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Minimization of Food Waste in Retail Sector using Time-Series Analysis and Object Detection Algorithm

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Abstract— **One-third of the total food produced gets wasted according to the Food And Agriculture Association of the United Nations. This wastage accounts for 1.3 billion tonnes and the scarcity of food is one of the major concerns globally. This paper presents comprehensive research on various factors that lead to the wastage of food in the retail sector. And a robust methodology is proposed which aims at reducing the waste to as minimal as possible in this sector. A method is proposed which integrates the inventory prediction and forecasting technique with smart dustbins which uses state of the art object detection technique to analyze the waste that gets thrown into bins in order to provide with insights to help optimize the use of raw materials that are used in preparing food and further redistribution and valorization of unpredictable waste. Thus producing minimal food waste.**

Index Terms— **Food Waste Management, Waste in Retail Sector, Time-Series Forecasting, Inventory Prediction, SARIMAX model, Object Detection, Deep Learning, Convolution Neural Network, YOLO v3**

I. INTRODUCTION

Approximately, 1.3 billion tonnes of food waste is generated every single day. In 2015, UN made an announcement for the companies to reduce the food wastage by 2030 to half of what it is now. if this issue is not resolved it can cause dire repercussions. According to the United Nations Development Program, "40% of food produced in India is wasted". Wastage of food can harm the environment severely. When dumped in a landfill, methane and other greenhouse gases are released by the waste. As food degrades, harmful gases which are trapped in the food are produced. All of these results in global warming and can cause climate change.

Food wastage is caused mainly by inefficient harvesting, storage facilities, infrastructure conditions. Also, cultural habits, meal planning, and shopping behavior have an effect on food wastage. Mainly the waste caused by consumers and the food industry leads to food waste. Our Economy gets affected severely due to wastage of food.

In this paper, we propose a method in order to reduce the food waste generated by the restaurants. Since it is observed that most of the waste generated results due to unorganized stock management practices and wasteful methods of residual food.

Further, in section II we discuss the literature survey conducted for this research and the existing methods that are used to tackle the problem.In section III we introduce the proposed methodology, which consists of three sub parts and detail explanation and understanding of these methods is provided. Section IV depicts the results from the methods discussed. And the section V concludes the research.

II. LITERATURE SURVEY

A. *Literature Review on Food Waste Analysis*

According to the study conducted by Centre for Consumer Studies [14], that there is a loss of approximately 23 million tons of cereals, with 21 million tons of vegetables and 12 million tons of fruits in India each year. Ministry of Food Processing conducted a research and found that agriculture food items worth 580 billion are wasted every year in the country. According to this research, researchers found that India lacks the infrastructure to handle food from production, handling and storage, processing, distribution to consumption[11]. This study is also aimed to get an insight of the food wasted at different consumption sources that is, the households, social gatherings (parties/marriages/festivals) and retail outlets (restaurant, hotels canteen).

Study found that the 70% population which resides in rural areas and dependent on agriculture based income are the least probable to waste food. On the contrary the food waste is very high in the urban counterpart with high requirement for foodstuffs and higher purchasing power.

They also undertook a research where they found about the food wastage in New Delhi. According to that, India's waste problem is aggravated by the festivals and celebrations that take place throughout the year. Events like marriages, banquets and receptions usually tend to waste 30% of the food prepared. Food wastage occurs at two main stages:
1) Excessive amount of food and dishes are ordered by the host which is left uneaten
2) People tend to take too much amount of food in their plates which eventually is wasted.

