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# Deep Learning Based Automated Fruit Nutrients Deficiency Recognition System

YOGESH[1], ASHWANI KUMAR DUBEY[2,*], RAJEEV RATAN ARORA[3] AND ALVARO ROCHA[4]
[1,2]*Department of Electronic and Communication Engineering*
*Amity University*
*Uttar Pradesh, Noida, UP, 201313 India*
[3]*Department of Electronic and Communication Engineering*
*MVN University*
*Palwal, Haryana, 121105 India*
[4]*ISEG, University of Lisbon*
*Lisboa, 1200-781 Portugal*
*E-mail: {eceyogesh; dubey1ak; rajeevratanarora; amrrocha}@gmail.com*

The recent development in deep learning allows us to develop a computer vision-based system for recognition, detection, and localization of nutrients deficiency in fruits. Due to the time constraints, it is important to use an optimized and fast system for fruit quality inspection. In this paper, the input is taken as an image. A deep learning-based method extracts low level and high-level features such as edges, geometrical, statistical, texture, intensity, *etc.* After validation of the system with the test data, the output is predicted by the system. The processing time is optimized by avoiding fully connected layers which further minimize the requirement of neurons in the network. The convolutional neural network extracts the features of the fruits, Rectified Linear Unit (ReLu) removes the non-fruit pixels. Pooling shrinks, the image by selecting the maximum value of the pixel. The process is repeated until the size of the image is at the desired level. The aim is to identify the objects and recognize them. The foreground region objects are of our interest and being segmented for higher-level image processing. The proposed system attains the accuracy of 99.30 % with the processing time of 3.207 sec.

***Keywords:*** object recognition, pixel classification, quality analysis and evaluation, training, nutrients deficiency

## 1. INTRODUCTION

Fruit color grading is an important factor that is directly related to the profitability of commercial production. Based on surface defects, the fruit color quality is inspected [1]. Another factor affecting fruit quality is nutrient deficiency. If the fruit is lacking any particular nutrient, the characteristics are observed by visual symptoms. Non-visual symptoms are estimated by plant and soil analysis. Nutrient deficiency in fruit causes poor quality of fruits that results in differences in starch content, protein, oil, *etc.* Further fruits are affected by delayed and abnormal maturity. Internal abnormalities affect the tissue that results in irregular shape and size of the fruits. It is possible that visual symptoms cause due to multiple deficiencies. Sometimes it is difficult to distinguish the visual symptoms caused by disease or insect damage due to similarities with nutrient deficiency. Deficiency of mineral elements such as Zn, N, S, Mg, Mn, K and Fe refers to Chlorosis disorder. Lack of P, Mg, S, and N develop Anthocyanin causing color spots. Ca, K, Zn, Mo and Mg deficiency

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causes dead tissues that refer to Necrosis [2]. To identify the disorder in fruits caused due to macro and micronutrient imbalance, various methods are specified that recognize and diagnose nutrient deficiency. The biochemical parameters also help to specify the disorder [3].

## 2. PREVIOUS WORK

The earlier method based on simple digital image processing that includes image acquisition using an image sensor such as black and white camera, thermal camera, color camera, spectral camera, *etc.* For the preprocessing various filters are used such as Gaussian, Wiener filter, *etc.* Thresholding is used for the image segmentation. The SVM classifier is used for image classification. Edge is detected using Canny method. The color feature and defected region of apple are used for grading of the fruit. The process involves image transformation from RGB to the HIS system. Otsu algorithm used for the segmentation of fruit and its background. The edge information of the defected region is extracted using the Canny edge detection method. Finally, the SVM classifies with an accuracy of 91% [4]. A spot removal method applied to remove the spot on the fruit surface. Artificial neural network (ANN) based recognition rate of 630 sample images of pears achieve an accuracy of 90.3% [5]. The fruit surface defect caused by chemicals, pests or natural effects. The manual process consumes lots of time. The system takes the fruit features as input and detects the defects of the fruit. This non-invasive method is completely automated without the involvement of any human labor [6]. In fruits and vegetables an automated accurate information of moisture content (MC) is vital for grading evaluation, and quality estimation [7]. Mordi *et al.* [8] propose an automated technique to identify the defect on apple skin color. The process involves the conversion of the sample image to the L*a*b color space. Then the active contour model (ACM) algorithm used to extract the fruit shape. Statistical histogram based fuzzy *c*-means (SHFCM) algorithm is applied for the segmentation of the defected region of the sample. It is observed that the SHFCM algorithm is faster than the FCM algorithm and attains the accuracy of 91% for healthy pixels and 96% for defected pixels [8].

