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Automatic Detection and Classification of Nutrients Deficiency in Fruit Based on Automated Machine Learning

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Abstract*: Machine learning-based classification and detection of surface defect of fruit involve manual feature identification and selection from input datasets. Deep learning discovers the useful features from the input data. This approach simplifies the training of the neural network and makes them faster. The selection of useful patterns from the fruit features results in better accuracy. The number of layers represents the depth of the model. Neural network provides learning to the model. As the dataset contains many features. It is obvious that all features are not relevant to the system. The proposed system learns from these features by identifying the pattern and select the relevant features. This is the most crucial phase of the machine learning to identify the appropriate features to make the system faster and accurate. In this paper, we propose solving fruit surface defect detection using Automated Machine Learning (AML). The outcome is the prediction of the fruit surface defect in terms of probability due to nutrient deficiency

Keywords: Automated machine learning, Surface defect, fruit classification, Convolutional Neural Network, fruit defect.

I. INTRODUCTION

Machine vision-based automatic fruit recognition is a challenging task in the real world. It is due to the similarity among different types of fruits. Lighting condition also plays an important role due to change in the external environment. Nutrient deficient images are provided as input to the Deep Convolution Neural Network (DCNN) for training the model and recognizing the output without extracting the features manually. DCNN learns the pattern of datasets and chooses the relevant features for classification. The outcome of the classification process is based on probability mechanism. The accuracy achieved by the model is 99% [1]. With the rapid development of the fruit industry, there is a requirement of an effective method for classification of various fruits. The manual inspection is obsolete as it consumes lots of time. Computer vision-based pattern recognition technology is capable of processing complex information automatically. Further fuzzy SVM provides a better result [2]. But, high High-quality datasets are essential for designing a good classifier. The image contains the object and the noisy background. This could lead to the classification of the incorrect object. Therefore, preprocessing of sample images are required before feeding to the model. The datasets are used to train the deep neural network which is capable of identifying the fruit surface defects from the images. The fruits may have various categories and complex shape. The variation in fruit color also a challenging task. Apples may have various color as red, yellow, green, pink etc. If a classifier is trained based on color, then fruit recognition model need to be trained with all possible color variation for better classification accuracy. One possible solution is to increase the size of the dataset.

II. PREVIOUS WORK

Altaheri et. al [3] proposes a framework consists of three classification models in real-time that is based on the type of maturity and harvesting. The classification model uses deep convolutional neural network for transfer learning. The dataset consists of 8000 images. For industrial application, fruit classification is an important task. The fruit classification system helps for the identification of fruit species and its price. Hossain et. al [4] propose deep learning architecture that consists of 6 convolutional neural network layers and fine-tuned pre-trained network. The classification accuracy obtained is 96.75% [4]. Another classification model based on a convolutional neural network that is capable of extracting the features automatically with an accuracy of 97.19% [5]. A fully convolutional network (FCN) is trained and segmented the image in two categories: one in the fruit pixels and other in non-fruit pixels [6]. The convolutional neural network-based an effective model is developed for the classification of various Durio Zibethinus. The dataset consists of 800 images of Durio. The process starts with the pre-processing and image conversion followed by data labeling. After training and validation, the predicted accuracy of 82.50% is obtained [7]. The manual methods are unreliable, non-productive and costly. Artificial Intelligent (AI) based technique is capable of solving higher order non-linear classification problems. The samples are categorized in three main groups: ripe, unripe and defective. The hybrid CNN-ANN based algorithm is observed superior during the validation and testing. The classification accuracy for the ripe and defective sample is found to be 90% [8].

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Basri et.al [9] proposes a faster R-CNN method based on deep learning for multi-fruit detection using MobileNet model on TensorFlow platform. The dataset consists of two fruits: mango and pitaya. The accuracy achieved is 99%. Further, the method is applied to sort multi-fruits in real-time for maintaining the quality of the fruits.

