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A HIGH QUALITY EMBEDDED SYSTEM FOR ASSESSING FOOD QUALITY USING HISTOGRAM OF ORIENTED GRADIENTS

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Abstract

A low cost high quality system for accessing quality of food samples by finding the presence of fungus is proposed. Most of the food items kept for long intervals will have fungal infection in them. The proposed system uses Histogram of Oriented Gradients algorithm along with Support Vector Machine classifier to detect the presence of fungus. The features of the food samples captured in real time using a webcam are extracted using Histogram of Oriented Gradients algorithm. The extracted features are given to SVM classifier which compares these features with the trained one and displays the quality of food samples. The algorithms are implemented using ARM Cortex A-53 processor. Experimental results indicate that very good sensitivity and specificity is obtained and the execution time of the algorithms implemented in ARM processor is much lesser compared to the results obtained using MATLAB software.

Keywords:

Accuracy, Fungus Detection, Histogram of Oriented Gradients, OpenCV, Support Vector Machine

1. INTRODUCTION

In order to guarantee the final quality of food products it is very important to detect the potential microbiological contamination that can threaten the consumer health. It was feasible to carry out such analysis only for a small quantity of food products in laboratories and it required a considerable amount of time. The rapid advancement in semiconductor industry and image processing techniques has enabled the availability of low cost high quality embedded system for quick analysis of wide range of food products. Accessing the quality of food using a low cost system at a reduced response time will result in food products with a better quality in the food market.

Fungus belongs to group of eukaryotic organisms which are classified as kingdoms that contain microorganisms like yeasts and molds. The Kingdom fungus plays a vital role in maintaining ecological conditions. Some of them provide useful products like penicillin and other antibiotics which are of medicinal value.

But if food items are affected by fungus it could result in food poisoning either due to mycotoxin or bacterial contamination or both. Eating fungus affected food is risky and should be avoided at all times. So, it is important to detect the presence of fungus in food materials because certain species of fungus can be pathogenic in humans. Further the world is becoming a global market due to increased trade between countries and there is a demand for an automated system to access the quality of food that is being transported. In the food supply chain parameters such as temperature, humidity and CO2 are monitored [14] but the presence of fungus is rarely detected. The presence of fungus need to be monitored as it grows rapidly. If manual labor is employed for quality checking productivity and efficiency becomes a concern. It is a slow and tedious process and lead to quality lapses. Cost involved in the process is also very high. Hence there is a real need to automate this process for better and predictable quality control. The advancements in machine learning algorithms and artificial intelligence have now made it possible to replicate manual visual inspection using machines.

In the proposed work HOG Algorithm along with SVM classifier are used. Since it is a real time application the algorithms are implemented in ARM Cortex processors thus reducing the time complexity. The proposed work is based on an embedded system consisting of Raspberry Pi 3 as a low-cost ARM powered Linux based computer. Raspberry Pi 3 is a useful platform for machine learning development, where a camera can be connected as an add-on module for developing image classification applications. The ARM Cortex 64-bit embedded platform in the Raspberry Pi 3 supports floating point operations thus improving the real time performance of the system. Further Raspberry pi 3 has an inbuilt Wi-Fi module and hence can be used to monitor the quality of food samples remotely.

Section 2 deals with prior work, section 3 describes the image processing algorithm viz., HOG, section 4 describes the machine learning algorithm viz., SVM, section 5 describes the Hardware part of the proposed work. Experimental result and conclusion is given in section 6 and section 7 respectively.

2. LITERATURE REVIEW

Customer's judge food based on the impact on their palate and cost but for a food brand with staying power requires not only a killer recipe but food companies need to alleviate food contamination and spoilage control [12]. Hence food quality systems in food supply networks have become a critical issue for food companies. By employing visual inspection machines food companies not only reduces losses but also reduces the risk of food related scandals. Hence there is a necessity of early warning systems to predict the quality of food and give suggestions for proactive control [13]. Many automated systems have been proposed to check quality of food products.