Data Analysis that we undertook

We performed a survey in Mumbai to get to the root of the food wastage problem in the city. We took a survey of 50 major and minor food chains around Mumbai incorporating

TABLE I
PREDICTION OF FOOD REQUIRED[14]

S. No.	Food Items	2010	2020
1	Rice	97.99	118.93
2	Wheat	72.07	92.37
3	Other Cereals	14.11	15.57
4	All Cereals	181.12	221.11
5	Pulses	14.58	19.53
6	Food Grains	195.69	240.64
7	Mil & Milk Product	106.43	165.84
8	Edible Oils	7.67	10.94
9	Meat and Fish	7.25	10.80
10	Sugar and Gur	17.23	25.07
11	Fruits and Vegetables	75.21	113.17

Source: Planning Commission, Food Security and Nutrition: Vision 2020

TABLE II
FOOD REQUIREMENT URBAN VS RURAL[14]

Decile class of MPCE (MMRP) %	Per capita expenditure (Rs.) on (Rural)			Per capita expenditure (Rs.) on (Urban)		
	Food	Non-Food	Total	Food	Non-Food	Total
0-10	294.03	158.95	452.98	370.11	229.16	599.27
10-20	375.90	208.50	584.40	490.83	340.13	830.96
20-30	428.37	246.98	675.35	583.25	428.59	1011.84
30-40	480.19	280.61	760.79	659.27	536.81	1196.08
40-50	527.07	321.00	848.07	741.06	656.93	1397.99
50-60	573.60	370.76	944.35	835.11	798.31	1633.42
60-70	636.03	426.89	1062.93	939.01	991.94	1930.96
70-80	704.38	516.21	1220.59	1059.33	1270.54	2329.87
80-90	827.34	642.98	1470.33	1285.18	1765.52	3050.69
90-100	1156.68	1360.01	2516.69	1845.08	4018.17	5863.25
All Class	600.36	453.29	1053.64	880.83	1103.63	1984.46

Source: NSSO 66th Round Survey, 2009-10

TABLE III
OCCASION WISE FOOD WASTAGE[14]

Occasion	Very High	High	Average	Less	Very Less
Marriages	98.0	1.5	0.2	0.2	0.0
Anniversary /birthday/ parties	1.2	22.5	36.7	6.8	32.8
Business Parties	0.0	8.5	19.3	60.7	11.5
Political Events	1.9	61.8	19.1	11.8	5.3
Conference/Seminars	0.8	5.9	15.2	18.4	59.8

Source: Field Survey, Centre for Consumer Studies, IIPA

a mixture of different cuisines, income ranges, and locations. We asked the managers, chefs and the staff some basic questions like their daily footfall, monthly footfall, the average time period for ordering inventory, the inventory used during a particular time period, the amount of food that is wasted, etc. We also managed to collect data of some of the popular restaurants around the city. By this study, we were able to recognize that high-end fine dining restaurants and buffets prepare 35% more food than they require to in case the crowd is more than usual, and they often throw it away to maintain their standards. Preparatory raw materials refer to the vegetables that are cut at the start of the business day in order to use it in different dishes. Since cut vegetables rot faster and cannot be used the next day it is necessary to optimize the preparation and thus cut out on waste produced by throwing out rotten vegetables.The leftovers were treated by either throwing it away and most of it was refrigerated by restaurants and some of it was also reused the next day by some restaurants. It was also found that local fast food joints have the least tendency to waste food with the majority of the food being reused. Big multinational food chains weren't able to answer the survey because of various constraints that were forced on them. Effectively fine dining restaurants and five-star hotels with 24/7 buffets were the main producers of wastage. Some of these places have also implemented complex algorithms to prevent the food from going waste, that is by maintaining the inventory and reducing the extra margin of the food.

B. *Literature Review on Stock Management and Demand Estimation*

Traditionally ARIMA[4] (AutoRegressive Moving Average) and ANN (Artificial Neural Networks) approaches have been used for prediction models. Efforts were taken continuously to design a a right algorithm and by the study found in various papers that it is not really feasible to use this approach. This algorithm cannot take into the short time span of the change due to seasonality and holidays in time series data and hence cannot be used to predict demand accurately.

To take seasonality into account SARIMA[1] (Seasonal Autoregressive Integrated Moving Average) model is used. It takes into account both the non-seasonal and seasonal factors with a multiplicative model methodology. But this model is not sufficient enough to accurately determine the inventory and food prediction in restaurants because it does not take into account the discrepancies caused due to any external factors. We have to take into account any holidays, price reductions, festivals and other news which might affect the food and inventory required in the kitchen.