## 3. TYPES OF NUTRIENT DEFICIENCY

Nutrients Deficiency in soil affects the plant, twig, fruit, *etc.* The growth of the plant is also affected. The fruits are unable to gain their normal size. Dry soil and waterlogging cause corky structure over the outer region of the fruit and with time this region dried and reflects cracks on the external surface of the fruit. This is because of the deficiency of nutrients that are essential for the plants growth. The roots of the plant take the nutrients from the soil and provide to the plant. But, lack of nutrients in soil causes insufficient supply of the nutrients and affects the plant growth which results in the deficient fruits.

### 3.1 Boron Deficiency

The first sign of Boron deficiency is found in the fruit. The symptoms are similar in pears, apricots, and apple. Boron imbalance causes cork development and results in dry and withered tissue. Further, fruit growth is slow and fails to gain actual size. The fruit skin becomes rough, scabby and finally crack. The crack appears anywhere around the surface of the fruit [9].

### 3.2 Iron Deficiency

Iron imbalance affects the leaves and changes its color to yellow. There is the development of dead tissue either around the edges or within the body of the leaf. The main cause of Iron deficiency is alkaline soil. If too much water applied, the situation becomes more severe [9].

### 3.3 Manganese Deficiency

Manganese deficiency affects the older leaves and changes the leaves' color to yellow. A higher scale of Manganese deficiency may affect the young leaves. The veins and its nearby tissue remain green. It also occurs on alkaline soil. But unlike iron deficiency, it is less severe on wet solids. The probability of Manganese deficiency is very less compared to Iron deficiency [9].

### 3.4 Copper Deficiency

Copper deficiency affects the apple and pear trees. The leaves turn yellow and fall. Most of the trees having dead tips. Initially, the shoots grow normally but later leaves change color and start falling [9].

### 3.5 Zinc Deficiency

Yellow leaves are the sign of Zinc deficiency and causing the smaller size of leaves whereas leaf spacing is normal. The light deficient tree has a normal leaf size with yellow color [9].

### 3.6 Magnesium Deficiency

Magnesium deficiency occurs only on apple. The symptom causes a yellow area between veins and edges of the leaves. This results in brown color and starts falling. The highly deficient tree loses almost half of the leaves and fruit are not able to attain original size [9].

### 3.7 Sulfur Deficiency

The plant growth affected due to Sulfur deficiency. The symptom causes leave color to turn yellow. The intensity of the yellow color is more compared to Nitrogen deficiency [9].

### 3.8 Nitrogen Deficiency

The growth is affected due to Nitrogen deficiency. The fruit size is also reduced. The leaves are smaller and have a pale green color. The shoots are also shorter. The leaves of Peach have dead spots and start falling [9].

### 3.9 Potassium Deficiency

It is a common deficiency for most of the trees. The symptoms cause purplish-brown edges of the leaves. The deficiency appears on all types of soils. Fine textured and poorly drained soils are more severe [9].

## 4. METHODOLOGY

The proposed Automated Dynamic Fruit Recognition System (ADFRS) used to recognize apple defects due to boron deficiency. The proposed system is developed on Microsoft Azure Machine Learning Studio that provides a Graphical user interface (GUI) based integrated environment. First of all, the input image is provided to the system. The system transforms the input image into 3 color channels *i.e.* RGB of (180*180*3) pixel image. Further dataset of 50,000 images of fruit with various defects has been created. The process involves mainly four layers: convolution, ReLu, pooling, and fully connected layers.