III. METHODOLOGY

Data holds lots of secrets. The system examines the data and find the patterns that are too complex for human if large amount of data is provided. The system generates the code that are used for the recognition of these patterns in the new data. The application uses these generated code to make predictions. The development of these smart applications help reducing the processing time substantially. We propose visual interface based machine learning model for prediction of fruit surface defect detection due to nutrient deficiency. The dataset involves around 10,000 samples of various fruits. The training dataset involves area, major axis length, minor axis length, perimeter, eccentricity, Euler number, orientation and equivalent diameter. First of all, the training datasets are uploaded to the model. A new experiment is started for the prediction of the outcome. Before training, data transformation is required due to possibility of any missing features. Once the data transformation is completed next step is the selection of features from the training datasets that are needed for the training of the model. The missing data in training datasets are replaced with the mean value. The datasets are split in two parts: one for the training purpose and second for the validation. For training purpose 70% datasets are utilized and remaining 30% used for the validation of the model. For the prediction, regression model is used. The regression model is initialized. The Boosted Decision Tree regression model is used in this paper. The learning rate is set to 0.1. Now the train model is set-up and choose the target value as Eccentricity, that is required for the prediction. The actual prediction of the trained model is done by introducing the square model. Finally, the model is evaluated. The experiment is executed on different datasets and found to be accurate compared to the traditional model as shown in Table 1.

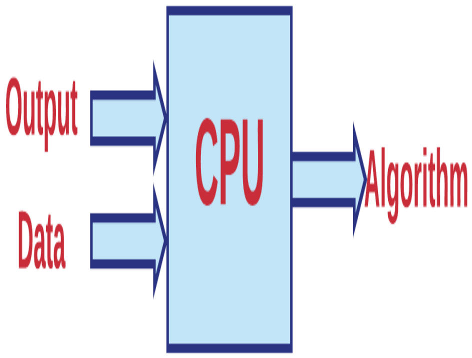

Fig. 1 Model of Machine Learning

The system receives outcome and datasets as the input and generate the outcome as an algorithm as shown in Fig. 1. The algorithm represents the model that is used for the prediction of the outcome.

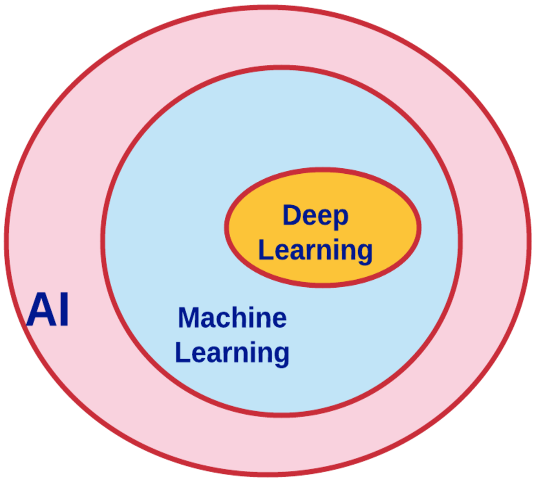

Fig. 2 Hierarchy of Deep Learning

Machine learning is subset of the Artificial Intelligent and Deep Learning is the subset of Machine Learning as shown in Fig.2.

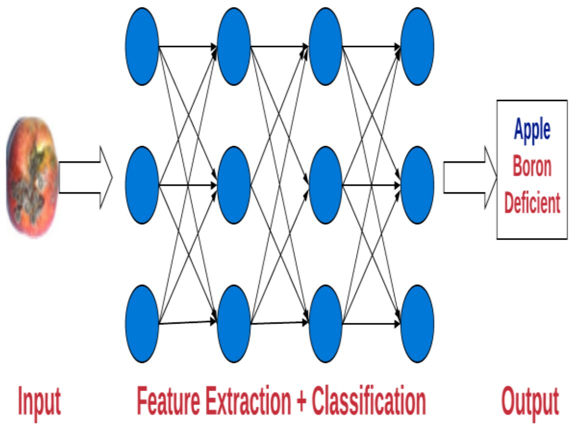

Fig. 3 Steps Involved in Deep Learning

Fig. 4 Datasets of Apple Fruit

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Table- I: Classification Accuracy of Fruit Defect Detection