C. *Literature Review on Smart Dustbins*

One of the methods to reduce waste is to use Smart dustbins which uses IoT to help manage waste.There have been many research in this field which provide complete management of waste from handling the waste to disposal

TABLE IV
WHEN FOOD WASTAGE IS MORE[14]

Reason for wastage	Very High	High	Average
Number of Dishes is more	74.6	17.8	7.6
Number of Guests is more	13.7	74.9	11.5
Both	10.5	1.7	87.8

Source: Field Survey, Centre for Consumer Studies, IIPA

TABLE V
FOOD WASTAGE URBAN AND RURAL[14]

Decile class of MPCE (MMRP) %	Per capita expenditure (Rs.) on (Rural)			Per capita expenditure (Rs.) on (Urban)		
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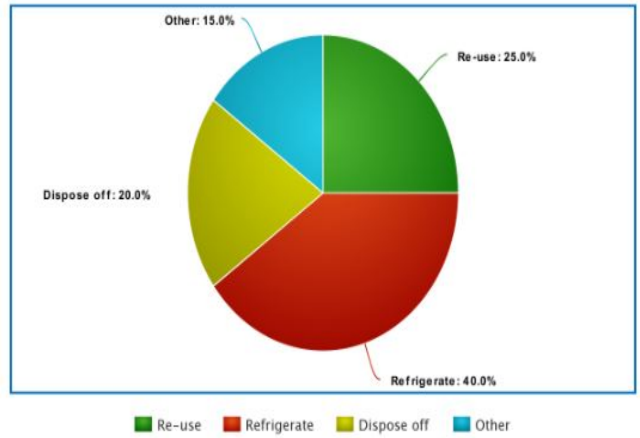
30-40	480.19	280.61	760.79	659.27	536.81	1196.08
40-50	527.07	321.00	848.07	741.06	656.93	1397.99
50-60	573.60	370.76	944.35	835.11	798.31	1633.42
60-70	636.03	426.89	1062.93	939.01	991.94	1930.96
70-80	704.38	516.21	1220.59	1059.33	1270.54	2329.87
80-90	827.34	642.98	1470.33	1285.18	1765.52	3050.69
90-100	1156.68	1360.01	2516.69	1845.08	4018.17	5863.25
All Class	600.36	453.29	1053.64	880.83	1103.63	1984.46

Source: NSSO 66th Round Survey, 2009-10

of waste in a sustainable way and also recycling of waste using embedded system[2].[13] proposes a method in which the garbage bin should be cleaned in specific time, and if it is not done then the details are sent to higher authority.Which in turn helps in decreasing the number turns cleaner has to make in order to collect garbage.The aim of these system was to collect waste at regular intervals of time [7]. It was interesting that there was a decline by 33% in waste generated by consumers just by charging them according the weight food waste generated by them.In this paper we propose a methodology to cater the problem of food waste specifically with retail by extending this smart dustbins by using computer vision which would analyze the waste that is being thrown into garbage in order to identify what are those food preparation that should be cut down by the restaurants.Image classification is used to classify the food thrown into bins by processing the top surfaces of waste thrown. Images are captured by placing the camera above the bin. For the task of image classification we use Deep convolution neural network. Deep convolution Neural Network are used

Fig. 1. Treatment of Leftovers



to perform intricate tasks with text,sound,images,videos etc. they use supervised machine learning algorithms and the neural network contain tens of thousands of convolution layers which are trained on labeled data to perform the required task.

D. *Literature Review on Food Redistribution*

Other ways to deal with waste include redistributions of Foods. Nowadays there are many startups in the food industry with this innovative approach where they sell the leftovers from restaurants[15][12]. These left outs include products that are about to expire and also some startups sell food dishes that are prepared beforehand by restaurants at the start of the day but remain unsold due to low demands but one can buy such dishes through such platforms. Another such method to prevent food waste is valorization.Valorizations[16][9][5] aim at increasing feed stocks supply and thereby produce energy. So in valorization the food waste is used as feed stock which acts as fuel for anaerobic digestion or co-digestion in order to produce renewable sources of energy such as biogas or to produce biofuels, bioplastics through using it in biorefineries.

