Enhancing Yam Quality Detection through Computer Vision in IoT and Robotics Applications

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Abstract

This study introduces a comprehensive framework aimed at automating the process of detecting yam tuber quality attributes. This is achieved through the integration of Internet of Things (IoT) devices and robotic systems. The primary focus of the study is the development of specialized computer codes that extract relevant image features and categorize yam tubers into one of three classes: "Good," "Diseased," or "Insect Infected." By employing a variety of machine learning algorithms, including tree algorithms, support vector machines (SVMs), and k-nearest neighbors (KNN), the codes achieved an impressive accuracy of over 90% in effective classification. Furthermore, a robotic algorithm was designed utilizing an artificial neural network (ANN), which exhibited a 92.3% accuracy based on its confusion matrix analysis. The effectiveness and accuracy of the developed codes were substantiated through deployment testing. Although a few instances of misclassification were observed, the overall outcomes indicate significant potential for transforming yam quality assessment and contributing to the realm of precision agriculture. This study is in alignment with prior research endeavors within the field, highlighting the pivotal role of automated and precise quality assessment. The integration of IoT devices and robotic systems in agricultural practices presents exciting possibilities for data-driven decision-making and heightened productivity. By minimizing human intervention and providing real-time insights, the study approach has the potential to optimize yam quality assessment processes. Therefore, this study successfully demonstrates the practical application of IoT and robotic technologies for the purpose of yam quality detection, laying the groundwork for progress in the agricultural sector.

1.0 INTRODUCTION

There are over 600 species of yam. The crop yam belongs to a plant family called “Dioscoreaceae” of a genus described as “Dioscorea L.” (Alexander & Coursey, 1969; Kalloo and Bergh, 1993; Sugihara et 2021; Bazoumana et al., 2022; Ema et al., 2023). There are many postulation of the origin of yam. Nevertheless, archeological facts has pointed toward America, Asia and Africa (Scarcelli et al.,2019; Mendoza et al., 2022; Xiong et al. 2023). A single tuber of yam is reported to contain approximately around 494 kJ (118 kcal) of energy, with different proportion of vitamins, proteins and carbohydrates (Nwafor et al 2020; Li et al., 2023). These qualities are enough for yam to be used by world governments to fight global hunger and attain food security. The global production of yam is over 73 million metric tonnes, being cultivated in roughly 61 countries (Audu et al 2023). The highest exporting nations of yam as a commodity in 2019 were United States, India, Belgium, Japan and Jamaica. Their total export was 50,593.4 tonnes valued at $ 81,321,244 million. Though, the largest producer of yam is Nigeria, accounting for over 70% of the world's production. (Kalloo and Bergh 1993; Saranraj et al. 2019; Kennedy et al 2019; Nabeshima et al 2020; Yam Market Report. 2022; Ema et al., 2023). Yam export volume is low compare to export volume of other tuber crops. This low export volume could be linked to yam export quality control problems. So, the need to examine yam export quality using automated robotic and IoT systems become necessary. Also, consumers do not need to be expert in quality evaluation before selecting good yam to buy when shopping. Again, the need to use IoT mobile apps to detect quality yam when shopping become necessary.

According to Oikonomidis et al., (2022) crop market quality determines its acceptability and sales. Human determination of crop quality is laborious and strenuous. So, there is need to introduce machines and devices to do this job. Çetin (2023) reported that color, size and shape are predominately the parameters used by human and machine to determine crop quality. These parameters help humans to decide purchase decision and machine decision to sort, grade and packaging of agricultural produces. Therefore, for machine to achieve this quality detection decision, computer vision technology is employ.

Though, computer vision is an interdisciplinary field of study. It is mostly use in the field of artificial intelligence. According to Shetty (2022) computer vision is an aspect of artificial intelligence that train and enable computers or computing devices to derive, gain, interpret and understand high-level meaningful data and information from videos, digital images and other visual inputs from visual world. The different types of computer vision include pattern detection, feature matching, image classification, edge detection, image segmentation, object detection, facial recognition, event detection, object detection, scene reconstruction, object recognition, video tracking, 3D pose estimation, motion estimation, 3D scene modeling, visual servoing, image restoration and machine vision (Wang et al 2023; Wu et al 2023; Moore et al., 2023). The final results from computer vision are mostly used to operate IoT (internet of things) apps and robotic devices.

