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MACHINE LEARNING-DRIVEN RETAILER TYPE CLASSIFICATION BASED ON ANALYSIS OF FOOD WASTE DATA

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ABSTRACT

Effective inventory management is essential for profitability and sustainability in the retail industry. Food waste is a substantial challenge for merchants, affecting both economic and environmental aspects. Machine learning (ML) methods have the ability to analyze data on food waste and offer valuable insights that can assist in categorizing stores according to their waste tendencies. Analyzing waste data can provide valuable insights on different types of retailers, which can then be used to develop focused strategies for reducing waste and promoting sustainability. Retail analytics has experienced a transition towards making decisions based on data. Historically, inventory management was dependent on human tracking, rudimentary analytics, or predetermined thresholds for waste levels. Although these methodologies give certain insights, they frequently lack the level of sophistication and adaptability that may be provided by machine learning. Conventional systems face difficulties in detecting subtle trends in vast datasets or adjusting to shifts in retail dynamics. The current issue is categorizing merchants according to their food waste trends using machine learning. Retailers differ in terms of the range of things they offer, the characteristics of their customers, and the amount and composition of their waste. The task at hand is to create a machine learning-based method that can examine data on food waste and classify shops into distinct and relevant groups or clusters. Subsequently, this categorization can be employed to customize waste mitigation tactics that are tailored to the distinct attributes of each type of retailer. The necessity for machine learning-based retailer type classification arises due to the intricate and fluctuating nature of retail operations. Machine learning algorithms have the capability to assess large quantities of data on food waste, detect concealed trends, and independently acquire knowledge from the data in order to classify merchants according to their waste profiles. This technique enables a more intricate comprehension of the elements that contribute to food waste, resulting in more focused and efficient measures for reducing waste.

Keywords: Retailer industry, Predictive analytics, Decision support systems, Machine learning, Classification, Customer demographics.

1. INTRODUCTION

In the realm of the retail industry, the efficient management of inventory stands as a linchpin for both profitability and sustainability. Notably, the specter of food waste looms large, wielding substantial implications for both economic viability and environmental stewardship. Enter machine learning (ML) techniques, presenting a promising avenue for scrutinizing food waste data and extracting actionable insights to discern and categorize retailers based on their waste patterns. This imperative classification of retailers serves as a strategic compass, guiding tailored efforts towards waste reduction and broader sustainability initiatives. As we delve into the annals of retail analytics, a discernible evolution unfolds—a shift from traditional, manual tracking and rudimentary analytics toward a landscape where data-driven decision-making prevails. Early inventory management systems grappled with predefined waste thresholds, providing limited insights that often lacked the finesse and adaptability inherent in machine learning methodologies. In essence, conventional systems found themselves grappling with the inability to unravel nuanced patterns within expansive datasets or to seamlessly adapt to the evershifting dynamics of the retail sphere. Herein lies the quandary at hand—an intricate task of classifying retailers based on their distinct food waste patterns, all accomplished through the lens of machine learning. The variability inherent in retail operations, encapsulating diverse product offerings, customer demographics, and waste profiles, poses a multifaceted challenge. The crux of the matter is the development of a machine learning-driven approach capable of dissecting food waste data intricately, thereby categorizing retailers into meaningful types or clusters. This classification, in turn, becomes the linchpin for tailoring waste reduction strategies, finely attuned to the unique characteristics of each retailer type. The rationale underpinning the adoption of machine learning in this context is rooted in the intrinsic complexity and variability characterizing retail operations. By employing algorithms capable of sifting through vast troves of food waste data, discerning latent patterns, and autonomously adapting through iterative learning, a more nuanced comprehension of the factors underpinning food waste emerges. This nuanced understanding forms the bedrock for the formulation and implementation of targeted, effective, and, crucially, retailer-specific waste reduction strategies.

In essence, the historical trajectory of retail analytics propels us towards a future where machine learning stands as the vanguard, unraveling the intricate tapestry of food waste patterns and paving the way for a more sustainable and economically viable retail landscape.