In [1], the authors have used a HOG algorithm to detect the fungus in air samples which are captured using an optical sensor system. In this system fungal spores in air samples are detected by collecting the air samples and using a microscopic camera to capture the images of the samples which are processed using various filters. The disadvantage is that it cannot be predicted how efficient microscopic camera detects the presence of fungus in air since it is very naked and the images from camera will not be very accurate when passed over an optical sensor system because factors like temperature, pressure, noise and radio wave propagation model affects it either directly or indirectly. In [2] authors have proposed an Automatic Identification of fungi in

Microscopic leucorrhea images. Identifying fungi in microscopic leucorrhea images provides important information for evaluating gynecological diseases. Subjective judgment and fatigue can greatly affect recognition accuracy. This proposed work uses a convolutional neural network, the histogram of oriented gradients algorithm, and a binary support vector machine. A Computer Vision Systems is proposed in [3]. It is used for online and real-time evaluation of quality control of food. This method is less accurate, since it uses piecewise linear function to approximate the boundary of the object. In [4], authors have used an infrared thermal imaging system for finding fungus in stored wheat. The features of stored wheat are extracted using four ways and are checked using Leave-One-Out and bootstrapping methods. Disadvantage is that proper temperature has to be maintained since the system is not automated. The authors in [5] have proposed a system for detection of fungus infected corn kernels using near infrared reflectance spectroscopy and color imaging. Using the image processing and spectral analysis technology, parameters related with leaf miner infection were analyzed and confirmed but the method is suitable only for large quantities of corn kernels. In [6] an early detection of infection is identified using hyper spectral image system under laboratory conditions. Genetic algorithms have been used for optimizing the number of samples and Independent Component analysis was used for separating the good kernels from damaged ones. In [7] the fungus in fresh vegetables is detected using hyper spectral image technique. The input is fed through hyper spectral camera and various parameters are calculated using analyzers and artificial neural networks. In [8] a chemical analysis method is used for identifying fungus and to produce the quality and safety maize. It is more convenient method for detection at early stages but a very complex one.

In [9] computer vision system is used to find quality of fruits and vegetables based on parameters such as colour, texture, size, shape and defects. Various methods proposed by researchers such as pre-processing, segmentation, feature extraction, classification are explored and compared. They have concluded that even though number of algorithms are available, a robust computer vision based system with better performance need to be built.

The authors in [10] have used gas and temperature sensors to detect the gases emanating from the food and the temperature and humidity of the food storage area is measured. The collected data is send to the cloud server for analysis. Format of the food information is viewed through a Thingspeak web application. The disadvantage of their method is features obtained from different sensors are not optimal for each sensor and better performance can be obtained if machine learning algorithms are used.

In [11] authors have used a gas sensor to detect the microbial activity in the milk and a level sensor to find the level of the milk. The weight and FAT of the milk is also measured. They have used an Arduino microcontroller. Again better results can be obtained by using image processing algorithms because the values obtained from sensors may not be optimal.

In the existing works, fungus is not detected at early stages and the process is complex with a large delay. The proposed system identifies the presence of fungus at early stage using image processing techniques quite accurately. The system also detects fungus in real time with a less delay.

Using OpenCV implemented in ARM Processor to identify the fungi is more reliable and time efficient than using MATLAB.

3. HISTOGRAM OF ORIENTED GRADIENTS

The steps involved in HOG algorithm such as pre-processing, gradient computation, orientation binning, descriptor block, block normalization and object recognition is shown in Fig.1.

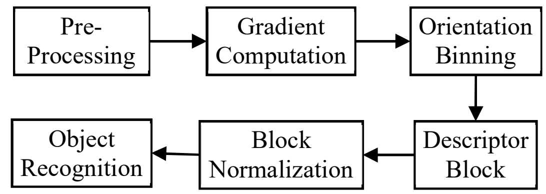

Fig.1. HOG Algorithm

3.1 PRE-PROCESSING

In this, RGB image is converted into gray scale image to reduce the complexity as RGB is a 3D pixel value whereas gray scale is a 1D pixel value.

3.2 GRADIENT COMPUTATION

The gradient values of an image present in both horizontal and vertical directions are computed. It is computed by using 1D centered derivative mask. It also requires filtering which is done by filter kernel Sobel [-1,0,1].