The Internet of things (IoT) is a terminology use for the technological system where sensors with processing ability (software) are embedded into mechanical machines, digital machines, computing devices, objects, animals or people with the ability to connect and interact with the cloud (Internet) to achieve a specific given task or goal (Guo et al., 2021; ORACLE report, 2022; Sadeghi-Niaraki et al., 2023). ORACLE report (2022) estimated that there are about 10 billion connected IoT devices in the world as at 2020 and will exceed to 22 billion by 2025. Climatic change, increasing population, water and food shortage is forcing agriculture to increase its efficiency. Hence, there is need to employ IoT (internet of things) technology to increase this demanding efficiency. Shahbandeh (2018) reported that 52 million agricultural IoT (internet of things) devices were shipped globally in 2016. The report also stated that, 0.8 million agricultural IoT cellular connections were installed globally and this is expected to rise to 3.1 million devices by 2021. Global agriculture IoT market is an emerging market with great potentials. It is estimated that it will grow from USD 11.4 billion in 2021 to USD 18.1 billion by 2026 at a CAGR (compound annual growth rate) of 9.8%. Another emerging market is the agricultural robotics market.

Robotics is the combination of science, technology and engineering to develop autonomous or semi autonomous machines (robots) that perform tasks that human can do. There are five types of robots which are pre-programmed robots, humanoid robots, autonomous robots, teleoperated robots and augmenting robots (Ravichandar et al., 2020; Semeraro et al., 2023). According to Zion market research report (2022) global industrial market was worth around $ 41.7 billion in 2021. This is estimated to grow to about $ 81.4 billion by 2028. This is also expected to be with a compound annual growth rate (CAGR) of approximately 11.8 percent over the forecast period. Market research future report (2022) reported that the global robotics market size to be over $ 214.68 billion by 2030, Growing at a CAGR of 22.8%. This is a hung market that agriculture needs to tap into. Presently, the market survey by BlueWeave report (2022) show that, global agricultural Robots Market will surpass $81 Billion by 2028, at a CAGR of 9.9% during the forecast period. The use of robots in agriculture has become necessary due to the increase in world food demand. This study only reviews researches done on tuber crops or tuber like crops using computer vision technology. This is because of the scarcity of literature on computer vision application on yam tubers.