III. PROPOSED METHODOLOGY

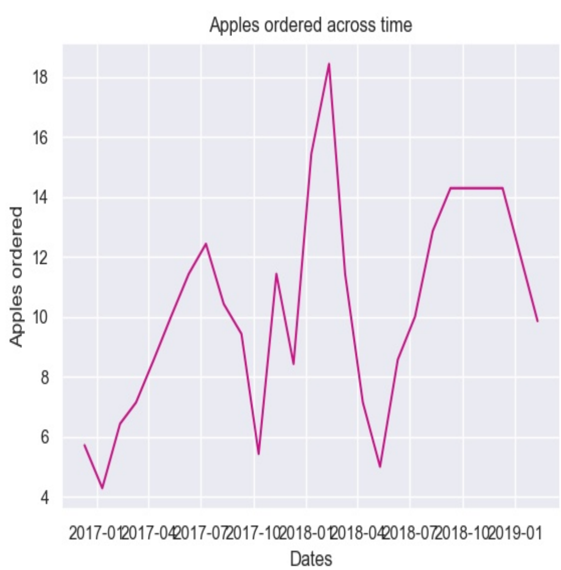
It is evident that most of the waste generated in the retail sector is due to poor stock management, no optimization on the quantity of raw materials to be used for preparation and poor handling of waste. Our methodology attacks these three main causes of waste by using stock analysis for management of stocks, deep learning in order to analyze waste generated and to get insights in order to optimize the use of raw materials and even after employing such techniques it cannot be guaranteed that no waste would be generated so to handle waste left even after employing such techniques can be handled by redistribution of food that is healthy to consume and valorization of food that cannot be redistributed.

A. *INVENTORY PREDICTION*

As stated above ARIMA and SARIMA, have their own faults and hence cannot be used to predict and forecast the inventory accurately. In this paper SARIMAX [1] model is based on SARIMA model with Multiple Linear Regressions. It also takes into account holiday effect which can further increase the accuracy of prediction. The Holiday Effect takes into account major holidays as well as any dates where the restaurants are closed for various reasons. Apart from this, the decrease or increase of prices of commodities is also taken while evaluating the inventory for next month. Theses play a major role in deciding the quantities of food that will be required and be ordered. The restaurants can also add discounts and promotional offers on certain items and hence another variable should be taken into account while predicting the inventory.

*1) **Data**:* For this research the data set is collected from a restaurant located in Mumbai. The data depicts the inventory bought by the restaurant over the period of two years that is from the year-2017 to year-2019. The data from the year 2017-2018 was take for the training of the model and the the from july of 2018 to 2019 was considered as test data. This data set was for the inventory of only the apples that were ordered by the restaurant in kilograms, Since the apples are available throughout the year. Figure 2 represents the variation in apples ordered in kg (Y-Axis) over the time duration of 2 years (X-Axis)

Fig. 2. APPLES ORDERED



*2) **Factors affecting Inventory Forecasting**:*

1) **Seasonality**: A proper understanding of seasonal pattern is very useful for inventory forecasting in the retail sector. Season some the food items are available during only specific season during the year this affects forecasting because of the unavailability of the data during non-seasonal period. Hence, all time season fruit apple is taken into consideration for the research.
2) **Effects Of Price Reduction**: Retail sectors performs common practices of providing seasonal discounts and promotional price reduction. This leads to higher demand and thus can affect the forecasting.
3) **Holidays**: Retail sector experiences high traffic during the holiday season. So taking holiday season into consideration for forecasting is important since the demands increase during this period of time.