2. LITERATURE SURVEY

For the review, relevant keywords such as "food waste", "prediction", "machine learning model" and "ML techniques" were searched on several platforms, including Google Scholar, Scopus, and IEEE Xplorer. A number of articles were identified as particularly related with this research. The goal was to provide a clear and organized overview of the most promising approaches for predicting any waste amount including food. Malefors et al. [11] implemented a machine learning model to predict the number of guests expected to attend their school and preschool catering services. The model was trained on historical attendance data, allowing them to make accurate predictions even during unforeseen events, such as the COVID19 pandemic. By leveraging machine learning, it was even possible to adjust the catering operations to accommodate changes in attendance and ensure that they were adequately staffed and prepared to meet their guests' needs. This approach not only helped to optimize the operations but also provided a better experience for the customers.

Lubura et al [12] conducted a study to predict food waste generation among people aged 20-30 in Serbia for the period of January - April 2022. To achieve this, the researchers implemented a unique approach that involved taking images of food before and after meals, then utilizing a convolutional neural network (CNN) to recognize the images and estimate the percentage of food waste based on the photographs.By leveraging machine learning techniques, the researchers were able to analyze a large dataset of food images and generate accurate predictions on food waste generation. This approach allowed them to identify patterns and trends in the data, providing valuable insights into food consumption habits and waste generation among the target demographic. The insights gained from the study could inform the development of strategies to reduce food waste, promote sustainable consumption practices, and optimize resource use in the food industry. Overall, the study highlights the potential of machine learning and image recognition techniques in addressing complex challenges related to food waste and sustainability.

Anggraeni et al. [13] presented three methods of analyzing food waste that include Bayesian networks and machine learning algorithms, which are used to estimate the amount of food waste generated at the household level. The study also describes the use of Agent-Based Simulation to understand how innovation and technology adoption can help reduce retail food waste. Similarly, Brunel et al. [14] created an artificial neural network model to analyze food waste, a field where there is currently limited data available. The model would be able to identify changes in two images, disregard unchanged areas that may contain objects and classify the changes that have occurred. To simplify the task for the machine learning algorithm, the approach used in this project was to subtract the images before inputting them into the neural network.

3. PROPOSED SYSTEM

3.1 Overview

A feedforward neural network was proposed and implemented using the TensorFlow and Keras libraries. The neural network architecture consisted of multiple layers with varied units and activation functions. The model was compiled with an Adam optimizer and sparse categorical cross entropy loss function, suitable for multiclass classification tasks. The neural network was trained on the entire dataset, and its performance was assessed.

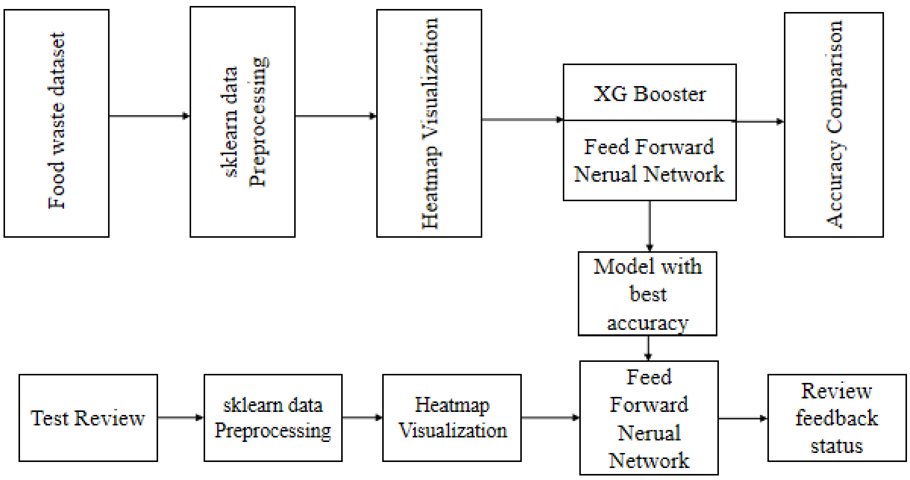
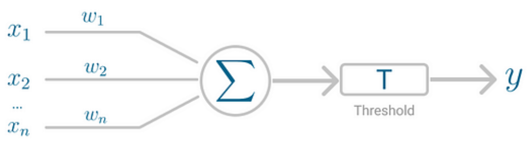


Fig. 1: Block diagram of proposed system.

