

Application of Machine Learning Techniques for the Prediction of Tomato Price

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Abstract: Agriculture is the main occupation in India. Farmers face many problems including identifying the tomato quality, fixing their price etc. For this purpose, the farmers have to manually monitor the harvest and take advice from experts for detecting the quality of tomato and fixing the price. This manual process does not give agreeable results always and requires continuous monitoring by the experts. Recently Machine learning has been used with image processing techniques for data analysis that has a huge potential. These techniques can be widely adopted in the field of agriculture to detect the quality of the tomato using various algorithms. The goal of this work is to construct an application, which makes the farmers easily know the quality of tomato fruit and present cost in the city. The proposed system uses algorithms such as Linear Regression and Convolution Neural Network with their effective application for tomato price prediction which uses AWS cloud for storage. At the end, the performance of both the algorithms is also compared.

Index Terms: Machine learning, Classification, Price, Color, Linear Regression, Convolution Neural Network, AWS cloud storage.

I. INTRODUCTION

China ranks first in production of fruits and vegetables. After China, India is listed as second top country in producing fruits [1]. Most of the people in India depends only on agriculture for their living [2]. In India both pre-harvesting and post-harvesting processes are done manually. Manual processing is a prolonged method, less efficient and also expensive. Thus, to obtain the optimum result, automatic technique is needed in agricultural domain. Some of the post-harvesting processes involves grading and sorting of crops, and vegetables etc. Various factors are analyzed for grading and sorting of the fruits. Mentioned quality factors involve both internal and external factors. Deciding the quality of the fruit is nothing but deciding its internal factors. Internal factors are decided based on the external factors like color, size, texture, shape etc. of the fruit.

Solanum lycopersicum scientific name of tomato is one of the largest growing fruits in the world. It is produced about 170 million tons all over the world [3]. India is the second largest

tomato producing country in the world. There is a debate going on whether to consider tomato as fruit or vegetable. Since it shows some of the features of fruit, tomato is considered as a fruit. As the image processing technology and computer software and hardware fields progresses, it becomes convenient to detect the quality of the fruits by using detecting technologies. Most of the current quality detecting and grading systems lack speed, efficiency in terms of cost and complexity. Therefore, it is important to introduce a quality predicting system that has improved cost and speed is effective. Fruits and vegetables are graded based on their appearance that plays an important role in deciding the price and existing work [4] gives a proof. People decide the quality, ripeness, defects, damage etc. of the fruit based on its color. As a result, color is a very important factor to be considered. The ability of identifying the quality of the crops may be hampered because of the adaptive behavior of the human eye to discernable color changes and effect of background on sensed color and its intensities. Various attempts have been carried out to adopt multiple quality features in order to construct new methods and systems that indulge the required prospects. Utilizing non-destructive techniques in food industry seem to be more promising. This can also fulfil the customers' requirements, adoption, reliance etc. which in turn enhances market competitiveness and profitability.

II. PREVIOUS WORK

Machine learning techniques are getting a bigger scope day by day because of its vast applications. Lot of works is also being conducted on agricultural domain, fruits, quality detection by using machine learning techniques, image processing and classification of images based on ripeness quality etc. The techniques were also studied for their performance and efficiency. Different methodologies were used to extract the features from the images. The literature reviews also cover the proofs and solutions for the problem's statements stated before. Various measures were taken out in each paper and are discussed here.

Manali R. Satpute et.al [1] considered manual ways of sorting and detecting the fruit quality were inefficient. So they aimed to propose an automatic system which does both on its own. The system gathers fruit images, applies appropriate image processing techniques and then extracts desired features. Defected fruits were classified using blob detection. Finally, the sorting was performed based on the fruit colors. Hongshe Dang et.al [4] aimed to present a fruit size detecting and grading system. The pictures of fruits were taken at different angles using CMOS camera.

Revised Manuscript Received on 30 May 2019.

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The necessary features were extracted based on the captured pictures using appropriate algorithms. The grade of the fruit was decided based on the outcomes of the algorithm. The experiment showed that the grading system had high accuracy, high speed with great efficiency.