3) Method: For cross-validating, the time-series data has been classified into training and testing data. The the data from the duration of 3rd Jan 2017 to 31st July was taken as the training data and the data from 1st July 2018 to 15th Jan 2019 was taken as test data. The training data is used to find the auto-regressive, moving-average stock of apples for the SARIMAX model. The stationarity of the model is checked by ADF test [8]. From this, it was found that the data is stationary. Method of maximum likelihood, gives us the parameters of model which are required. The adjusted coefficient of determination is calculated for the model. The forecasting performance is improved by adding external variables like holidays and promotions.

B. SMART DUSTBINS

*1) **Data**:* It is extremely time consuming to build training data set for image detection and segmentation,For building training data set for image segmentation one has to mark every pixel in the image with the class label and for image detection one has to manually annotate thousands of images by manually defining bounding boxes around every object in the image.For this research dataset was taken from Open Image Dataset v4[10].For our application the class labels were the different vegetables that are to be captured when the waste is thrown into bins. These dustbins are placed above the food weight sensors so that every time the waste is thrown into the bin the waste sensor can calculate the difference in weight and thus determine the weight associated with every dump made into the bin. Also when the waste is about to be thrown into bins the camera sensors detect the movement and thus capture the image of the waste in the tray before it is thrown into the bins.The working of sensors is out of scope for this research. Each image captured is associated with a class label of food in the image, timestamp.Each image was manually annotated for labels and there were around 15 food class labels. Some of the labels were carrot, broccoli, banana, cucumber.The dataset consisted of 95,000 images.

*2) **Method**:* Our model consisted of two steps primarily, Data augmentation, and object detection model using convolution neural networks. Data augmentation was used to expand the dataset by adding lightning condition, rotating and translating images in order to generate multiple images from a single image. For object detection l we use v3 library which free and open sourced.

*3) **Data Augmentation**:* One of the challenges that goes into implementation is that when the image of the upper surface of the waste is captured the lightning condition may differ according to time, environment and other such factors. In order to tackle this problem each image in the data set is simulated to be in different lightning condition by adding Gaussian noise in the image. Images were translated so that the model can recognize objects present in any part of the image.For this is shifted in different directions by adding background noise. Also since images contain veggies rotating images would help the model train better to recognize objects in every orientation.

Fig. 3. DUSTBIN PROTOTYPE

*4) **Convolution Neural Network for Food Waste Reduction**:* The Garbage bins are placed upon weight sensors and cameras are placed above the bins so whenever waste is thrown into bins the camera sensors would detect the movement and capture the image of the waste and the weight sensors would detect the change in weight and this would give the weight of the waste being thrown into the bins.The working of sensors is out of the scope of this research. Figure 3 represents the prototype of the dustbin proposed for this research. The YOLO v3 library divides each image into 255×255 grid of cells.The cell at the center of each object present in the image is said to be responsible for predicting it.Each grid cell predicts B number of bounding boxes as well as C class probabilities. Each bounding box predicted has 5 components (x,y,w,h, confidence). The center of the box is represented by (x,y) co-ordinates, relative to grid cell location and if the center of the bounded box does not lie inside that grid cell than that cell is not responsible for that bounding box.The confidence score shows how confident the model is that the object lies in that bounding box.width(w) and height(h) are predicted relative to the whole image.The network consists of convolution layer and max pooling layers which are followed by fully connected 2 layers.These Convolution and max pooling layers comprise of first 24 layers.The loss of function of YOLO v3 consist of 2 parts.The loss associated with the predicted bounding box position represent by (x,y) is computed using below equation.It gives a value of 1 if the object lies in grid cell i and jth box predicted and it gives 0 if the object is not present in the bounding box.

$$\lambda_{coord}\sum_{i=0}^{S^2}\sum_{j=0}^{B}\mathbb{1}_{ij}^{obj}[(x_i-\hat{x}_i)^2+(y_i-\hat{y}_i)^2] \tag{1}$$