Though, many researchers had used computer vision technology to perform many agricultural task and operations. This study review, only concentrated on quality detection of tuber crops or tuber like crops. Tuhaise et al. (2014), Ninsiima et al. (2018) and Tusubira et al. (2020) all used computer vision technology and machine learning algorithms to detect and classified brown streak disease (CBSD) in cassava tubers from healthy tubers. Ninsiima et al. (2018) used their study result to develop mobile phone detection application software with an accuracy of detection of 52%. On the other hand, Tuhaise et al. (2014) and Tusubira et al. (2020) developed cassava disease classification models with their study results and obtained classifier performer's best of 0.7 and 0.9 respectively. Research on potatoes using computer vision technology was carried out by Go¨kmen et al. (2007), Tian et al. (2016), Oppenheim et al. (2019), Ropelewska (2021), Korchagin et al. (2021) and Dolata et al. (2021). Tian et al. (2016), Oppenheim et al. (2019) and Korchagin et al. 2021 detected and classified diseased potatoes from healthy potatoes using machine vision camera that capture images, then with machine learning algorithms the study achieved accuracy of detection ranging from 80–97%. Go¨kmen et al.(2007) and Ropelewska (2021) studied the effect of acrylamide concentrations and boiling respectively of slice potatoes chips using computer vision image processing technique with machine learning algorithms. These studies show accuracy success range of 80–100%. Dolata et al. (2021) developed a simulation-based learning using computer vision technology for detecting root crop physical dimensions. The study used potatoes tubers as samples and then used deep learning to develop a monitoring system that can estimate physical dimensions of root crops directly on-line. Molto and Harrell (1993) and Yimyam (2019) used computer vision technology with machine learning algorithms, to separate embryo morphology in sweet potatoes harvesting machine and then analyzing and grading sweet potatoes tuber by sizes of their quality respectively. These studies detection accuracies for sweet potatoes range from 75 to 97%. Sugar beet tuber damage computer vision detection systems for sugar beet harvesting machine was developed and evaluated by Nasirahmadi et al. (2021) and Osipov et al. (2022). These studies used video camera images mounted on a sugar beet harvester to detect damaged sugar beets during harvesting with an accuracy range of 86 to 99%. Deng et al. (2017) and Örnek & Hacısefero˘gulları (2020) used computer vision to detect surface crack, fibrous root, misshapen, surface defects, sizes of carrots and foreign objects during processing. These two studies used real time video camera programmed with OpenCV and open source codes to develop and evaluate computer vision system for carrot sorting and grading. The accuracies for these openCV systems range from 80 to 100%. Dorokhov et al. (2021) and Nafi'iyah et al. (2020) used computer vision system to detect qualities of more than one tuber crops at a time. Nafi'iyah et al. (2020) used this technology to develop two models for detecting sweet potatoes and cassava tubers, with accuracies of 97 and 93% respectively. Dorokhov et al. (2021) also used this technology to detect the external damages and removal of impurities in onions and potatoes automated Sorting System, with overall accuracy of 91%. Little or no studies had been carried out on yam tuber quality detection using computer vision technology. Nevertheless, Zhaoyuxi et al. (2014) used a single-chip microcomputer control using a length measuring photoelectric sensors and weight measuring sensor to automatically control yams picking on a conveyor belt for packaging. Ayodeji et al. (2015) developed control system for a poundo yam flour processing plant. The control system was not a computer vision system but uses a micro processor programmed with C + + programming language to control the electric motors, electric heaters and fans in the processing plant. This control system increases the efficiency of the plant from 73.4–84.90%. So, due to lack of information in computer vision recognition system in yam tuber processing, this study developed a computer vision recognition system of yam quality detection for deployment into IoT and robotic devices.

2.0 MATERIALS AND METHODS

2.1 Sample collection

Yam tuber samples used in this study were white yam (*Dioscorea rotundata*). Some samples were purchase from Zaki-biam yam market in Benue State Nigeria. The other samples were sourced from local farms in Benue state Nigeria. Samples were taken for physical identification, in the department of crop production at the Joseph Sarwuan Tarkaa University, Makurdi, Nigeria (Formally, Federal University of Agriculture, Makurdi, Nigeria). During physical identification the samples were grouped into Good yams, diseased yams and insect infected yams. Figure 1 show a typical pictures of the samples used for this study.

2.2 Image acquisition

Pictures of 100 good yams, 100 diseased yams and 100 insect infected yams were taken, with a digital camera (Samsung NX1) on white background. Total number of images acquired was 300 images. These images were transferred into personal computer for features extractions.

2.3 Image feature extraction

MATLAB software was used for features extractions. Features considered for extraction were red, green, blue, gray scale, width and height, all in pixel measurement units. The command codes used for extracting red, blue, green, gray scale, height and width is shown in Fig. 2. The extraction of the yam height and width was done directly on the colour histogram plotted (sub plot) by the commands codes that extract the gray scale feature.

2.4 Development of yam tuber detection codes for deployment to IoT devices

The codes for the yam tuber detection for IoT devices was developed using MATLAB software programing language. The ‘Classification learner’ GUI (graphic User Interface) was used to train 22 machine learning algorithms. Then, the five best algorithms classification with the highest accuracies were used to develop three separate codes for deployment into IoT devices. Receiver Operating Characteristic (ROC) Curve, 6D (six dimensions) parallel coordinate plot and confusion matrix were used to test and display the strength of the classification. Separate data sets that were not used for developing the codes were then used to test the deployed codes.

2.5 Development of yam tuber detection codes for deployment to robotic devices

The codes for the yam tuber detection for robotic devices was developed using MATLAB software programing language. The ‘Neural network pattern recognition app’ was used to train neural network algorithm. The developed neural network architecture consisted of 6 input layers, 10 hidden layers and 3 output layers. This network architecture was used to develop the codes for deployment into robotic devices. Receiver Operating Characteristic (ROC) Curve, cross - entropy validation performance plot, training state gradient/validation fail plot, error histogram plot and confusion matrix were used to test and display the strength of the classification. Separate data sets that were not used for developing the codes were then used to test the deployed codes.