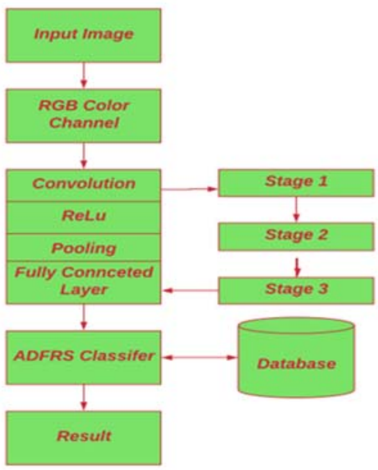


Fig. 1. Proposed ADFRS classifier system.

Fig. 2. Sample of boron deficient apples.

Fig. 1 shows the workflow of the proposed fruit defect classification system. The traditional method involves the comparison of input image and database image samples. The classification may be compromised if the input image is deformed. In this paper, the features are selected for the convolution process. These features are also used as filters. The size of the filter is kept smaller for better accuracy. One of the features is put on the input image and if the feature matches then the image is classified as defected. The filter is moved to every possible position on the image and multiplies each image pixel by the corresponding feature pixels. Then they are added together and divided by the total number of pixels in the feature pixels. All the values of the filter are mapped to one place in the form of the matrix. The process is repeated for the other features. Now, we have three matrices as an outcome of the convolution.

The features are represented in tabular form. As the data in the table that contains numeric and labeled data. The tabular form is the easiest way for data presentation during the classification process. As the dataset is large therefore Holdout validation is used. The slider control selects a percentage of data for testing. The training dataset used for training the system and performance is assessed by the test dataset.

The system is tested on various traditional classifier methods and the classification accuracy is observed to be 85.3% using an ensemble classifier that is the highest compared to the other classifier as shown in Table 1. The prediction speed is 4900 obs/sec. The training time is 4.0604 sec. Fig. 2 represents some of the samples of boron deficient apple. Fig. 3 represents the generation of the proposed system with an accuracy of 99.30 % as shown in Table 2. The features of nutrient-deficient apples are taken as input to the system in a comma-separated value format. Then the data is converted to the dataset. The column of the dataset represents features. In this paper 8 features are used for prediction. For the separation of various classes Fisher Linear Discriminant Analysis (FLDA) is applied. As there are very large datasets therefore in precaution missing data are replaced with the zero value. Then the dataset is split for training and validation purposes. For classification, a binary classifier based on a Boosted Decision Tree algorithm is used. Now the system is trained by selecting the feature eccentricity. The regression system is created by the score model. Finally, the system is executed using evaluate model.

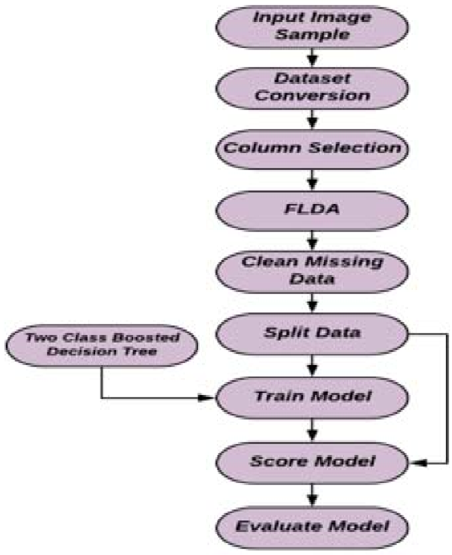


Fig. 3. Proposed generated system.

## 5. RESULT

Fig. 4 represents the plotting of different pairs of predictors on the scatter plot. The predictors separate the classes. During the plotting of the original dataset, the orientation and eccentricity parameters separate one of the classes well. The other classes are also separated by plotting other predictors. It is important to select the most useful predictors for efficient separation of the classes. Fig. 5 shows the scatter plot of system prediction that result after the training of the classifier. In the case of holdout validation, the predictors are the predictions on the hold-out observations. Each measurement is accessed using a system that was trained without using corresponding consideration. The cross represents the incorrect and dot shows the correct prediction.

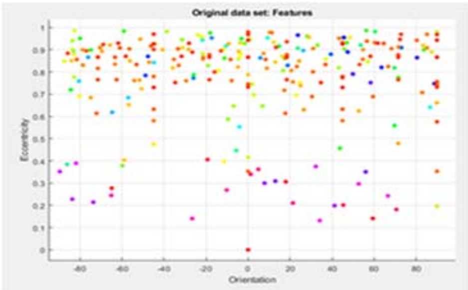


Fig. 4. Scatter plot of original dataset.