The loss associated with width and height of the predicted box is calculated using the below equation

$$\lambda_{coord}\sum_{i=0}^{S^2}\sum_{j=0}^{B}\mathbb{1}_{ij}^{obj}[(\sqrt{w_i}-\sqrt{\hat{w}_i})^2+(\sqrt{h_i}-\sqrt{\hat{h}_i})^2] \tag{2}$$

Now the loss associated with the confidence value of each bounding box predicted in the image Is computed using below equation.C is the confidence score and Ĉ is the intersection over union of the predicted bounding box with the ground truth

$$\sum_{i=0}^{S^2}\sum_{j=0}^{B}\mathbb{1}_{ij}^{obj}(C_i-\hat{C}_i)^2 \tag{3}$$

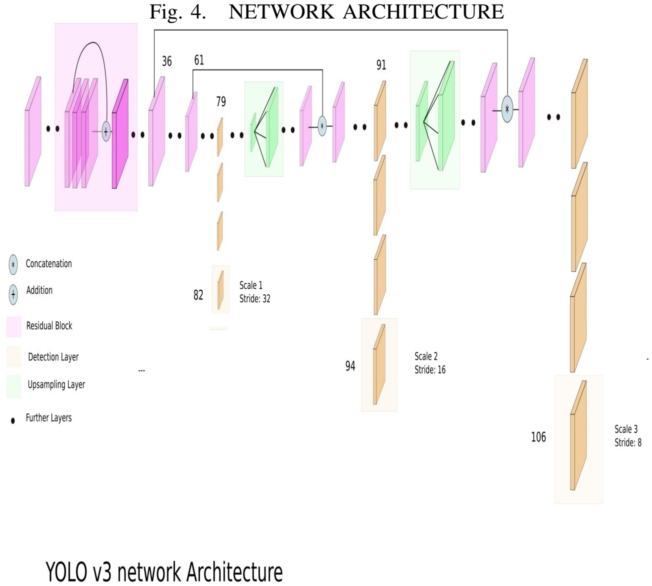
The classification loss associated with each object predicted in the image is computed using the below

$$\sum_{i=0}^{S^2}\mathbb{1}_{i}^{obj}\sum_{c\in classes}(p_i(c)-\hat{p}_i(c))^2 \tag{4}$$

The total loss is given by summing up equation [1,2,3 & 4]

*5) **Network Architecture**:* YOLO v3 comprises a pre-trained network trained on Imagenet and this pre-trained network comprises of 53 layers. Figure 4 represents the network architecture of YOLO v3. 53 more layers are stacked upon for object detection, this gives us a total of 106 layer architecture. The detection in YOLO v3 is done at three different places in the network by applying 1×1 detection kernels on three different sizes of feature maps. The shape of the kernel is given by $1 \times 1 \times (B \times (5 + C))$.The dimensions of the input image are down sampled by 32,16 and 18 respectively and thus makes prediction at three scales. The first 81 layers of the network down sample the image and the first detection is made at 82nd layer.For our data set we have an image of 224×224 so the resultant feature map would be of size 7×7.Each detection is made using 1×1 kernel,thus giving us a feature map of $7 \times 7 \times 255$. The feature maps from layer 79 and layer 61 are depth concatenated after subjection them through few convolutions.This is again subjected 1×1 convolution layers in order to fuse together the feature maps from layer 61.Then the detection feature map of $14 \times 14 \times 255$ is made by the 94th layer.Following the same procedure feature map from 91 layer is depth concatenated with feature map of layer 36 after subjection it to few convolution layer.Then finally at 106th layer, a feature map of size $28 \times 28 \times 255$ is obtained