3.3 ORIENTATION BINNING

Cell histograms are created based on weighted vote of each pixel and the values obtained from gradient computation. The shape of the cells can be either radial or rectangular. The channels of histogram are distributed evenly from 0 to 180 degrees, if the gradient is unsigned and if the gradient is signed the angle is from 0 to 360 degrees. The Eq.(1) indicates the calculation of the magnitude of gradient,

$$Magnitude = \sqrt{g_x^2 + g_y^2} \tag{1}$$

3.4 DESCRIPTOR BLOCKS

In order to normalize the strengths of gradient, cells are combined together into larger and spatially connected blocks which overlap. HOG descriptor is formed by vectors that are concatenated in the normalized cells histogram components from all the block regions.

3.5 BLOCK NORMALIZATION

Normalization factor can be calculated using anyone of the Eq.(2) or Eq.(3).

$$L1-norm: f = \frac{v}{\|v\|_1 + e} \tag{2}$$

$$L2-norm: f = \frac{v}{\|v\|_2^2 + e^2} \tag{3}$$

where v = non-normalized vector.

3.6 OBJECT RECOGNITION

The above obtained HOG descriptor is given as features to machine learning algorithm. The algorithm used in the proposed work is SVM classifier.

4. SUPPORT VECTOR MACHINE CLASSIFIER

SVM is a supervised machine learning algorithm. SVM constructs a hyperplane between the vector points of the images. The images are trained in such a way that they are separated into one or more categories.

The Fig.2 shows hyperplane between two categories that is constructed by SVM. For better separation, the hyperplane which is constructed should be far from the nearest training data of any category.

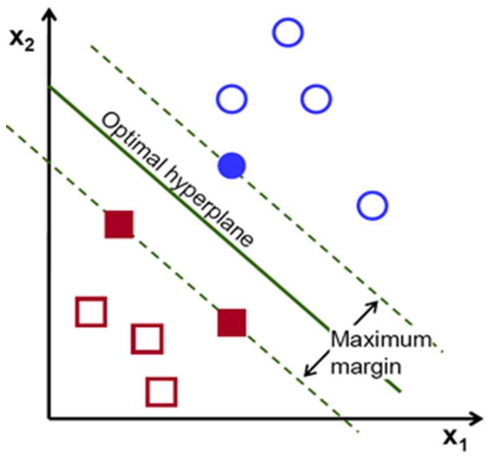

Fig.2. Hyperplane

The Fig.3 shows the process of SVM classifier. The images are converted into vector points and then trained and tested. The images are captured from web camera. These images are then converted into vector points. This conversion happens in formatted vectors block. The vectors are split into two. The vectors are trained in training data block and are tested in test data block. The trained data moves to K-fold cross validation which evaluates predictive models by partitioning the original sample into training set to train the model, and a test set to evaluate it. In k-fold cross-validation, the dataset is randomly partitioned into k equal size subsamples and any one of the k-subsamples is considered as validation set whereas then other subsamples are considered as training set. This process goes on till all k-subsamples are considered as validation set. Finally, the tested and cross-validated data is sent to SVM classifier.

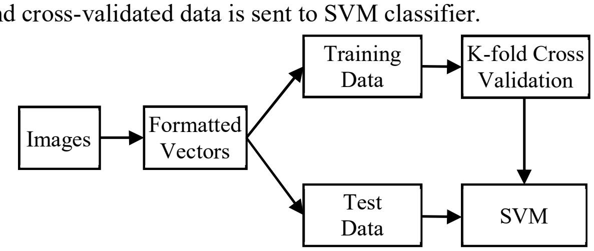

Fig.3. SVM classifier

The Fig.4 shows the algorithm for detection of fungus in food samples. A normal image and fungal image are pre-processed and their features are extracted using HOG algorithm. The SVM is trained and the trained output is given to the SVM Classifier. The web camera captures the image of the food samples and they are stored in the memory. The images from web camera are then pre-processed and its features are extracted using HOG algorithm. The extracted features of the image without SVM training is given to the SVM Classifier. The SVM Classifier compares both SVM trained and untrained features. Then SVM Classifier gives the output indicating the presence or absence of fungus in the given food samples. This process is carried out in both in MATLAB and OpenCV, which is installed in Raspberry Pi 3 kit.