Classification Method			
Method	***Fruit Type***	***Accuracy (%)***	***Authors***
CNN	Mangosteen	97	L. M. Azizah et. al [10]
Computer Vision	Pear	90.3	Z. Han et. al [11]
Six-layer CNN	Longan	91.44	S. Lu et. al [12]
SVM	Strawberry	95.3	R. S. S. Kumari et. al [13]
Fuzzy logic	Apple	91.66	E. D. S. Mulyani et. al [14]
CNN	Apple	94	Z. M. Khaing et. al [15]
Fuzzy	Guava	93.4	R. Hasan et. al [16]
ANN	Passion	90	S. W. Sidehabi et. al [17]
Nearest Neighbours	Fruit	90	Woo Chaw Seng et. al [18]
CNN	Fruit	95.6	G. Zeng [19]
Texture-based	Apple	80	Z. S. Pothen et. al [20]
ANN	Pears	97.4	H. S. Choi et. al [21]

Table 1 shows the various classification methods of the fruits along with their accuracy. CNN based Mangosteen classification achieved an accuracy of 97%, SVM classification of Strawberry reached the accuracy of 95.3%. ANN based pears classification attained 97.4% of accuracy.

In Fig. 3, an apple fruit image is provided as input. The model automatically extracts the features and classify the output. The input is given a defective apple sample. The network predicts the outcome as Apple with Boron deficiency. Fig. 4, shows a small portion of the database of apple samples. In this paper around 10,000 samples are used for training and testing process.

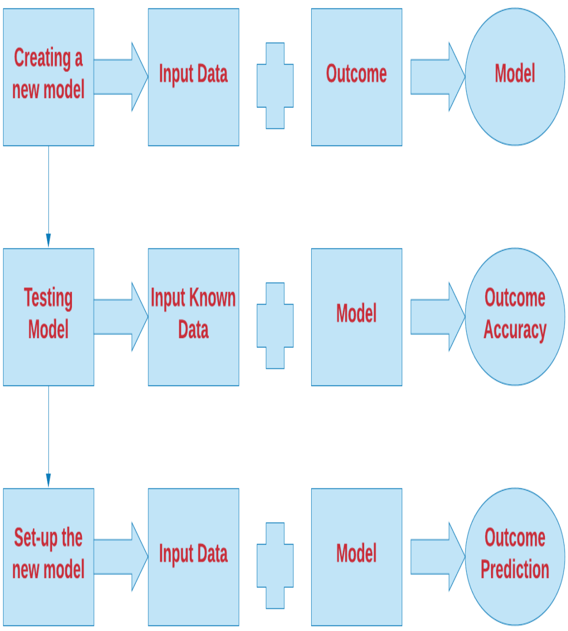

Fig. 5 Proposed Method

Fig. 5 represents the proposed method. It involves basically three major steps: Creation of new model, testing of model and set-up of the new model. In the first step, input and outcome are provided to the system and it generates a predictive model. In the second step, testing is done by applying data and, model is validated for accuracy. And in the third step, the model is set-up that predicts the outcome.