3.0 RESULT AND DISCUSSION

3.1 Image feature extraction

The purpose of this study was to improve the detection of yam quality using computer vision in the context of Internet of Things (IoT) and robotics applications. To achieve this goal, the study utilized computer vision techniques to analyze and develop computer codes for deployment using various features from images of yams. These features were then used to categorize the yams into different quality classes.

The extracted features for the yam images, along with their corresponding quality classes, are presented in Table S1 (included as a supplementary document). These features include the Red, Green, Blue, and Grey scale pixel values, as well as the width and height of the yam images.

The study found that yams classified as "Good" had higher pixel values for Red, Green, Blue, and Grey scale compared to those classified as "Diseased" or "Insect Infected." This suggests that healthy yams tend to have more intense coloration and higher grey scale values, while yams with diseases or insect infestations have lower pixel values, indicating a loss of color intensity.

Moreover, the research observed that the width and height of the yam images for the "Good" quality class were generally larger than those of the "Diseased" and "Insect Infected" classes. This finding suggests that larger yams are more likely to be of better quality, while smaller yams may be more susceptible to diseases or insect attacks.

Additionally, during the analysis of the extracted features, it was noticed that there is some overlap in the feature values between the different quality classes, which could lead to misclassifications. This underscores the significance of refining the classification algorithm further and including more diverse and informative features to enhance accuracy.

3.2 Development of yam tuber detection codes for deployment to IoT devices

3.2.1 Machine Learning Algorithm Selection

. In this section, the research presents the results of evaluating different machine learning algorithms to develop yam tuber detection codes for IoT devices. Now, each algorithm's performance was assessed based on accuracy, prediction speed, training time, and the use of Principal Component Analysis (PCA) for dimensionality reduction.

Table 1 displays the test results for various machine learning algorithms, their respective classifier algorithm settings, and the performance metrics obtained during evaluation.

The study evaluated decision trees, linear discriminant analysis, quadratic discriminant analysis, support vector machines (SVM), kernel nearest neighbor (KNN), boosted trees, subspace discriminant, and RUSBoosted trees. Each algorithm underwent specific settings and parameter tests to determine its suitability for yam tuber detection.

Among the decision tree algorithms, the "Simple Tree" achieved the highest accuracy of 96.7%, closely followed by the "Complex Tree" and "Medium Tree" with 95% accuracy. Decision trees showed computational efficiency, with prediction speeds ranging from 1300 to 2000 observations per second. The training times for decision trees were relatively low, with the "Simple Tree" requiring only 1.065 seconds.

Linear discriminant analysis and quadratic discriminant analysis both demonstrated an accuracy of 95%, showing their effectiveness in yam tuber detection. However, linear discriminant analysis performed better in terms of prediction speed, requiring only 720 observations per second, while quadratic discriminant analysis achieved 1300 observations per second.

The study also evaluated support vector machines (SVM) with different kernel functions. The "Medium Gaussian SVM" and "Linear SVM" achieved the highest accuracy of 96.7%, while other SVM variants achieved accuracies ranging from 83.3% to 95%. The "Medium Gaussian SVM" demonstrated the fastest prediction speed, processing 1700 observations per second. The training times for SVM algorithms were relatively low, with the "Medium Gaussian SVM" requiring only 0.776 seconds.

Kernel nearest neighbor (KNN) algorithms were tested with different distance metrics. The "Cubic KNN" outperformed other KNN variants, achieving an accuracy of 96.7%. The "Medium KNN" followed closely with an accuracy of 96.7%. KNN algorithms generally showed fast prediction speeds, with the "Medium KNN" processing 1700 observations per second. The training times for KNN were also low, with the "Medium KNN" requiring only 0.661 seconds.

Boosted trees, bagged trees, subspace discriminant, and RUSBoosted trees achieved accuracies of 93% to 95%, showcasing their effectiveness for yam tuber detection. Boosted trees demonstrated relatively fast prediction speeds and training times, making them suitable candidates for deployment on IoT devices.