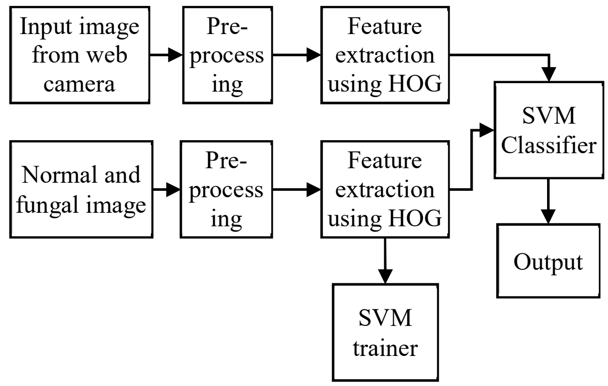

Fig.4. Algorithm for detection of fungus

5. HARDWARE DESCRIPTION

The proposed embedded system consists of Raspberry Pi 3 board and web camera for capturing the images of the food samples.

5.1 BLOCK DIAGRAM

The block diagram of the proposed system using machine learning algorithm is shown in the Fig.5. The webcam is used to capture the image of the food sample whose quality is to be accessed. The HOG algorithm and SVM classifier are implemented in OpenCV-Python. The algorithms are processed in the ARM Cortex processor. PC monitor is used to display the results. A LCD can also be used to display whether the food sample is fungus affected or not.

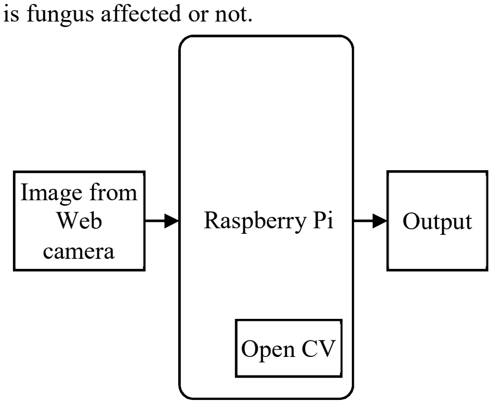

Fig.5. Block Diagram of the Proposed System

6. EXPERIMENTAL RESULTS

6.1 EXPERIMENTAL SETUP

The Fig.6 shows the Experimental setup of this project. Raspberry Pi 3 board with ARM Cortex processor is the main processing unit. A webcam interfaced with the board is used to capture the images and the images are stored in the memory. Power supply to the Raspberry Pi 3 board is through the USB cable from PC. The board can also be powered from a DC adaptor. The algorithms are executed by the ARM Cortex processor and the images are processed and the histogram equalization values are displayed in the monitor. These values are then processed to find the presence of fungus in food samples. The output is displayed in the monitor. If a LCD is connected to observe the output, the system can be made available as a low cost mobile unit.

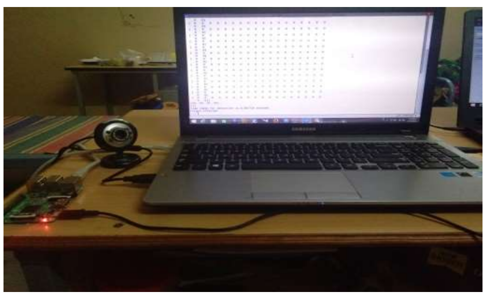

Fig.6. Experimental Setup

6.2 RESULT ANALYSIS

About seven food samples (as given in Table.1) were taken for training and detection of fungus. The images of the fresh food samples without fungus were recorded. The food samples were kept for a day or two and images were captured. The Fig.7, Fig.9, Fig.11 and Fig.13 shows the stages involved in the detection of fungus in gravy, cake, juice and dal. The original image is converted to gray scale image to reduce the complexity. The noise in the gray scale image is removed using median filter. Then the unwanted portions in the denoised image are removed and the features are exact rated. The image is pre-processed, filtered, compressed and extracted which results in image acquisition.