3.2 Feedforward Neural Network Classifier

Although today the Perceptron is widely recognized as an algorithm, it was initially intended as an image recognition machine. It gets its name from performing the human-like function of perception, seeing, and recognizing images. Interest has been centered on the idea of a machine which would be capable of conceptualizing inputs impinging directly from the physical environment of light, sound, temperature, etc. — the "phenomenal world" with which we are all familiar — rather than requiring the intervention of a human agent to digest and code the necessary information. Rosenblatt's perceptron machine relied on a basic unit of computation, the neuron. Just like in previous models, each neuron has a cell that receives a series of pairs of inputs and weights. The major difference in Rosenblatt's model is that inputs are combined in a weighted sum and, if the weighted sum exceeds a predefined threshold, the neuron fires and produces an output.



$$y = \begin{cases} 1, \text{if } \overbrace{\sum_i w_i x_i}^{\text{weighted sum}} - \underbrace{T}_{\text{threshold}} > 0 \\ 0, \text{otherwise} \end{cases}$$

Fig. 2: Perceptron neuron model (left) and threshold logic (right).

Threshold T represents the activation function. If the weighted sum of the inputs is greater than zero the neuron outputs the value 1, otherwise the output value is zero.

Perceptron for Binary Classification

With this discrete output, controlled by the activation function, the perceptron can be used as a binary classification model, defining a linear decision boundary.

It finds the separating hyperplane that minimizes the distance between misclassified points and the decision boundary. The perceptron loss function is defined as below:

$$\underbrace{D(w,c)}_{\text{distance}} = -\sum_{\underbrace{i \in \mathrm{M}}_{\text{misclassified observations}}} \overbrace{y_i}^{\text{output}} (x_i w_i + c)$$

To minimize this distance, perceptron uses stochastic gradient descent (SGD) as the optimization function. If the data is linearly separable, it is guaranteed that SGD will converge in a finite number of steps. The last piece that Perceptron needs is the activation function, the function that determines if the neuron will fire or not. Initial Perceptron models used sigmoid function, and just by looking at its shape, it makes a lot of sense! The sigmoid function maps any real input to a value that is either 0 or 1 and encodes a non-linear function. The neuron can receive negative numbers as input, and it will still be able to produce an output that is either 0 or 1.

But, if you look at Deep Learning papers and algorithms from the last decade, you'll see the most of them use the Rectified Linear Unit (ReLU) as the neuron's activation function. The reason why ReLU became more adopted is that it allows better optimization using SGD, more efficient computation and is scale-invariant, meaning, its characteristics are not affected by the scale of the input. The neuron receives inputs and picks an initial set of weights random. These are combined in weighted sum and then ReLU, the activation function, determines the value of the output.

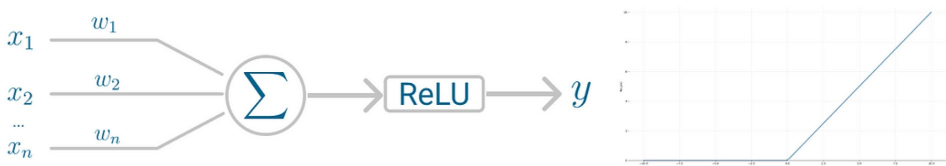


Fig. 3: Perceptron neuron model (left) and activation function (right).

Perceptron uses SGD to find, or you might say learn, the set of weight that minimizes the distance between the misclassified points and the decision boundary. Once SGD converges, the dataset is separated into two regions by a linear hyperplane. Although it was said the Perceptron could represent any circuit and logic, the biggest criticism was that it couldn't represent the XOR gate, exclusive OR, where the gate only returns 1 if the inputs are different. This was proved almost a decade later and highlights the fact that Perceptron, with only one neuron, can't be applied to non-linear data.