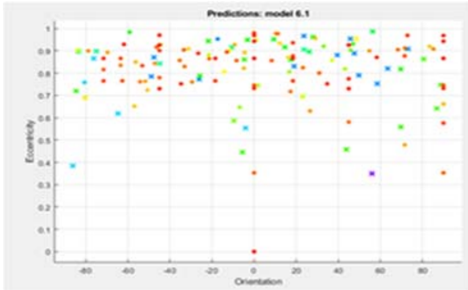


Fig. 5. Scatter plot of system prediction.

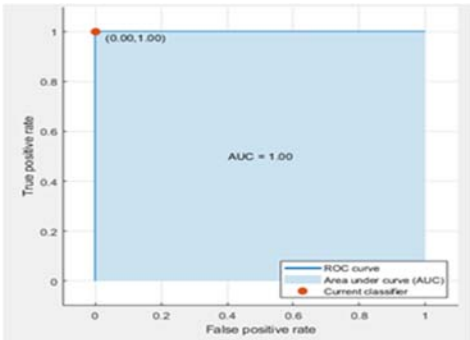


Fig. 6. ROC curve.

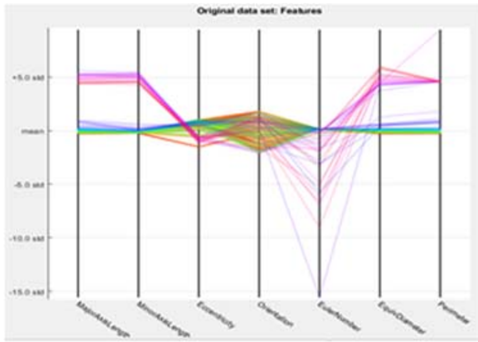


Fig. 7. Features of original datasets.

Fig. 6 shows the receiver operating characteristic (ROC) curve. It demonstrates true and false-positive rates. For the currently selected classifier, it represents the curve of true positive rate versus false-positive rate. In the ROC curve, the true positive rate of 1 is observed that illustrates the selected classifier assigns 100% of the observations accurately to the positive class. Fig. 7 represents the features of the original dataset in the parallel coordinate plot. It investigates the features and chooses the best features *i.e.* features to include or exclude based on performance. Computer vision based system aids analysis and detection of nutrient deficiency in fruits [10]. Fig. 8 shows the visualization of high dimensional data in a 2-dimensional pattern on a single plot. This plot illustrates the relationship between features and helping to identify the useful predictors for separating classes. The misclassified points are indicated by a dashed line. The predictor scale is considered as standardized. The mean of each predictor is at zero and the predicted scale is a standard deviation. Fig. 9 shows the receiver operating characteristic (ROC) curve of the proposed system. True positive is observed to be 216 and False positive is observed as 1. Fig. 10 shows the histogram of the scored probability. For clarity the number of bins selected is 1.

The logarithm scale of scored probability and frequency are used for better accuracy. The linear graph is the cumulative distribution and the parabolic curve represents the probability density of the scored probability.

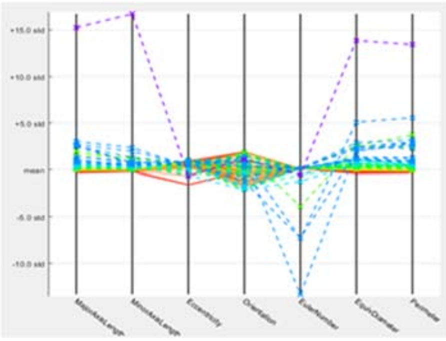

Fig. 8. System prediction parallel coordinate plot.

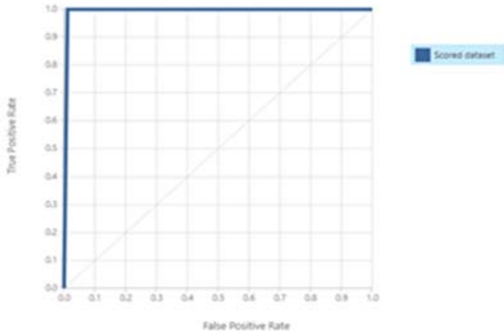


Fig. 9. ROC curve of proposed system.