Ashwini Awate et.al emphasized that since there is a great demand for the agriculture, it is very important to have proper growth and yield of the fruit. It was found that manual way of monitoring and managing the yield was not efficient. The main agenda of their work was to build a system which automatically diagnoses, detects and classifies external disease in the fruit with very less human efforts. A system was proposed which can be used to detect the diseases present in grapes, apple and pomegranate using image processing techniques [5].

Devrim Unay and Bernard Gosselin [6] introduced a system that automatically sorts the fruit apple based on quality. Artificial neural networks were used to detect the affected area in the fruit. It was observed that under-segmentation was present because of the variation in the color of the fruit. Performance of linear discriminant, nearest neighbor, fuzzy nearest neighbor, adaboost and SVM classifiers were compared. It was seen that accuracy level was high for adaboost and support vector machine.

Rushika Ghadge et.al [7] proposed a system which detects the quality of soil, so that farmers would become aware about the crops they can grow in that soil. The authors suggested the comparison of performance of BPN (Back Propagation Neural Network) and Kohonen's SOM (Self Organizing Map) algorithms. The algorithm with the highest accuracy would be given to the user.

Prof. D.S. Zingade et.al [8] discussed about a system which gathers information about soil, weather and previous years data related to crop cultivation. With the help of machine learning algorithm like multiple linear regression, it would suggest all the cultivable crops in that area using the collected data.

Dong Zhang et.al [9] suggested a color grading method that automatically examines the maturity level of the harvested dates and decides its quality using machine learning algorithms and artificial neural networks. Their system used 2D histograms of color to identify the concurrent frequency. Mapping matrix was adapted to map the input color of the crop to its desired color indexes. After observing the color of the dates, which defines maturity and quality, it was classified into different grades.

Grazia Lo Sciuto et.al [10] proposed a system which classifies the defected oranges from the good ones. This system uses RBPN (Radial Basis Probabilistic Neural Network) based classifier to classify the oranges. They observed that taking the pictures of oranges at different angles and feeding them as the input to the algorithm gives an improved result. It was also noticed that accuracy level reached around 88% when the algorithm was fed with multiple images.

The main objective of Shah Rizam M. S. B. et.al [11] was to introduce an automatic system to figure out and measure the ripeness and quality of watermelon. External images of watermelon were taken using high resolution camera. These images were filtered using image processing techniques to enhance the resolution of the image. Any noise present in the

images was removed. Then the filtered images were given as input to train ANN, which predicts the quality of watermelon.

Authors of [12], in their survey observed that the tomato price in Turkey was stationery for the last few years. They also studied SARIMA model, which predicted that there will not be any remarkable changes in the price of tomato for next 3 years. Hence, they concluded that the stationery structure of tomato price might negatively influence the tomato producers.

D. Patel, I. Hannah and E.R. Davies [13] aimed to obtain products free from any foreign objects like glass, stone, metal etc. In their paper, they presented a method which detects any impurities present in frozen products. The inspection process was carried out before the product/bag was sealed and packed. X-ray imaging was used to have a vision inside the bag. Machine learning algorithms like Multilayer Perceptron, Back Propagation were used to classify the foreign objects.

III. METHODOLOGY

As shown in the Fig. 1 end user enters the necessary features and uploads an input image through a web application. The sent image and the other features entered are collected and stored in a database of the AWS cloud to access the data from anywhere. An account is created on AWS and used to store various images to improve the efficiency. The stored data is then given to data preparation step, where the image features are extracted and all stored images are given different labels. The output of this phase is then given to one of the machine learning algorithms. Then machine learning algorithms classify the tomato and predicts its price. These results are brought back to the web server which displays the output to the user.