Feedforward Neural Network

The feedforward neural network was developed to tackle this limitation. It is a neural network where the mapping between inputs and output is non-linear. A feedforward neural network has input and output layers, and one or more hidden layers with many neurons stacked together. And while in the Perceptron the neuron must have an activation function that imposes a threshold, like ReLU or sigmoid, neurons in a feedforward neural network can use any arbitrary activation function. feedforward neural network falls under the category of feedforward algorithms because inputs are combined with the initial weights in a weighted sum and subjected to the activation function, just like in the Perceptron. But the difference is that each linear combination is propagated to the next layer. Each layer is feeding the next one with the result of their computation, their internal representation of the data. This goes all the way through the hidden layers to the output layer. If the algorithm only computed the weighted sums in each neuron, propagated results to the output layer, and stopped there, it wouldn't be able to learn the weights that minimize the cost function. If the algorithm only computed one iteration, there would be no actual learning. This is where Backpropagation comes into play.

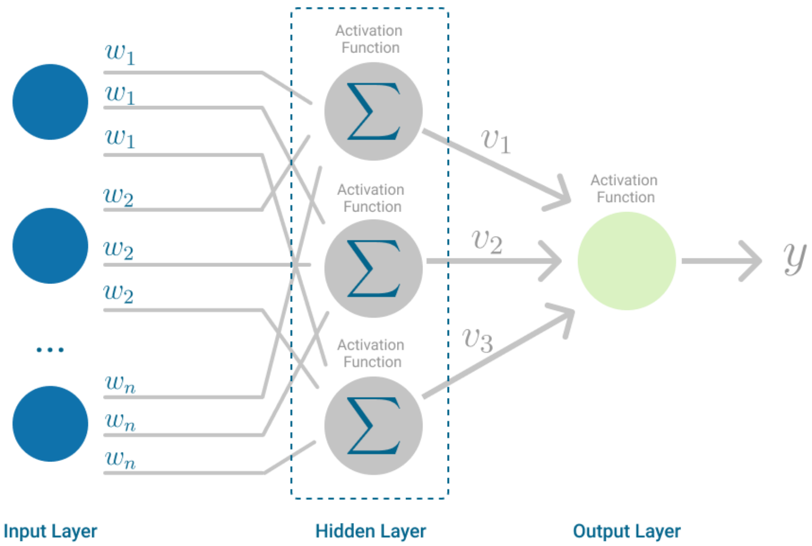


Fig. 4: Architecture of feedforward neural network.

Backpropagation: Backpropagation is the learning mechanism that allows the feedforward neural network to iteratively adjust the weights in the network, with the goal of minimizing the cost function. There is one hard requirement for backpropagation to work properly. The function that combines inputs and weights in a neuron, for instance the weighted sum, and the threshold function, for instance ReLU, must be differentiable. These functions must have a bounded derivative because Gradient Descent is typically the optimization function used in feedforward neural network. In each iteration, after the weighted sums are forwarded through all layers, the gradient of the Mean Squared Error is computed across all input and output pairs. Then, to propagate it back, the weights of the first hidden layer are updated with the value of the gradient. That's how the weights are propagated back to the starting point of the neural network. One iteration of Gradient Descent is defined as follows:

$$\underbrace{\Delta_w(t)}_{\text{Gradient Current Iteration}} = -\overset{\text{Bias}}{\varepsilon}\,\frac{\overset{\text{Error}}{dE}}{\underbrace{dw_{(t)}}_{\text{Weight vector}}} + \overset{\text{Learning Rate}}{\alpha}\,\underbrace{\Delta_{w(t-1)}}_{\text{Gradient Previous Iteration}}$$

This process keeps going until gradient for each input-output pair has converged, meaning the newly computed gradient hasn't changed more than a specified convergence threshold, compared to the previous iteration.