Additionally, Principal Component Analysis (PCA) was used to reduce the dimensionality of the feature space. PCA effectively preserved essential variance while reducing computational complexity. Notably, PCA with the "Simple Tree" algorithm resulted in a slightly reduced accuracy of 95% compared to the original 96.7%, indicating a minimal loss of information during the dimensionality reduction process.

The evaluation of different machine learning algorithms for yam tuber detection revealed several viable options with high accuracy and fast processing speeds. The Simple Tree, Linear SVM, Medium Gaussian SVM, Medium KNN, and Cubic KNN achieved the highest accuracy of 96.7%. Also, the use of Principal Component Analysis (PCA) proved beneficial in reducing dimensionality without significant loss of accuracy. These findings provide a foundation for developing efficient and accurate yam tuber detection codes suitable for IoT devices with limited resources. This will enable real-time quality assessment and enhance overall productivity in the yam industry.

Several studies have explored the use of machine learning algorithms for detecting and classifying tubers. For instance, a study on intelligent determination of potato and sweet potato quality using imaging spectroscopy and machine learning found that the Random Forest algorithm achieved the highest accuracy of 96.7% (Su & Xue, 2021). Another study on predicting end-of-season tuber yield and tuber set in potatoes using UAV-based hyperspectral imagery and machine learning found that the Random Forest algorithm achieved an accuracy of 91.9% (Sun et al. 2020). These results are comparable to our yam tuber detection study, which found that the Simple Tree, Linear SVM, Medium Gaussian SVM, Medium KNN, and Cubic KNN achieved the highest accuracy of 96.7%. The use of Principal Component Analysis (PCA) for dimensionality reduction was also found to be effective in both studies, reducing computational complexity without significant loss of accuracy (Sun et al. 2020; Su & Xue, 2021; Audu et al., 2023).

Table 1: Test for different machine learning algorithms performance

S/N	Machine learning Algorithm	Classifier Algorithm Setting	Accuracy (%)	Prediction speed (obs/sec)	Training Time (secs)	Principal component Analysis (PCA)
1	Complex Tree	Gini's diversity index	95.000	750	10.608	PCA is keeping enough components to explain 95% variance.
2	Medium Tree	Gini's diversity index	95.000	1300	1.248	
3	**Simple Tree**	**Gini's diversity index**	**96.700**	**2000**	**1.065**	
4	Linear Discriminant	Diagonal covariance	95.000	720	2.066	
5	Quadratic Discriminant	Diagonal covariance	95.000	1300	1.182	
6	***Linear SVM**	**Kernel function**	**96.700**	**360**	**5.722**	
7	Quadratic SVM	Kernel function	95.000	1300	1.295	
8	Cubic SVM	Kernel function	83.300	1600	9.509	
9	Fine Gaussian SVM	Kernel function	95.000	1800	0.919	
10	***Medium Gaussian SVM**	**Kernel function**	**96.700**	**1700**	**0.776**	
11	Coarse Gaussian SVM	Kernel function	93.300	1800	0.769	
12	Fine KNN	Euclidean distance	93.300	1200	1.378	
13	***Medium KNN**	**Euclidean distance**	**96.700**	**1700**	**0.661**	
14	Coarse KNN	Euclidean distance	95.000	2000	0.726	
15	Cosine KNN	Cosine distance	66.700	1800	0.758	
16	***Cubic KNN**	**Minkowski (cubic) diatance**	**96.700**	**1900**	**0.680**	
17	Weighted KNN	Euclidean distance	93.000	2100	0.562	
18	Boosted Trees	AdaBoost	93.000	480	4.277	
19	Bagged Trees	Bag	93.000	500	2.903	
20	Subspace Discriminant	Subspace dimension	95.000	440	3.326	
21	Subspace KNN	Subspace dimension	93.000	240	2.525	
22	RUSBoosted Trees	RUSBoost	95.000	540	2.897	

*highest accuracy, SVM = Support Vector Machine, KNN = Kernel Nearest Neighbor, Tree = Decision Tree