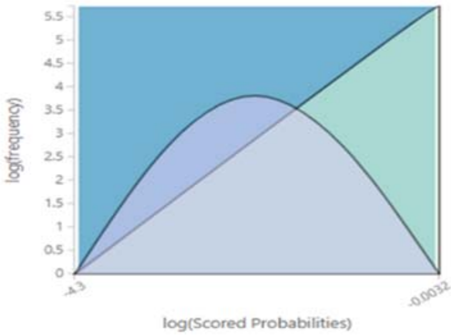


Fig. 10. Histogram of scored probability for 1 bin.

**Table 1. Experimental classification methods.**

| | Method | | Accuracy (%) |
|---|---|---|---|
| 1 | SVM | Linear SVM | 70 |
| 2 | | Quadratic SVM | 2.6 |
| 3 | | Cubic SVM | 12.7 |
| 4 | | Fine Gaussian SVM | 14.4 |
| 5 | | Medium Gaussian SVM | 33.7 |
| 6 | | Coarse Gaussian SVM | 12.7 |
| 7 | KNN | Fine KNN | 60.1 |
| 8 | | Medium KNN | 49.7 |
| 9 | | Coarse KNN | 50.7 |
| 10 | | Cubic KNN | 49.7 |
| 11 | | Weighted KNN | 59.8 |
| 12 | | Coarse Gaussian SVM | 12.7 |
| 13 | ENSEMBLE | Boosted Trees | 85.3 |
| 14 | | Bagged Trees | 80.4 |
| 15 | | Subspace Discriminant | 60.8 |
| 16 | | Subspace KNN | 67.6 |

Table 3 shows the various segmentation methods used for fruit defect segmentation. In apple, the segmentation accuracy is observed to be 93% [18]. Table 4 represents the system validation technique using the existing technique. Three validation techniques are used based on the Boosted Trees classifier. In case of Hold-out validation, the accuracy observed is 85.3% with training time of 4.0604 sec. In the case of cross-validation of 5 fold, the accuracy attained is only 66.7% with the highest training time of 14.909 sec. For no validation method, accuracy is around 70.1% with the training time of 5.229 sec. For all, the system execution number of observations taken is 613. The highest accuracy is 85.3% that is not competent and unacceptable in the world of advanced computer vision-based deep-learning environment. Therefore, further a new system is developed based on deep learning. It provides a GUI based interface for the generation of a more efficient and optimized system using Microsoft based Azure Machine Learning Studio.

**Table 2. Proposed system parameters.**

| | Parameter | Experimented Response |
|---|---|---|
| 1 | Elapsed Time | 3.207 sec |
| 2 | Accuracy | 99.30% |
| 3 | F1 Score | 0.995 |
| 4 | Precision | 0.995 |
| 5 | True Positive | 216 |
| 6 | False Positive | 1 |
| 7 | Positive Level | 0.1408 |
| 8 | Recall | 0.995 |
| 9 | Threshold | 0.5 |

**Table 3. Various segmentation methods.**

| | Type of Fruit | Segmentation Method | Accuracy (%) | References |
|---|---|---|---|---|
| 1 | Orchard fruit | Multi-spectral feature | 88 | Hung *et al.* [11] |
| 2 | Fruit | Hybrid Technique | 99.1 | Aibinu *et al.* [12] |
| 3 | Tomato | Region segmentation | 74.3 | Zheng *et al.* [13] |
| 4 | Passion | K-Means Clustering | 90 | Sidehabi *et al.* [14] |
| 5 | Apple | Ohta-color-space | 90 | Feng *et al.* [15] |
| 6 | Citrus | Fuzzy divergence | 93.5 | Argote *et al.* [16] |
| 7 | Banana | Background subtraction | 95 | Senthilarasi *et al.* [17] |
| 8 | Apple | K-Means clustering | 93 | Dubey *et al.* [18] |
| 9 | Pomegranate | K-Means clustering | 90 | Dhakate *et al.* [19] |
| 10 | Orange | NIR component | 95 | Abdelsalam [20] |