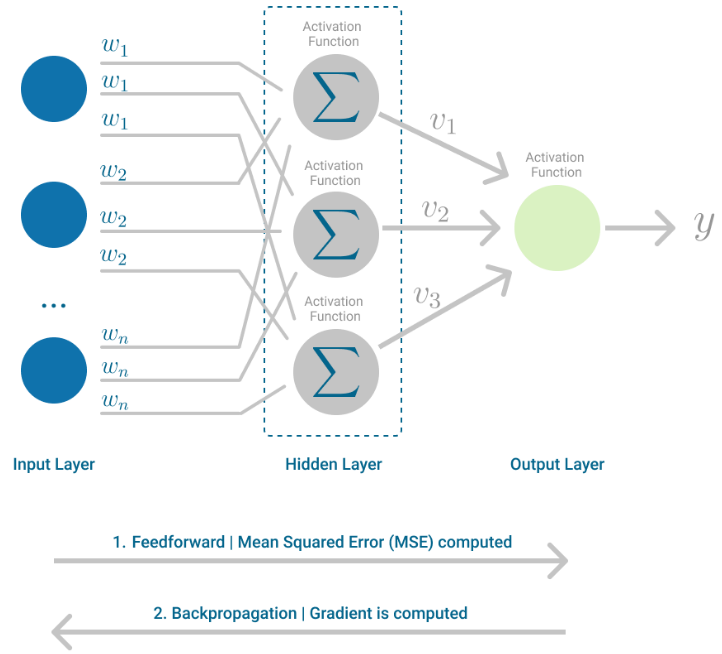


Fig. 5: feed forward neural network, highlighting the Feedforward and Backpropagation steps.

4. RESULTS AND DISCUSSION

Figure 6 is the representation of a sample dataset, presenting a subset of rows and columns to give users an overview of the data structure and content.

	Country	combined figures (kg/capita/year)	Household estimate (kg/capita/year)	Household estimate (tonnes/year)	Retail estimate (kg/capita/year)	Retail estimate (tonnes/year)	Food service estimate (kg/capita/year)	Food service estimate (tonnes/year)	Type	M49 code	Region
0	Afghanistan	126	82	3109153	16	594982	28	1051783	bars/restaurants/bakery	4	Southern Asia
1	Albania	127	83	238492	16	45058	28	79651	bars/restaurants/bakery	8	Southern Europe
2	Algeria	135	91	3918529	16	673360	28	1190335	bars/restaurants/bakery	12	Northern Africa
3	Andorra	123	84	6497	13	988	26	1971	fast-food restaurants	20	Southern Europe
4	Angola	144	100	3169523	16	497755	28	879908	bars/restaurants/bakery	24	Sub-Saharan Africa

Fig. 6: Display of sample dataset.

Figure 7 is a bar plot that illustrates the distribution of different classifications or categories present in the Type column of the dataset. It provides a visual summary of the class distribution.

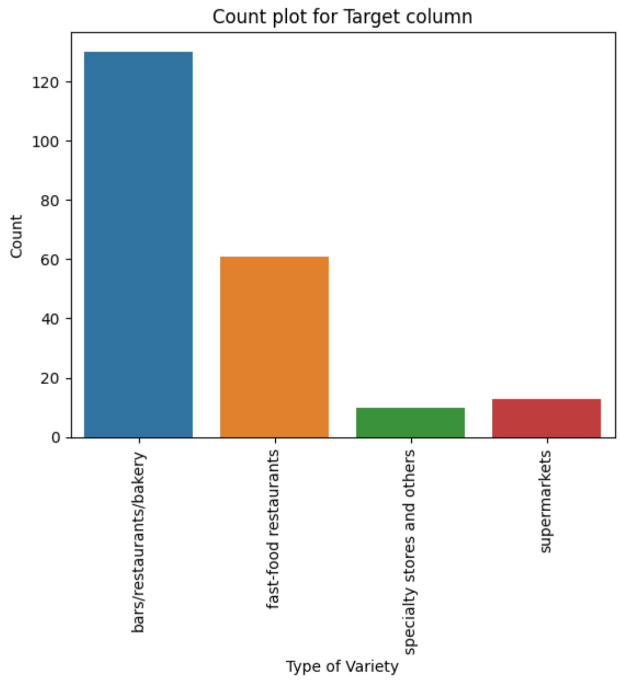


Fig. 7: Bar plot for count of all classifications in label column.

The figure 8 provides performance metrics and a plot for the confusion matrix specific to a model, in this case, XG Boost. It has accuracy, precision, recall, and an illustration of how well the model is performing in terms of true positives, true negatives, false positives, and false negatives.