3.2.2 Training, Testing and Validation of the Chosen Algorithms

The performance of the selected machine learning algorithms was discussed based on “Receiver Operating Characteristic” (ROC) curve analyses (Table 2). The study evaluated the ROC curve parameters, which include “True Positive Rate” (TPR), “False Positive Rate” (FPR), and “Area Under the Curve” (AUC), for each algorithm across three different yam quality classes: good, diseased, and insect infected. A typical “Receiver Operating Characteristic” (ROC) Curve plot is displayed in Figure 1. The (ROC) Curve plot for the selected machine learning algorithms are displayed in figure S1 (included as a supplementary document)

Simple Tree: The ROC curve analysis for the Simple Tree algorithm showed excellent performance across all yam quality classes. It achieved a TPR of 1 (100% sensitivity) for identifying good, diseased, and insect infected yams. The FPR was very low, indicating high specificity for identifying true negatives. The AUC values were also exceptional, with AUCs of 0.99 for good and diseased yams and 0.95 for insect infected yams. These results demonstrate that the Simple Tree algorithm is robust and accurate in classifying yam quality.

Linear SVM: The ROC curve analysis for the linear SVM algorithm exhibited a TPR of 1 for identifying good yams and 0.95 for diseased and insect infected yams. The FPR for identifying diseased and insect infected yams was very low, while it was slightly higher at 0.03 for good yams. The AUC values were high, with AUCs of 0.99 for good and insect infected yams and a perfect AUC of 1 for diseased yams. These results indicate that the linear SVM algorithm is effective in distinguishing diseased yams from other classes.

Medium Gaussian SVM: The ROC curve analysis for the "Medium Gaussian SVM" algorithm demonstrated a TPR of 1 for identifying good yams and 0.95 for diseased and insect infected yams. Similar to "Linear SVM", the FPR for identifying diseased and insect infected yams was low, with a slightly higher value of 0.03 for good yams. The AUC values were excellent, with a perfect AUC of 1 for good yams, 1 for diseased yams, and 0.99 for insect infected yams. These findings indicate that the "Medium Gaussian SVM" algorithm has high accuracy and reliability in classifying yam quality.

Medium KNN: The ROC curve analysis for the "Medium KNN" algorithm achieved a TPR of 1 for identifying good and diseased yams and 0.9 for insect infected yams. The FPR was very low for all three classes, indicating excellent specificity. The AUC values were high, with AUCs of 0.99 for good and insect infected yams and 0.98 for diseased yams. This indicates that the "Medium KNN" algorithm exhibits strong performance in classifying yam quality.

Cubic KNN: The ROC curve analysis for the "Cubic KNN" algorithm displayed a TPR of 1 for identifying good and diseased yams and 0.9 for insect infected yams. Similar to "Medium KNN", the FPR was very low across all classes. The AUC values were high, with AUCs of 0.99 for good and insect infected yams and 0.98 for diseased yams. These results illustrate the effectiveness of the Cubic KNN algorithm in yam quality classification.

The selected machine learning algorithms, including the "Simple Tree", "Linear SVM", "Medium Gaussian SVM", "Medium KNN", and "Cubic KNN", all exhibited strong performance in classifying yam quality based on the ROC curve analyses. These algorithms demonstrated high sensitivity and specificity, as reflected in their TPR and FPR values. Also, the AUC values indicated the algorithms' ability to discriminate between the different yam quality classes. These findings validate the suitability of these algorithms for yam quality assessment, paving the way for their deployment on IoT devices to facilitate real-time and accurate yam tuber detection and sorting in the agricultural industry (Sun et al. 2020; Su & Xue, 2021; Khazaee et al., 2022; Nakatumba-Nabende et al., 2023; Audu et al., 2023).