Table 5 illustrates the scored dataset of the predicted system. The last column shows the scored probability. The probability of zero shows the healthy class of the apple and 1 shows the deficient class of the sample. It is observed that the value of the scored probabilities varies between 0 to 1. Therefore, a threshold of 0.5 is taken which is used for distinguishing between the two classes of the sample either deficient or healthy. The system predicts the deficient class if the scored probability is greater than or equals to 0.5 otherwise the system predicts the sample as healthy. Further scored probability is divided into three intervals for the identification of the stage of the deficiency. The range of 0.5 to 0.6 represents the first stage of the deficiency. Further the range of 0.6 to 0.8 is considered as the second stage of the sample deficiency and the scored probability greater than 0.8 is considered as the final stage of deficiency.

Consider a variable $p$ whose range is [0, 1]:

If $0.6 > p > 0.5$,
Outcome: First stage of fruit deficiency
If $0.8 > p \geq 0.6$,
Outcome: Second stage of fruit deficiency
If $p \geq 0.8$,
Outcome: Final stage of fruit deficiency
Otherwise
Outcome: Healthy Fruit.

Where, $p$ represents the scored probability.

**Table 4. System validation using existing method.**

| S. No. | Parameter | Holdout Validation | Cross-Validation 5 Fold | No Validation |
|---|---|---|---|---|
| 1 | Preset | Boosted Trees | Boosted Trees | Boosted Trees |
| 2 | Ensemble Method | AdaBoost | AdaBoost | AdaBoost |
| 3 | Learner Type | Decision Tree | Decision Tree | Decision Tree |
| 4 | Max. no. of Splits | 20 | 20 | 20 |
| 5 | No. of Learners | 30 | 30 | 30 |
| 6 | Learning Rate | 0.1 | 0.1 | 0.1 |
| 7 | Dataset | Features | Features | Features |
| 8 | No. of Observations | 613 | 613 | 613 |
| 9 | No. of Predictors | 7 | 7 | 7 |
| 10 | Response Classes | 221 | 168 | 168 |
| 11 | Validation | Holdout Validation | 5 Fold Cross Validation | No Validation |
| 12 | Response | Perimeter | Perimeter | Perimeter |
| 13 | Accuracy | 85.3% | 66.7% | 70.1% |
| 14 | Prediction Speed | 4900 obs/sec | 1900 obs/sec | 4900 obs/sec |
| 15 | Training Time | 4.0604 sec | 14.909 sec | 5.229 sec |

**Table 5. Scored dataset.**

| | Feature1 | Feature2 | Feature3 | Feature4 | Feature5 | Feature6 | Feature7 | Feature8 | Scored Labels | Scored Probabilities | Recognition |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.866 | 74.327878 | 1.284598 | 0.69073 | 0.690326 | 0.179126 | 1.018453 | 0.999999 | 0.1317 | 0.995681 | Healthy |
| 2 | 0.1408 | 16.571853 | 0.508093 | 5.563272 | 4.281378 | 17.106702 | 21.039922 | 6.002025 | 0.1317 | 0.990732 | Healthy |
| 3 | 0.9588 | 17.625722 | 5.559826 | 0.269041 | 2.962043 | 0.22499 | 0.979971 | 1.000001 | 0.1317 | 0.995681 | Healthy |
| 4 | 0.689 | 25.471278 | 1.487578 | 1.593706 | 0.150933 | 0.235079 | 1.018358 | 0.999999 | 0.1317 | 0.995681 | Healthy |
| 5 | 0 | 0.384341 | 0.460434 | 0.839446 | 0.175624 | 0.243427 | 1.029895 | 0.999998 | 0 | 0.013005 | Deficient |
| 6 | 0.6186 | 52.311424 | 4.713519 | 6.53212 | 2.331838 | 0.701429 | 1.074242 | 0.999994 | 0.1317 | 0.995827 | Healthy |
| 7 | 0.86 | 0.37545 | 1.30688 | 0.69604 | 0.72442 | 0.158182 | 1.01904 | 0.99999 | 0.1317 | 0.99568 | Healthy |
| 8 | 0 | 0.38434 | 0.46043 | 0.83944 | 0.17562 | 0.243427 | 1.02989 | 0.99999 | 0 | 0.01300 | Deficient |
| 9 | 0 | 0.38434 | 0.46043 | 0.83944 | 0.17562 | 0.243427 | 1.02989 | 0.99999 | 0 | 0.01300 | Deficient |
| 10 | 0.8191 | 35.9564 | 3.22899 | 2.16974 | 0.65094 | 0.041191 | 1.00681 | 0.99999 | 0.1317 | 0.99568 | Healthy |