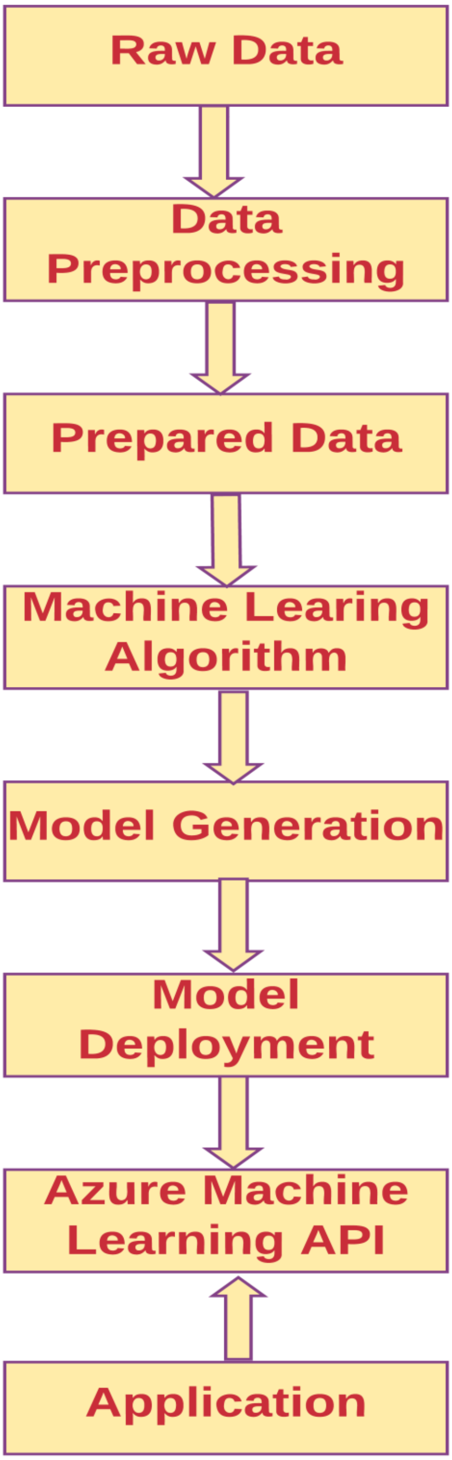

Fig.6 Automated Machine Learning Process

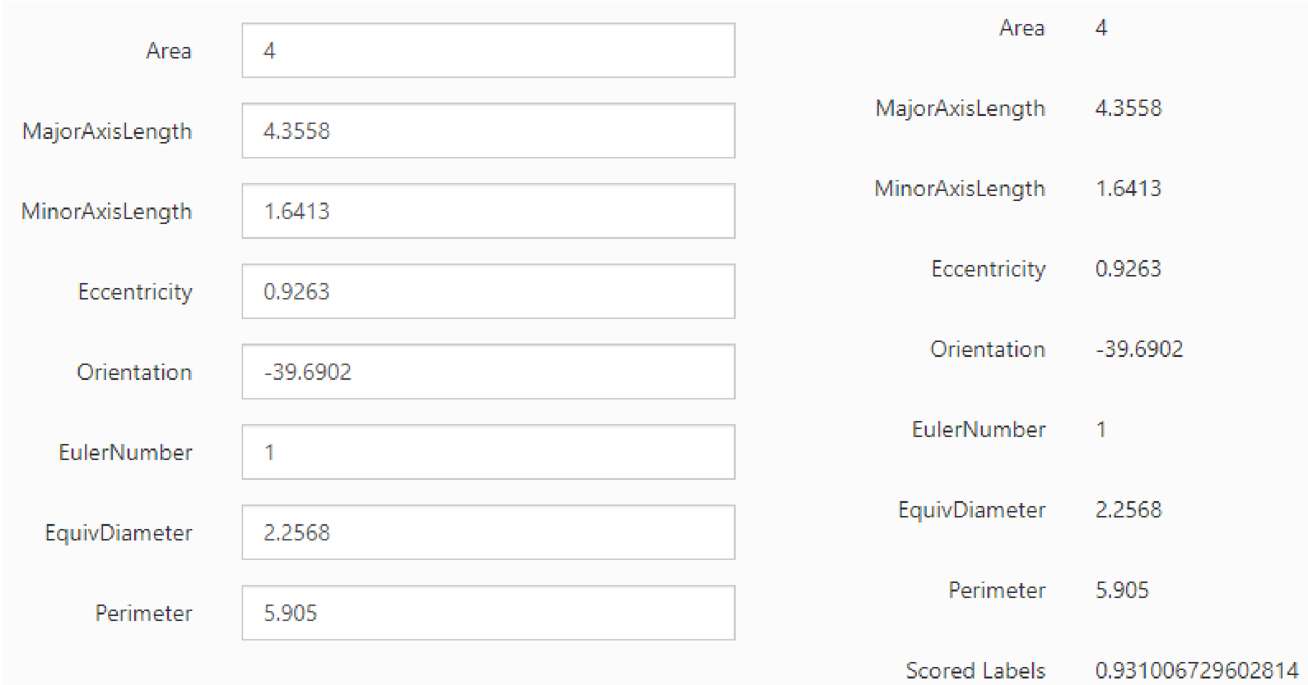

Fig. 7 Outcome of the Predictive Model

Statistics of Scored Labels	
Mean	0.4254
Median	0.4596
Min	0
Max	0.9921
Standard Deviation	0.417
Unique Values	56
Missing Values	0
Feature Type	Numeric Score

Table- 2: Statistical Features

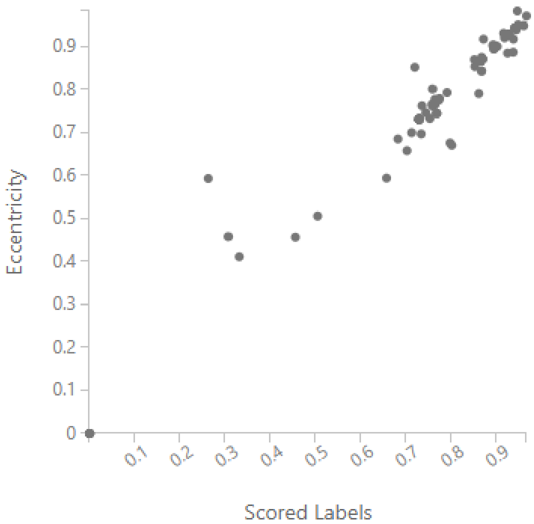

Fig.8 Scatter Plot

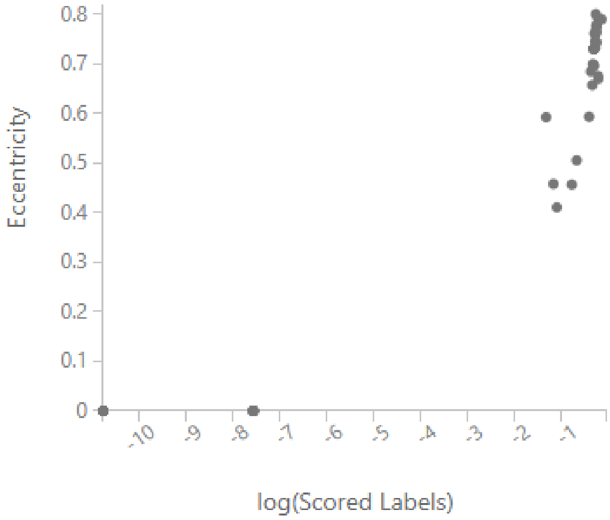

Fig. 9 Scatter Plot of Scored Labels log scale

Fig. 6 represent the process involed in Automated machine learning. First of all machine learing starts with data. The more data provides the better results. The data preprocessing fills in any missing values in the datasets. The data is stored in a table. Once the data preprocessing process is over, it is very importatnt to select the right algorithm for machine learning. It generates the model that need to be tested for the correct prediction. The model is tested by the validation dataset that demonstrates the model performance. Then the model is deployed using Azure studio that is further accessed by the application for prediction of the outcome.

Fig. 7 represents the outcome of the predicted model with scored labels. In Fig.8, scatter plot between the feature Eccentricity and scored labels is shown.

Fig. 9 depicts Scatter Plot of Scored Labels log scale between the feature Eccentricity and logarithm scored labels. Fig. 10 represents the Steps involved in Predictive Experiment.