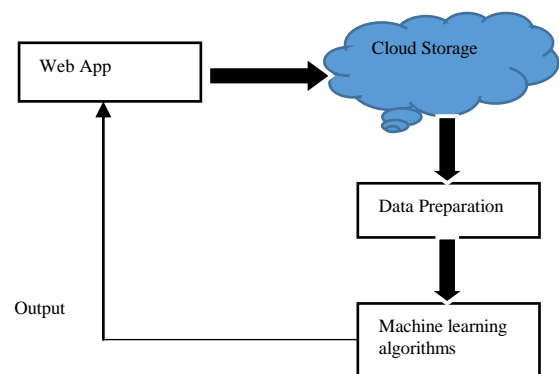


Fig. 1 Proposed Methodology

Fig. 2 shows comprehensive information about the architecture used for this project. The user has to enter the details of the tomatoes and upload its image at the front end. The front end is made with the help of PHP language. The python script is called by the MySQL database at the back end when it gets connected and processed by the web page at the front end. Then system categorizes the fruit as "Green" and "Red" by considering the dominant color in the image. Then the result of this is given to one of the machine learning algorithms, which then predicts the corresponding price and is displayed at the front end.



Eventually, the performance of Linear Regression and Convolution Neural Networks have been compared. The program is modeled for the proposed system and the detailed structure of the same is shown in the Fig. 2. The procedure includes collecting the dataset which has 300 entries and 11 different attributes like class, area, ph, season, type of soil etc. and variety of tomato images, which affect the qualities and cost of tomato. Preprocessing includes cleaning the dataset i.e. removing NaN values, truncating white spaces and apply the machine learning techniques to categorize the fruit as green or red. The result of this grouped images becomes the data for the subsequent design pace. In order to predict the cost of the tomato, Regression algorithm and Convolution Neural Network (CNN) algorithm are applied over CSV data files and captured images in the next step of the design phase. After performing the estimation process the models are checked for their accuracy.

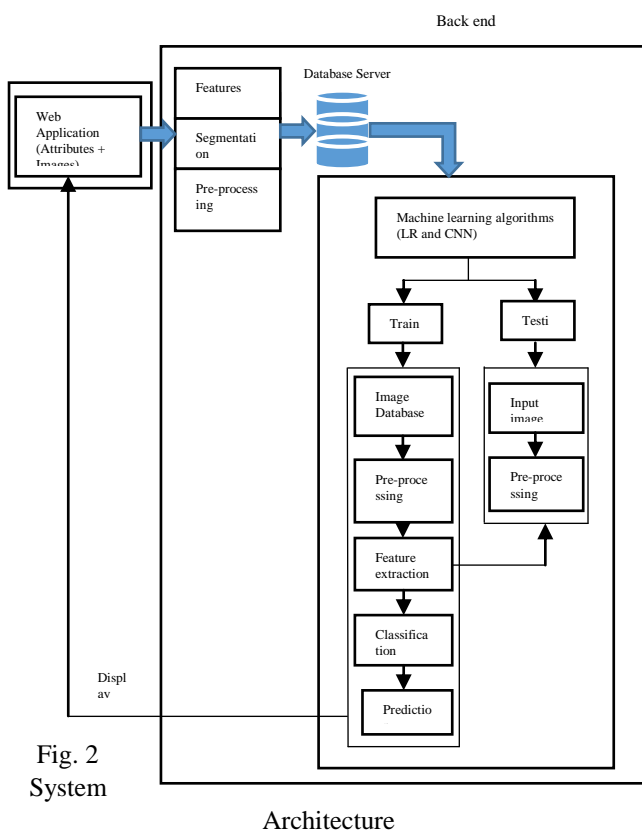


Fig. 2 System Architecture

A. Algorithms

1) Linear Regression

Linear Regression (LR) is an algorithm which uses supervised learning. It performs a regression task. In this algorithm, the independent variables play a very important role in predicting the target output. LR is widely used to find the relationship between the dependent and independent attributes. If a variable is dependent on multiple independent variables then it is called Multi-Linear Regression.

It performs the task to predict a dependent variable value (z2) based on a given independent variable (z1). So, in this way this algorithm discovers a linear connection between z1 (input) and z2 (output).

Steps:

- All continuous data are converted into categorical data since LR understands categorical data only.

- Multiple independent variables like season, area storage etc. are used to predict the dependent variable i.e. price.
- Splitting the dataset into training and testing set.