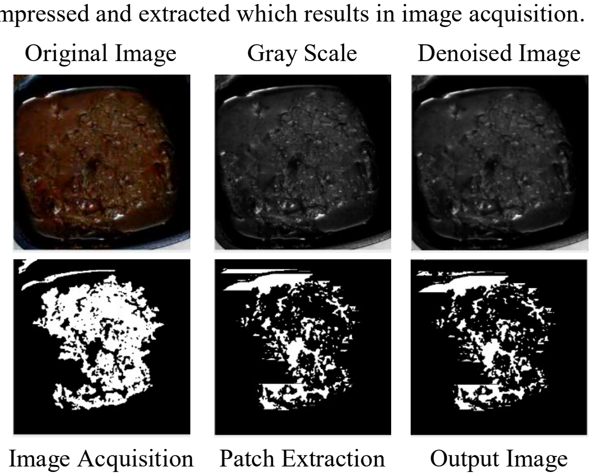

Fig.7. Stages involved in fungus detection in gravy

The patches which represent the fungus are extracted and the output image is obtained in which the orange spots indicate the presence of fungus.

The Fig.8, Fig.10, Fig.12 and Fig.14 shows the histogram variation graph for gravy, cake, juice and dal images. In this graphs the histogram equalization of the original image is compared with the histogram equalization of the fungus affected image and variation in histogram equalization is obtained in percentage for fungus affected sample.