Fig. 11 shows the Azure machine learning interface that is used for controlling the process from beginning to the end. The tool is used to apply data pre-processing module to the raw data and execute the experiment on the prepared data by the help of the machine learning algorithm. The model is validated and deployed over the Microsoft Azure for further accessed by the application.

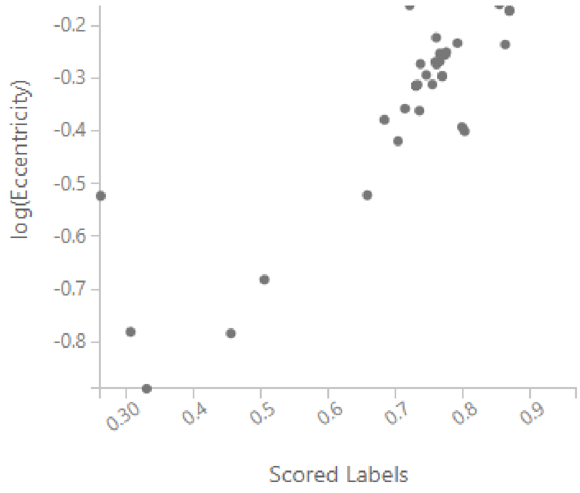

Fig. 10 Scatter of Eccentricity log scale

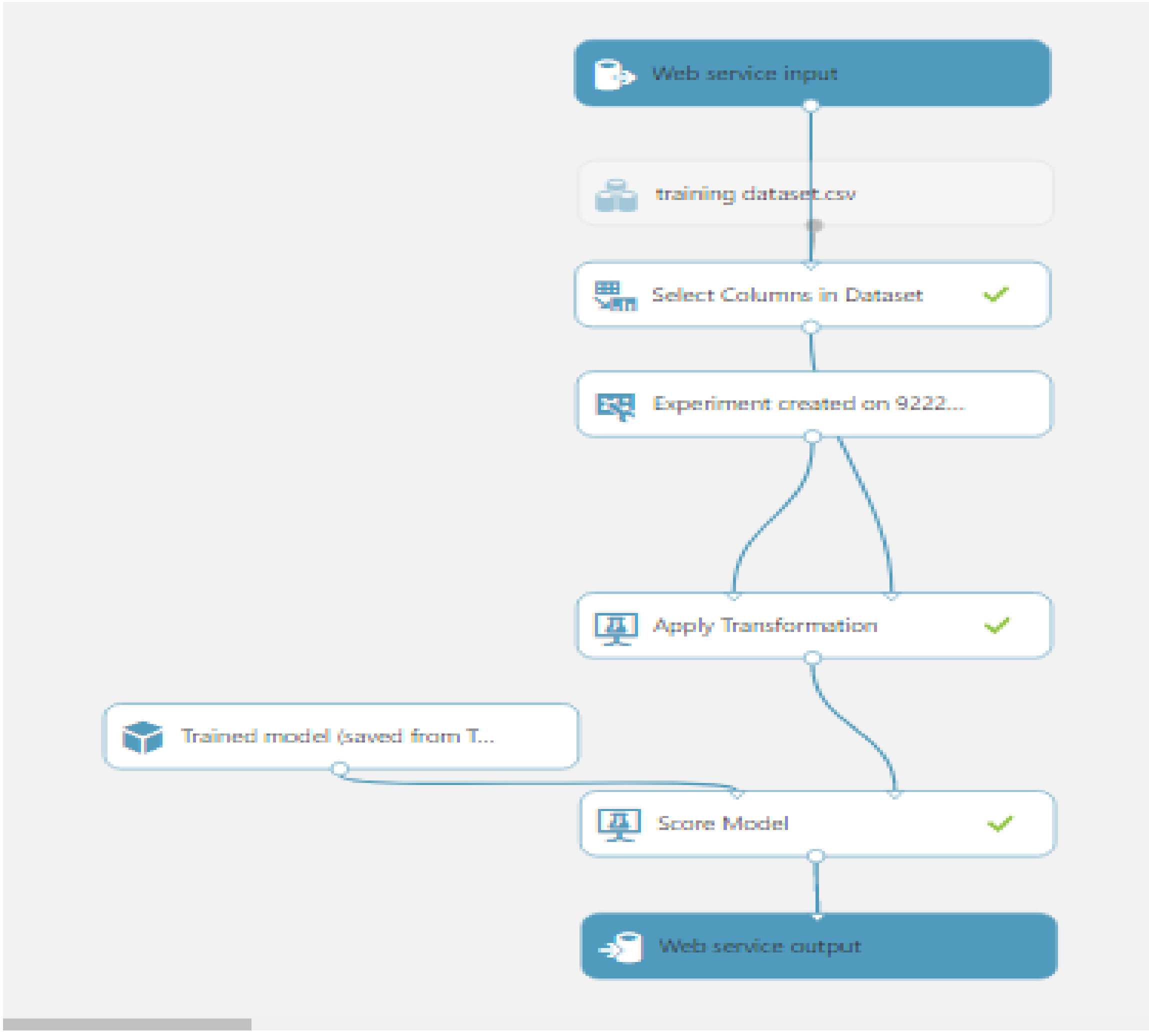

Fig. 11 Steps involved in Predictive Experiment

Table 3 Feature Extraction from the Dataset

Features Extraction								
Area	*Major Axis Length*	*Minor Axis Length*	*Eccentricity*	*Orientation*	*Euler Number*	*Equivalent Diameter*	*Perimeter*	*Scored Labels*
4	4.3558	1.6413	0.9263	-39.6902	1	2.2568	5.905	0.944899
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
6	4.4721	2.2111	0.8692	30.9638	1	2.764	7.22	0.840649
21990	231.3416	205.6821	0.4577	32.2787	-28	167.3276	1400	0.43071
9	5.4706	2.9478	0.8424	85.1812	1	3.3851	11.049	0.855234
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
6	3.4641	2.3094	0.7454	0	1	2.764	5.516	0.713614