Hypothesis function for Linear Regression is:

$$z2 = \Theta1 + \Theta2.z1$$

During the system training the following details are provided
z2: input training data (univariate – single input attribute)
z1: label given to data

While training the system – it chooses the best line to estimate the degree of z2 for a known degree of z1. The system obtains the optimum regression fit line by encountering the suitable $\Theta1$ and $\Theta2$ values.

$\Theta1$: co-ordinate of the point where a curve intersects an axis

$\Theta2$: coefficient of z1

2) Convolution Neural Network

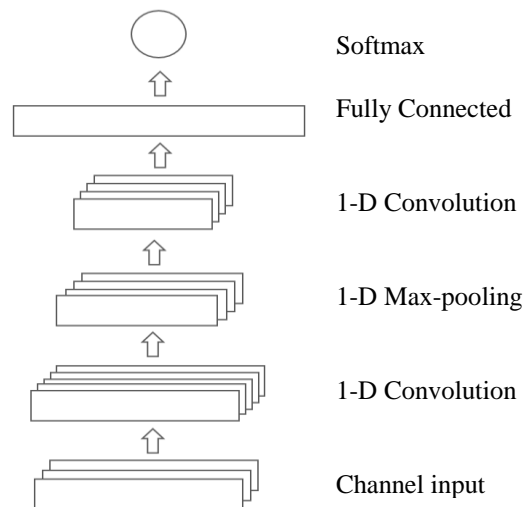


Fig. 3 Different layers of Convolution Neural Network

The above figure gives the CNN model architecture that is implemented using Tensorflow. The model is a combination of convolution layer and max pooling layer. Max pooling layer is placed above the convolution layer, on top of which is placed another convolution layer. The fully connected layer is present on top of the final convolution layer. Finally, the Softmax layer is implemented over fully connected layer. The convolution and pooling layers are 2D.

• Convolution

Convolutional layer is the crucial component of CNN. Convolution is an arithmetic operation which combines 2 sets of information. Convolution filter of size 3X3 is applied on the input image or data which then produces a feature map [8]. In the first and second layers of convolution 32 convolution filters are used. In the third layer 64 convolution kernels are used.

Left side of the Figure 4 shows the input to the first surface, i.e. the input figure. The right side of the image gives the convolution kernel, also known as the filter.

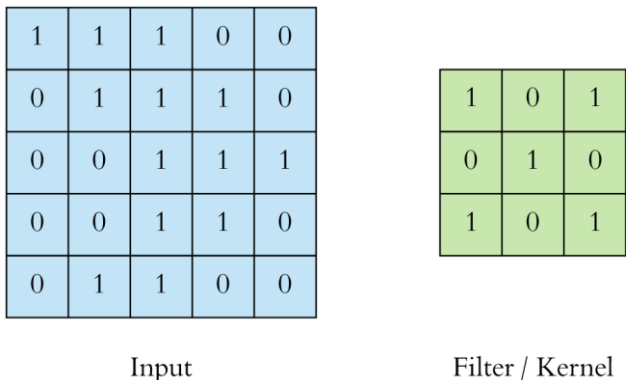


Fig. 4 Convolution layer's input and the filter

Convolution function is then executed by moving the convolution kernel on the given image. At every position, bit by bit matrix multiplication is performed and the result is added. This added output becomes the first value in the feature map.

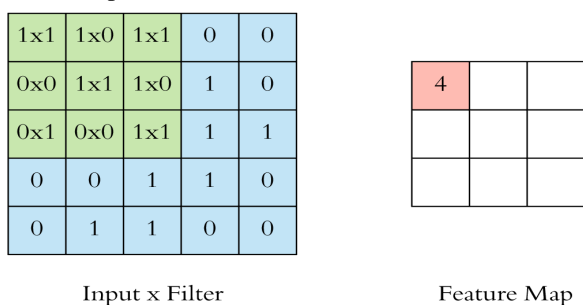


Fig. 5 Sliding the filter over the input to get the feature map

The kernel is shown in Fig. 5 in green color and the outcome of the convolution method “4” is colored pink in the subsequent feature map. Sliding the kernel to the right of the input by one step and executing the same operation and then adding the result to the feature map gives the second value of the feature map. Repeating the same operation until all the pixels are being covered and then aggregating the convolution results gives the complete feature map.