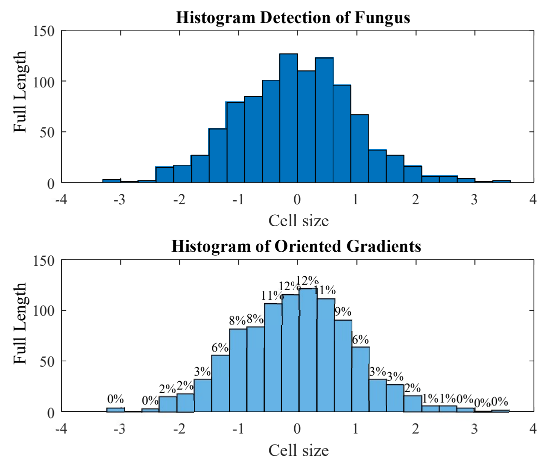

Fig.8. Histogram variation graph of gravy

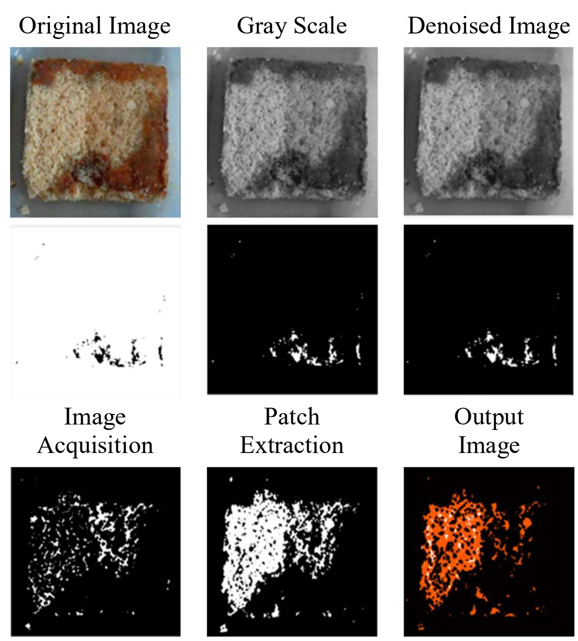

Fig.9. Stages involved in detection of fungus in cake

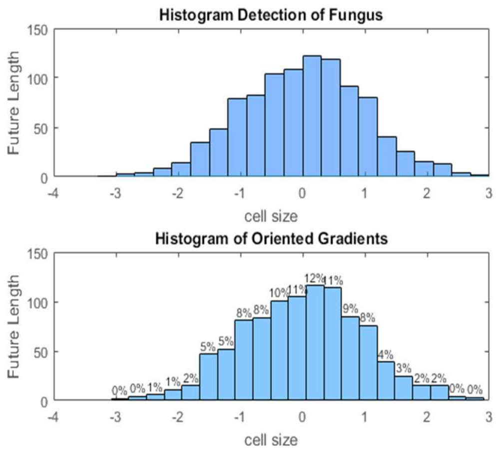

Fig.10. Histogram variation graph of cake

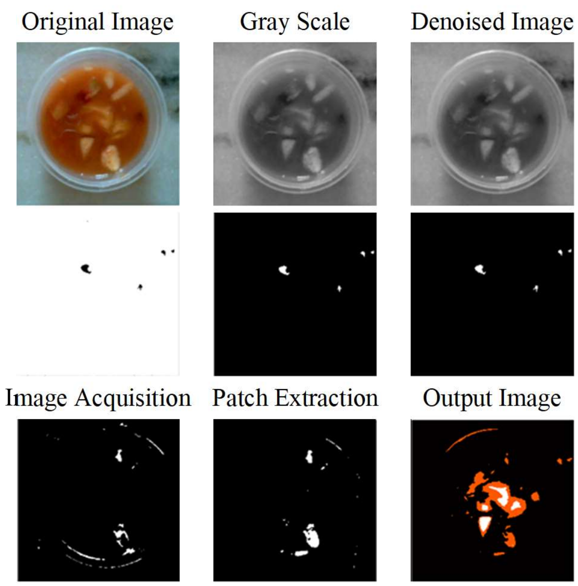

Fig.11. Stages involved in detection of fungus in juice

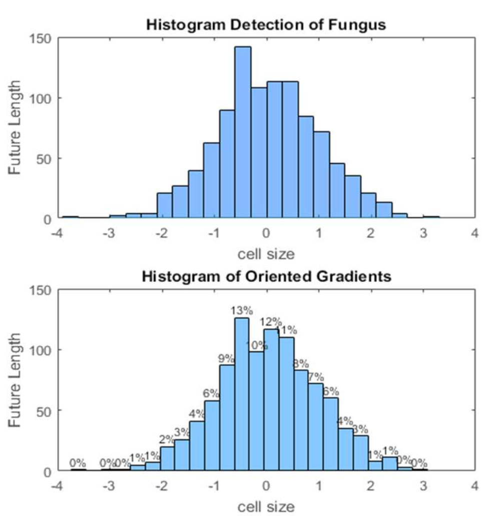

Fig.12. Histogram variation graph of juice

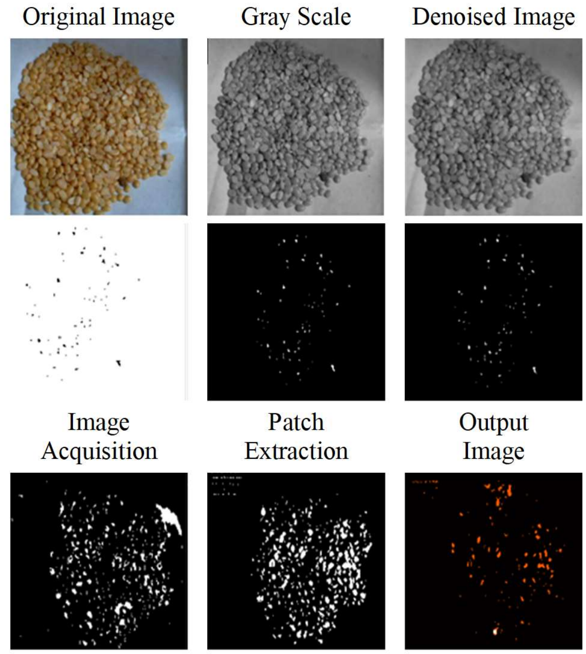

Fig.13. Stages involved in detection of fungus in dal

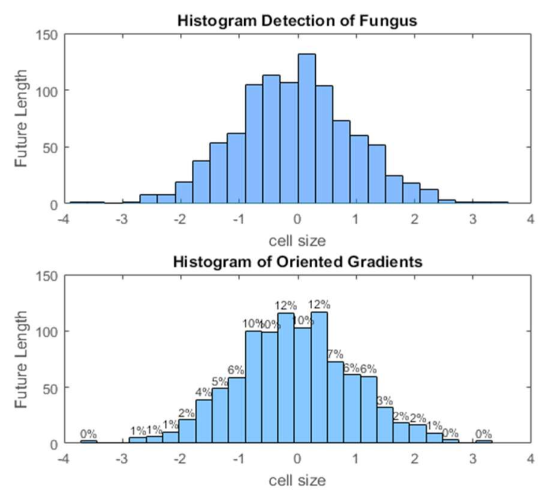

Fig.14. Histogram variation graph of dal

Various parameters such as accuracy, gain and entropy are measured for all the samples and tabulated.

6.2.1 Accuracy:

The measure of closeness of trained data to testing data is termed as accuracy. It is expressed in terms of percentage.

$$Accuracy = \left(\frac{Trained\ data}{Testing\ data}\right) \times 100\% . \tag{4}$$

6.2.2 Gain:

It is the mean value of segmented regions in the image.

$$Gain = Mean\ (\text{segments } 1, 2, 3, \ldots, N) \tag{5}$$

6.2.3 Entropy:

The measure of impurity is called entropy. It has no unit.

$$Entropy = \sum_i p_i \log_2 p_i \tag{6}$$

Table.1. Accuracy

Fungal samples	Accuracy (%)
Cake	60
Gravy	62
Dal	60
Juice	60
Coconut	62
Strawberry	51
Bread	50

From the Table.1, it can be inferred that the accuracy of the food samples is more than 50%. If more samples are trained the accuracy can be improved. Greater the accuracy means greater the probability of detection of fungus.

Table.2. Gain

Fungal samples	Gain (dB)
Cake	0.138447
Gravy	0.005778
Dal	0.074593
Juice	0.017185
Coconut	0.038200
Strawberry	0.009564
Bread	0.022766

The Table.2 shows the gain of the input images. The gain for various regions in the image are calculated, compared with each other and the mean is found. Gain indicates the purity of the image and entropy shows the impurity (fungus affected) of the image.