3	2.582	1.7638	0.7303	-45	1	1.9544	3.093	0.730305
2	2.3094	1.1547	0.866	90	1	1.5958	1.96	0.865982
3	3.8541	1.4264	0.929	-28.155	1	1.9544	4.59	0.92815
11	4.4969	3.2775	0.6847	-15.0707	1	3.7424	8.791	0.679345
4	2.3094	2.3094	0	0	1	2.2568	3.556	0.016981
10	4.2583	3.2083	0.6575	0	1	3.5682	8.146	0.690046
4	3.4359	1.6915	0.8704	58.2825	1	2.2568	4.408	0.885012
4	2.3094	2.3094	0	0	1	2.2568	3.556	0.016981
3	2.582	1.7638	0.7303	-45	1	1.9544	3.093	0.730305
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
3	3.8541	1.4264	0.929	61.845	1	1.9544	4.59	0.930522
107	18.3709	8.5032	0.8864	16.9322	1	11.672	48.24	0.882229
2	3.0551	1.1547	0.9258	-45	1	1.5958	2.812	0.92566
1	1.1547	1.1547	0	0	1	1.1284	0	0
4	2.3094	2.3094	0	0	1	2.2568	3.556	0.016981
4	3.0551	2.0817	0.7319	0	1	2.2568	4.59	0.729506
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
5	3.5298	2.3594	0.7438	34.0993	1	2.5231	5.814	0.819965
1	1.1547	1.1547	0	0	1	1.1284	0	0
3	3.4641	1.1547	0.9428	90	1	1.9544	3.92	0.940487
15	5.3914	3.8528	0.6995	81.8699	1	4.3702	11.603	0.740315
3	2.582	1.7638	0.7303	45	1	1.9544	3.093	0.73008
1	1.1547	1.1547	0	0	1	1.1284	0	0
2	2.3094	1.1547	0.866	90	1	1.5958	1.96	0.865982
1	1.1547	1.1547	0	0	1	1.1284	0	0