In this example, though the convolution method is shown in 2D using a 3x3 kernel. Yet in actuality, convolutions are implemented in 3D. An image is portrayed as a 3D array with aspects of height, width and depth, where depth is equivalent to RGB values. A convolution kernel has a specific height and width, such as 5x5, 7x7 etc. and it considers the whole depth of its image. Hence, it should also be a 3D array.

Several convolution functions are performed on the image where every convolution uses a different kernel which produces a typical feature map. At the end, all the calculated feature maps are grouped together to produce the end result of the convolution channel.

• Activation Function

In order to obtain the output of Neural Network activation function is being carried out. It assigns the resulting values within the range 0 to 1 or -1 to 1. Two kinds of activation functions are available i.e. linear and non-linear. ReLu (Rectified Linear unit) activation function is employed in this project to calculate the output of CNN. ReLu (Rectified Linear unit) function is then applied on the resultant of the convolution layer. Hence, the output of the corresponding

maps are not simply the additions, instead, ReLu method performed over feature maps.

• Stride and Padding

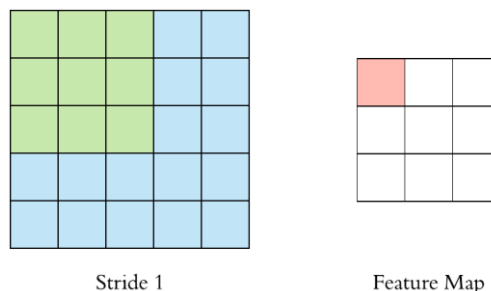


Fig. 6 Convolution filter with stride 1

It describes the extent to which the convolution kernel has to be moved at each step. The default values is set as 1. Bigger strides also can be used if necessary or if less overlap is needed among the receiving areas. By this, the resulting size of the feature map gets reduced as potential locations have been skipped.

The size of the feature map is always smaller than that of the input, since the convolution operation is performed on the input. If the same dimensionality is to be maintained, then padding can be used to add zeros or ones at the edge of the image.

Padding can be done with ‘0’s or the pixels at the border. Hence, the facet of the map is same as the incoming values. CNN generally uses this method to maintain the magnitude of the maps, else shrinkage may occur at each surface and is not preferable. The 3D convolution Fig. 7 has used padding. Therefore, the height and width of the feature map match that of the input (both 32x32), and only the depth is altered.

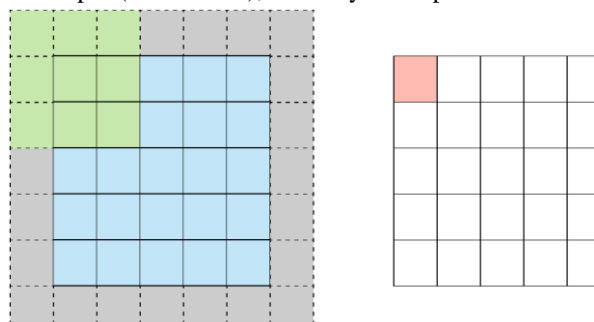


Fig. 7 Padding the input with zeros

• Pooling

After a convolution task pooling is implemented to lessen the dimensionality. Pooling is utilized to decrease the number of variables that reduces the training period as well as combats overfitting. This channel down-samples every element map autonomously, decreasing the height and width, maintaining the depth unaltered.

Max pooling is one such method that determines the maximum incentive in the pooling filter. In contrast to the convolution task, pooling does not contain any values. This layer moves a window over its information, and then finds the maximum value inside the window.

The window size and stride have to be specified like a convolution. Output of max pooling deploying a 2x2 filter with step 2 is shown in Fig. 8. Each shading indicates a particular window. As the window size as well as stride are 2, the windows are not intersecting.