Table.3. Entropy

Fungal samples	Entropy
Cake	0.559884
Gravy	0.040610
Dal	0.368281
Juice	0.125328
Coconut	0.189410
Strawberry	0.074687
Bread	0.156702

In Table.3, the entropies are calculated to find the impurities in the images which indicate the presence of fungus. The Fig.9 and Fig.10 shows a snapshot of the execution time and output that fungus is affected or not.

```
[0]
time taken for detection is 9.315952 seconds
Fungus Not Affected
>>>
```

Fig.9. Output of fungus not affected sample (gravy)

```
[1]
time taken for detection is 8.608793 seconds
Fungus Affected
>>>
```

Fig.10. Output of fungus affected sample (gravy)

Table.4. Results using MATLAB

True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)
Gravy	Bread	Gravy	Juice
Cake	Dal	Cake	Bread
Strawberry	-	strawberry	dal
Juice	-	Coconut	-
Coconut	-	-	-

$$Sensitivity = \frac{TP}{TP+FN} = \frac{5}{5+3} = 0.625$$

$$Specificity = \frac{TN}{TP+FN} = \frac{4}{4+3} = 0.667$$

From the Table.4, it can be inferred that both sensitivity and specificity are above 50% in MATLAB.

Table.5. Results of algorithm implemented in ARM Processor

True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)
Gravy	-	Gravy	-
Cake	-	Cake	-
Strawberry	-	strawberry	-
Juice	-	Coconut	-
Coconut	-	Bread	-
Bread	-	Dal	-
Dal	-	Juice	-

$$Sensitivity = \frac{TP}{TP+FN} = \frac{7}{7+10} = 1$$

$$Specificity = \frac{TN}{TP+FN} = \frac{7}{7+10} = 1$$

From the Table.5, it can be inferred that both sensitivity and specificity are 100% when implemented in ARM Processor. Sensitivity correctly classifies whether the food sample is fungus affected or not and specificity correctly denotes that the sample is fungus free. Hence any fungal affected images can be correctly detected at early stages.