4	2.3094	2.3094	0	0	1	2.2568	3.556	0.016981
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
2	3.0551	1.1547	0.9258	45	1	1.5958	2.812	0.926238
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
13	8.7856	3.0286	0.9387	-53.0822	1	4.0684	15.92	0.914348
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
2	2.3094	1.1547	0.866	0	1	1.5958	1.96	0.865899
6	3.8297	2.4037	0.7785	-45	1	2.764	6.459	0.746045
1	1.1547	1.1547	0	0	1	1.1284	0	0
4	3.6515	1.8257	0.866	71.5651	1	2.2568	5.053	0.87958
1	1.1547	1.1547	0	0	1	1.1284	0	0
18600	236.5011	215.6266	0.4108	-6.1789	-50	153.8904	705.079	0.417658
1	1.1547	1.1547	0	0	1	1.1284	0	0
9	6.3168	3.063	0.8746	-34.3747	1	3.3851	14.878	0.874199
32	10.6091	4.2321	0.917	-25.7477	1	6.3831	21.734	0.921341
1	1.1547	1.1547	0	0	1	1.1284	0	0
7	4.1633	2.4963	0.8003	59.0362	1	2.9854	7.402	0.831908
5	3.3066	2.1292	0.7651	-18.4349	1	2.5231	4.962	0.764737
3	2.582	1.7638	0.7303	-45	1	1.9544	3.093	0.730305
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
1	1.1547	1.1547	0	0	1	1.1284	0	0
2	2.3094	1.1547	0.866	90	1	1.5958	1.96	0.865982
2	2.3094	1.1547	0.866	90	1	1.5958	1.96	0.865982
1	1.1547	1.1547	0	0	1	1.1284	0	0
1727	63.5881	41.2831	0.7606	60.0052	-16	46.8923	352.627	0.765289
3	2.582	1.7638	0.7303	45	1	1.9544	3.093	0.73008
4	3.4359	1.6915	0.8704	31.7175	1	2.2568	4.408	0.870045
1	1.1547	1.1547	0	0	1	1.1284	0	0
5	3.3066	2.1292	0.7651	18.4349	1	2.5231	4.962	0.762677
1	1.1547	1.1547	0	0	1	1.1284	0	0
2	2.3094	1.1547	0.866	0	1	1.5958	1.96	0.865899
4	3.4359	1.6915	0.8704	-31.7175	1	2.2568	4.408	0.873122
2	3.0551	1.1547	0.9258	45	1	1.5958	2.812	0.926238
1	1.1547	1.1547	0	0	1	1.1284	0	0
2	2.3094	1.1547	0.866	90	1	1.5958	1.96	0.865982

4	2.3094	2.3094	0	0	1	2.2568	3.556	0.016981

IV. RESULT AND DISCUSSION

Table 2 shows the statistical features of Scored Labels. The Scored Label represents the prediction, and the Scored Label Standard Deviation depicts the uncertainty around that prediction. Table 3, represents all the features of the datasets. Each column represents one feature. In trained model, Eccentricity is selected as target feature that is used for the prediction of the system. Fig. 8 shows the correlation between target feature and scored labels for outcome prediction.It shows that how much target variable is affected by another and illustrate the linear relationship between two attibutes. The linear relationship predicts the highest degree of accuracy. The predicted class for each fruit is demonstrated by the Scored Labels column that is based on the Scored Probabilities column. It is predicted as deficient apple class if the scored probability of a fruit is greater than 0.5, otherwise, it is predicted as other class.

V. CONCLUSION

It is important to choose the relevant features from the datasets and apply the correct machine learning algorithm for the better prediction of the model. Manual selection of features consumes lots of time and degrade the accuracy level. A smarter way to let the system decide the relevant feature and machine learning algorithm for fast processing and higher level of prediction accuracy. Automated Machine learning simplifies the task involved in deep learning application. In future new area need to be explored in machine learning for adding more intelligence to the system for better accuracy and minimization of the datasets that will save the system resource.

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