vol. 15, no. 16, pp. 489-502, 2017.

[2] D. Miorandi, S. Sicari, F. De Pellegrini and I. Chlamtac, “Internet of things: Vision, applications and research challenges”, Ad Hoc Networks, vol. 10, no. 7, pp. 1497-1516, 2012.

[3] S. Yerpude and T. Singhal, “Internet of Things and its impact on Business Analytics”, Indian Journal of Science and Technology, vol. 10, no. 5, pp. 1-6, 2017.

[4] H. Kopetz, Real-time systems. New York: Springer, 2011. 13 International Journal of Pure and Applied Mathematics Special Issue

[5] L. Xu, W. He and S. Li, “Internet of Things in Industries: A Survey”, IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2233-2243, 2014.

[6] E. Fleisch, “What is the internet of things? An economic perspective”, Economics, Management & Financial Markets, vol. 5, no. 2, 2010.

[7] Sumit Maheshwari, Prerna Gautam & Chandra K. Jaggi, "Role of Big Data Analytics in supply chain management: current trends and future perspectives", International Journal, 2021 - Taylor & Francis.

[8] Huiying Zhang1, "Research on Supply Chain Inventory Replenishment and Pricing Model Based on Time in Big Data Environment", Journal of Physics: Conference Series, Volume 1648, computer technology.

[9] Ketan Rathor; Anshul Mandawat; Kartik A Pandya; Bhanu Teja; Falak Khan; Zoheib Tufail, "Management of Shipment Content using Novel Practices of Supply Chain Management and Big Data Analytics", 2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), IEEE,16 January 2023.

[10] Robert N. Boute, Joren Gijsbrechts, Willem van Jaarsveld, Nathalie Vanvuchelen,"Deep reinforcement learning for inventory control: A roadmap", European Journal of Operational ResearchVolume 298, Issue 2, 16 April 2022.

[11] JP Bharadiya,"A comparative study of business intelligence and artificial intelligence with big data analytics", American Journal of Artificial Intelligence, 2023 - researchgate.net.

[12] Santosh Kumar Srivastava, Susmi Routray, Surajit Bag, Shivam Gupta, Justin Zuopeng Zhang, "Exploring the Potential of Large Language Models in Supply Chain Management: A Study Using Big Data", Journal of Global Information Management (JGIM),2024.

[13] Shreyas Bailkar; Kunal Shenoy; Amogh Bedekar; Sandip Bankar; Pranav, "Smart Inventory Optimization using Machine Learning Algorithms", 2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT) IEEE,22 March 2024.
[14] Sutasinee Kusolchoo; Pittawat Ueasangkomsate, "Digital Technologies for Food Loss and Waste in Food Supply Chain Management", 2024 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), IEEE, 02 April 2024.
[15] Hanis, M. H., & Fernando, Y. (2024), "SMART LOGISTICS SOLUTIONS FOR REDUCING FOOD WASTE: A CASE OF D NIPAH CATERING", International Journal of Industrial Management, Vol. 18 No. 1: March 2024.
[16] Njiru, K. K., Namusonge, G. S., & Thogori , M. (2024), "Warehousing Operations and Supply Chain Performance in Kenyan Food & Beverage Manufacturing Firms: The Moderating Role of Warehousing Policy Framework", International Journal of Social Science and Humanities Research (IJSSHR), Vol. 2 No. 1 (2024).
[17] Khan, N.; Solvang, W.D.; Yu, H, "Industrial Internet of Things (IIoT) and Other Industry 4.0 Technologies in Spare Parts Warehousing in the Oil and Gas Industry: A Systematic Literature Review", Logistics 2024, Volume 8, 30 January 2024.
[18] Ben-Daya, M., Hassini, E., Bahroun, Z., & Banimfreg, B. H. (2021). "The role of internet of things in food supply chain quality management", Quality Management Journal, Volume 28(1), 17–40.
[19] Shashank Kumar, Rakesh D. Raut, Pragati Priyadarshinee & Balkrishna E. Narkhede. (2023), "Exploring warehouse management practices for adoption of IoT-blockchain", Supply Chain Forum: An International Journal, Volume 24:1, pages 43-58.
[20] Dadhaneeya, Harsh, Prabhat K. Nema, and Vinkel Kumar Arora, "Internet of Things in food processing and its potential in Industry 4.0 era", Trends in Food Science & Technology, Volume 139, September 2023.
[21] Alfian, G., Syafrudin, M., Farooq, U., Ma'arif, M. R., Syaekhoni, M. A., Fitriyani, N. L., ... & Rhee, J. (2020), "Improving efficiency of RFID-based traceability system for perishable food by utilizing IoT sensors and machine learning model", Food Control, Volume 110, April 2020.
[22] Wen, Zongguo, Shuhan Hu, Djavan De Clercq, M. Bruce Beck, Hua Zhang, Huanan Zhang, Fan Fei, and Jianguo Liu, "Design, implementation, and evaluation of an Internet of Things (IoT) network system for restaurant food waste management", Waste management, Volume 73 (2018): 26-38.