From the results in Table.6, it is inferred that the execution time in ARM Processor is on an average 88% improvement than that of MATLAB processing. Thus the system can be used to assess the quality of food with a high accuracy and with a short delay.

Fungal samples	Execution time in ARM Processor (s)	Execution time in Matlab (s)	Percentage increase in execution time in ARM Processor (%)
Cake	9.57946	69.6059	86.23
Gravy	8.60879	70.2442	87.74
Juice	9.96768	63.8756	87.31
Dal	8.37446	65.3879	87.19
Coconut	8.75491	84.4856	89.63
Strawberry	9.51949	60.1845	84.18
Bread	8.12451	64.1982	87.34

7. CONCLUSIONS

In this paper, a prototype design of food quality assessing system using machine learning algorithm is proposed. The system has also been validated for some food samples. The system can be made as a low cost and a real time portable system by using a LCD to display the quality of food. For the trained samples the system gives a good sensitivity and specificity results. For seven samples the system gives an accuracy of above 50%. If more number of samples is trained the accuracy of the system can be improved. Since the Raspberry Pi kit has an inbuilt Wi-Fi the data's can be sent to a central monitoring system or uploaded to a cloud for remote monitoring of food quality.

REFERENCES

[1] M.W. Tahir et al., "Detection of Fungus through an Optical Sensor System using the Histogram of Oriented Gradients", *IEEE Sensors*, Vol. 17, No. 16, pp. 5341-5349, 2017.

[2] J. Zhang, "Automatic Identification of Fungi in Microscopic Leucorrhea Images", *Journal of the Optical Society of America A*, Vol. 34, pp. 1484-1489, 2017.

[3] S. Gunasekaran, "Computer Vision Technology for Food Quality Assurance", *Trends in Food Science and Technology*, Vol. 7, pp. 245-256, 1996.

[4] V. Chelladurai et al., "Thermal Imaging for Detecting Fungal Infection in Stored Wheat", *Journal of Stored Products Research*, Vol. 46, No. 3, pp. 174-179, 2010.

[5] J.D. Tallada et al., "Detection of Fungus Infected Corn Kernels using Near Infrared Reflectance Spectroscopy and Colour Imaging", *Grain Marketing and Production Research Center*, Vol. 54, No. 3, pp. 1151-1158, 2011.

[6] E.A. Bauriegel et al., "Early Detection of Fusarium Infection in Wheat using Hyper-Spectral Imaging, *Computers and Electronics in Agriculture*, Vol. 75, No. 2, pp. 304-312, 2011.

[7] U. Siripatrawan et al., "Rapid Detection of Escherichia Coli Contamination in Packaged Fresh Spinach using Hyperspectral Imaging", *Talanta,* Vol. 85, No. 1, pp. 276-281, 2011.

[8] G. Firrao et al., "Prediction of Milled Maize Fumonisin Contamination by Multispectral Image Analysis", *Journal of Cereal Science*, Vol. 52, pp. 327-330, 2010.

[9] A. Bhargava, "Fruits and Vegetables Quality Evaluation using Computer Vision: A Review", *Journal of King Saud University, Computer and Information Sciences*, 2018.

[10] G. Rajakumar, T. Ananth Kumar, T.S. Arun Samuel and E. Muthu Kumaran, "IOT Based Milk Monitoring System for Detection of Milk Adulteration", *International Journal of Pure and Applied Mathematics*, Vol. 118, No. 9, pp. 21-32, 2018.

[11] Aman Naimat, "2018 could be the Year AI Kills Spam and Redefines Data Science", Available at: https://venturebeat.com/2018/04/01/food-and-beverage-cpg-enterprise-ai/ /, 2018.

[12] Adrie J.M. Beulens et al., "Possibilities for Applying Data Mining for Early Warning in Food Supply Networks", Available at: ftp://ftp.iiasa.ac.at/pub/mda/Pubs/csm06/pres/beulens_pap.pdf.