Fig. 4. NETWORK ARCHITECTURE



C. REDISTRIBUTION

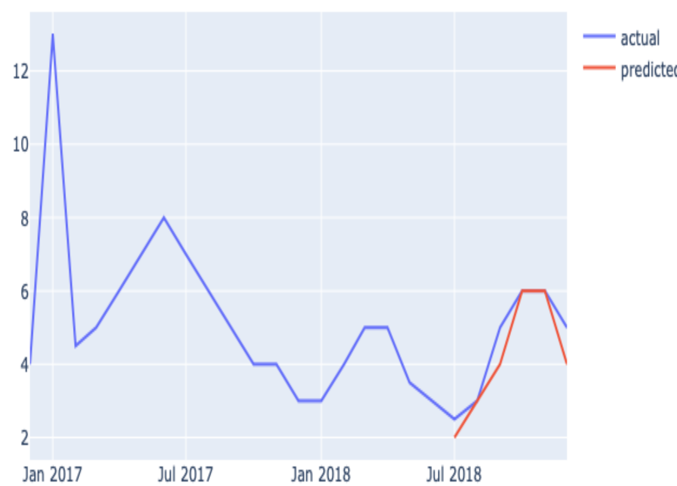
Food is wasted in two main ways in the restaurants that is, the excess food and the food left by the customers. To solve the problem of food wastage we propose to implement a website. In this website the staff just has to fill in the details about the food, quantity, its quality[6] and expected date of expiry as stated in the following paper[3]. This food can be packaged and redistributed to the poor and needy. They can also fill in about the wasted food matter like left food on plates, the peels of fruits and vegetables, the bones etc. This garbage can be used in many different methods like valorization and composting. The organisations that need these resources and can track and get whichever food they need. The problem with five star hotels and fine dining restaurants is solved by the help of the portal. They throw away perfectly good and eatable food according to its look and texture just to maintain standards. By this way, any food outlet can get that vegetables and fruits which might go waste. Most of the modern kitchens are trying to implement some way to reduce the food wastage. But an integrated ecosystem with the help of a website will enable this waste food to be utilised efficiently.

IV. RESULTS

A. *Inventory Forecast*

As stated above, we applied SARIMAX model to forecast the inventory needed by the restaurants in a particular time. This model with the reduction in price, the holiday effect and the month effect can be effectively used to explain 73% of variation. The decrease in the value MRSE and MAPE of the model over SARIMA implies that the addition of extra variables improves its accuracy. Theils U_1 factor for the model is 0.01 which is very negligible and hence proves that the model is effective. The analysis is on the assumption that the benchmark model is not does not change the performance of our model. As mentioned above, the data from the duration of 3$^{\text{rd}}$ Jan 2017 to 31$^{\text{st}}$ July was taken as the training data and the data from 1$^{\text{st}}$ July 2018 to 15$^{\text{th}}$ Jan 2019 was taken as test data. The graph 5 is of quantities of apples in the inventory against the time of order. The blue line indicates the actual data of the inventory and the red line indicates the predicted values by the model. As seen in fig. 5 the model is very efficient and has an accuracy of 93% against the test data.

Fig. 5. PREDICTION OF APPLES REQUIRED



B. *Object Detection for Food Waste Reduction*

In the preprocessing phase, we used data augmentation to improve upon the quality of dataset.In order to for object detection in the food waste, we used YOLO v3 model. The model considered about 10,000 images. Each image was labelled only with a food class. These labels described the food waste from the considered classes that were present in the waste being thrown into the bins.Although multiple food items were present in the images taken for dataset only 50 classes were considered for detection.An accuracy of 89.28% was achieved by the trained network for detecting the food items present in the images.

V. CONCLUSION

In this paper, we demonstrated that a large quantity of food waste is produced by food chains. After analysing the current practices, this paper focuses on three main points.

First is using time series analysis on the inventory which helps in the better management of stocks that is not expected by humans. This is beneficial as it improves the net income of the restaurants taking every parameter into account.

Second is the use of the smart dustbins which plays a very important role in our implementation. These bins use cameras and food weight sensors that give a better real time analysis on which food item is being thrown into the bin by using object detection. These methods help the food chains to reduce food waste to a large scale.

Since, 100% reduction is not possible, a website has been proposed by the paper which keeps all the necessary information of the leftover food and this way, needy and poor can be fed. Not only this, but these leftovers can also be used for valorization and composting. Therefore, this research marked the implementation of a system which makes sure that in literal terms, no food is being wasted.

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