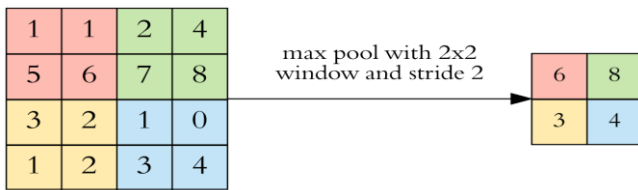


Fig. 8 Output of max pooling with a 2x2 window and step 2

The stride and window arrangement reduces the size or magnitude of the map by half. This is the important advantage of pooling, i.e. decreasing the size while retaining the crucial details of the feature map. Using the same methodology, the input to the pooling channel with dimensions 32x32x10, can be brought down to 16x16x10 feature map. Both the height and width of the feature map are reduced by 50%, but the depth remains unaltered as pooling works autonomously on each depth piece of the input.

By reducing the width and height by half, total weights to one fourth of the input are reduced.

- Fully Connected

The result of the previous channel is given as the input to the fully connected layer. Once the convolution and the pooling channels have been added, one or two fully connected layers are added on top of the pooling channel in order to converge the CNN structure. This layer is same as the fully connected channel in Artificial Neural Network.

The resultant of convolution as well as pooling channels are 3D measures, but a fully connected channel accepts only 1D vector of integer values. As a result, the outcome of the final pooling layer has to be flattened to a vector, which acts as the input to the fully connected channel. Flattening is clearly positioning the 3D measures of integers into a 1D vector. This is done by using flatten function in CNN.

- Softmax layers

Softmax layer is implemented just before the output layer. Number of nodes in this layer should match that of the output layer. It calculates the probabilities of each possible class. The class with the highest probability is given to the node in the output layer. Hence it helps to predict the desired class in better way.

IV. RESULTS

Fig. 9 Input details

File upload successfully

Output-> Price as predicted by CNN: [20.68] Price as predicted by Linear Regressor: [[17.1900245]]

Fig. 10 Price prediction for red tomato

File upload successfully

Output-> Price as predicted by CNN: [10.93] Price as predicted by Linear Regressor: [[17.5469049]]

Fig. 11 Price prediction for green tomato

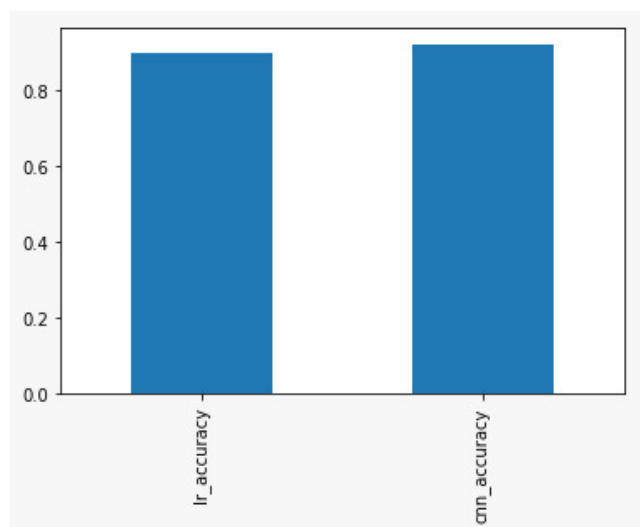


Fig. 12 Performance of CNN and LR

V. CONCLUSION AND FUTURE SCOPE

This paper exhibits a latest technique to predict the price of tomato based on different attributes. This application can be utilized effectively by farmers to detect the quality of the tomatoes grown in their farms and decide its price. This application helps the farmers by providing an easy access to the market rates of tomatoes prevailing in nearby cities or markets.

The farmers need to travel far off places to seek the guidance from the agriculture field experts to check the quality in order to decide its price. Since the data is always available on cloud, easy access of the information is an additional benefit of this application which can be used by anyone related to the business. From the results we can conclude that the performance of CNN whose accuracy is 92% in predicting the price of the tomato is better than that of Linear Regression which is 90% accurate. This proved that machine learning techniques can be used effectively to validate the quality and price of any fruit or vegetable taken into consideration as a subject.

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