## 6. CONCLUSION

The hold-out validation based prediction is observed to be better compared to cross-validation 5 fold and no validation methods as shown in Table 4. It is also observed that Holdout validation consumes less time of only 4.0604 sec compared to cross-validation 5 fold and no validation approach. The accuracy is also highest in the case of the Hold-out method *i.e.* 85.3% that is higher than the other two methods 66.7% and 70.1% for cross-validation 5 fold and no validation respectively. The hold-out validation computes the accuracy score employing the observations in the validation fold and predicts based on these observations. The highest accuracy score estimates the system performance. On the other hand, the deep learning-based proposed system attains the accuracy of 99.30% with the processing time of 3.2 sec. as shown in Table 2. The binary-based classifier uses probability-based prediction. It is further observed that the proposed system consumes less time and more efficient compared to other existing methods. In the ROC curve, a right angle is observed that demonstrates the perfect result with no misclassified points. The best overall score might not be the best system all the time.

There are certain factors that need to be considered while selecting predictors. The expensive or difficult data collection might be the cause of the exclusion of some predictors. In future, the system may be trained with the pre-trained network. As in absence of pre-trained network, the size of dataset increases rapidly for better accuracy but with the cost of time. Use of pre-trained system minimizes the data size and also reduces the processing time.

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**Yogesh** received the B.Tech. degree in Electronics and Communication Engineering from M.A.C.E.T. Patna, Bihar, India in 2007 and M.Tech. degree in Electronics and Communication Engineering from Amity University, Noida, Uttar Pradesh, India in 2013. He is currently pursuing the Ph.D. degree in the Department of Electronic and Communication Engineering, Amity School of Engineering and Technology, Amity University Uttar Pradesh, Noida, Uttar Pradesh, India. His current research interests include digital image processing and computer vision.

**Ashwani Kumar Dubey** received the M.Tech. degree in Instrumentation and Control Engineering from Maharshi Dayanand University, Rohtak, India, in 2007, and the Ph.D. degree from the Department Electrical Engineering, Faculty of Engineering and Technology, Jamia Millia Islamia (A Central Govt. University), New Delhi, India, in 2014. He is currently an Associate Professor with the Department of Electronics and Communication Engineering, Amity School of Engineering and Technology, Amity University, Noida, UP, India. His research interests include computer vision, image processing, bio-sensors, smart sensors, and wireless sensor networks.

**Rajeev Ratan Arora** received the M.Tech. degree in Instrumentation and Control Engineering from Maharshi Dayanand University, Rohtak, India, in 2007 and the Ph.D. degree from the Department of Electronics and Communication Engineering, Thapar University, Patiala, Punjab in 2014. Presently, he is an Associate Professor with the Department of Electronics and Communication Engineering, MVN University, Palwal, Haryana, India. His research interests include digital signal processing, FPGA design, embedded systems, image processing and biomedical instrumentation.

**Alvora Rocha** holds the title of Honorary Professor, D.Sc. in Information Science and Ph.D. in Information Systems and Technologies. Presently, he is a Professor at the University of Lisbon, President of AISTI (Iberian Association for Information Systems and Technologies), and Chair of IEEE SMC Portugal Section Society Chapter. He has served as Vice-Chair of Experts in the Horizon 2020 of the European Commission, as Expert in the Ministry of Education, University and Research of the Government of Italy, as Expert in the Ministry of Finance of the Government of Latvia, and as expert in the Ministry of Science and Higher Education of the Government of Poland. His main research interests are maturity models, information systems quality, online service quality, intelligent information systems, requirements engineering, software engineering, e-government, e-health, and IT in education.