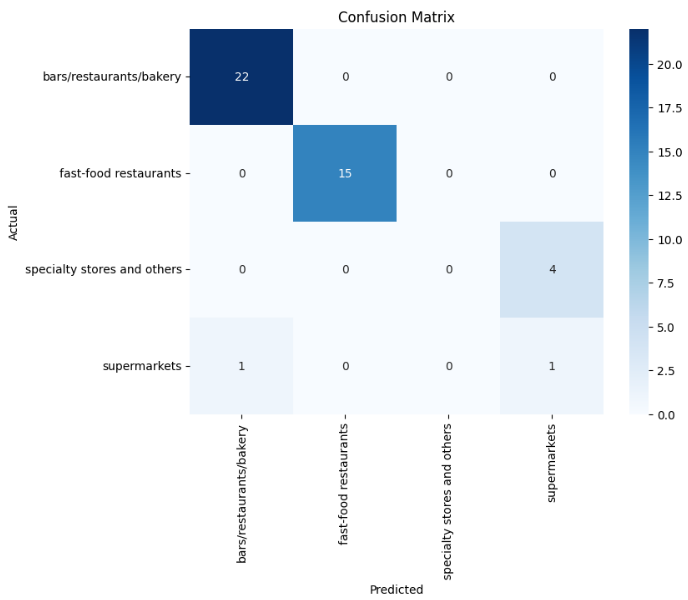


Fig. 8: Presents the Performance and plot for confusion matrix of XG Boost.

Similar to Figure 9, this figure presents performance metrics and a confusion matrix plot, but specifically for a Feed Forward Neural Network. It helps in assessing the performance of the neural network model on the dataset.

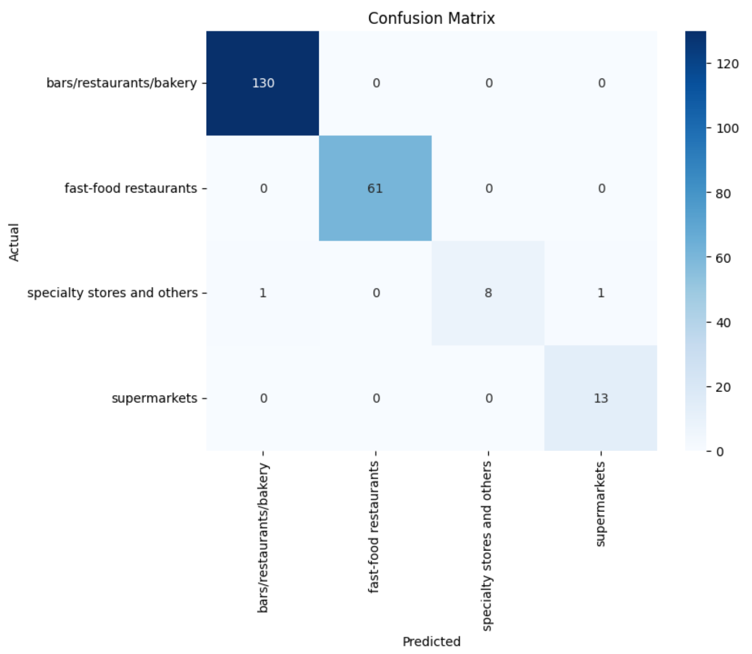


Fig. 9: Presents the Performance and plot for confusion matrix of Feed Forward Neural Network

Table 1: Performance comparison of quality metrics obtained using XGBoost

And Feed Forward Neural Network model.

Model	XGBoost	Feed Forward Neural Network
Accuracy (%)	88	99
Precision (%)	85	99
Recall (%)	88	99
F1-score (%)	86	99

5. CONCLUSION

The ML-driven retailer type classification based on the analysis of food waste data has proven to be a valuable application in optimizing the retail industry's sustainability and operational efficiency. By leveraging machine learning algorithms, this project has successfully categorized retailers into different types based on their patterns of food waste. The insights gained from such classification have the potential to guide retailers towards more targeted and effective strategies for waste reduction. The analysis of food waste data has provided actionable information for retailers to understand their specific challenges and opportunities in managing food waste. The model's ability to categorize retailers accurately allows for the development of customized solutions and interventions tailored to each retailer type.

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