Table 2: The Receiver Operating Characteristic (ROC) Curve Performances for the chosen algorithms

Selected Machine learning Algorithm	**Receiver Operating Characteristic (ROC) Curve Parameter**	**Yam Quality**		
		Good	**Diseased**	**Insect infected**
Simple Tree	True positive rate	1	1	0.9
	False positive rate	0.03	0.03	0
	Area Under Curve (AUC)	0.99	0.99	0.95
Linear SVM	True positive rate	1	0.95	0.95
	False positive rate	0.03	0	0.03
	Area Under Curve (AUC)	0.99	1	0.99
Medium Gaussian SVM	True positive rate	1	0.95	0.95
	False positive rate	0.03	0	0.03
	Area Under Curve (AUC)	1	1	0.99
Medium KNN	True positive rate	1	1	0.9
	False positive rate	0.03	0.03	0
	Area Under Curve (AUC)	0.99	1	0.98
Cubic KNN	True positive rate	1	1	0.9
	False positive rate	0.03	0.03	0
	Area Under Curve (AUC)	0.99	1	0.98

SVM = Support Vector Machine, KNN = Kernel Nearest Neighbor, Tree = Decision Tree

Parallel coordinates plot analysis was also used for the visualizations analysis of the multivariate numerical data of the image features extracted. A 6D parallel coordinates plot for the six image extracted features was plotted for selected algorithms. This plots are displayed in Figure S2 (included as a supplementary document). Nevertheless, a typical 6D parallel coordinates plot for image extracted features of different scaling conditions is displayed in Figure 2. The plots show similar behaviours for all the chosen algorithms plotted. This behaviour also changes similarly when the scaling conditions changes from normalization to standardization. The parallel coordinates plots show that there is a big different between the pixel's amount in red, blue, green, grayscale features to that of the size and width features. So, normalizing or standardizing the features scale equalize these features for better output.

3.2.3 Yam quality classification Performance of the chosen algorithms for IoT application

The summary result of the performance evaluation of the selected machine learning algorithms for yam quality classification based on the confusion matrix analysis is presented in Table 3. The complete result of the performance evaluation confusion matrix plots are shown in Figure S3 (included as a supplementary document). The confusion matrix provides valuable insights into the algorithms' classification accuracy by considering the number of observations, correctly classified samples, wrongly classified samples, true positive rate (sensitivity), false negative rate, positive predictive value, and false discovery rate. The evaluation was conducted for three yam quality classes: good, diseased, and insect infected.

Table 3: Confusion matrix classification for the chosen algorithms

Selected Machine learning Algorithm	Validation Parameter considered	Yam Quality		
		Good	Diseased	Insect infected
Simple Tree	No of Observation	20	20	20
	Correctly Classified as	20	20	18
	Wrongly Classified as	1	1	0
	True positive rate (%)	100	100	90
	False negative rate (%)	0	0	10
	Positive predictive value (%)	95	95	100
	False discovery rate (%)	5	5	0
Linear SVM	No of Observation	20	20	20
	Correctly Classified as	20	19	19
	Wrongly Classified as	1	0	1
	True positive rate (%)	100	95	95
	False negative rate (%)	0	5	5
	Positive predictive value (%)	95	100	95
	False discovery rate (%)	5	0	5
Medium Gaussian SVM	No of Observation	20	20	20
	Correctly Classified as	20	19	19
	Wrongly Classified as	1	0	1
	True positive rate (%)	100	95	95
	False negative rate (%)	0	5	5
	Positive predictive value (%)	95	100	95
	False discovery rate (%)	5	0	5
Medium KNN	No of Observation	20	20	20
	Correctly Classified as	20	20	18
	Wrongly Classified as	1	1	0
	True positive rate (%)	100	100	90
	False negative rate (%)	0	0	10
	Positive predictive value (%)	95	95	100
	False discovery rate (%)	5	5	0
Cubic KNN	No of Observation	20	20	20
	Correctly Classified as	20	20	18
	Wrongly Classified as	1	1	0
	True positive rate (%)	100	100	90
	False negative rate (%)	0	0	10
	Positive predictive value (%)	95	95	100
	False discovery rate (%)	5	5	0

Simple Tree: The “Simple Tree” algorithm achieved impressive results in Yam quality classification. Out of 20 observations for each class, it correctly classified all 20 instances of good and diseased yams, achieving a true positive rate of 100% for both classes. For insect infected yams, the algorithm achieved a true positive rate of 90%, correctly identifying 18 out of 20 samples. The false negative rate for all three classes was 0%, indicating that no instances were wrongly classified as negative. The positive predictive value was high, with 95% for Good and diseased yams and 100% for Insect infected yams. The false discovery rate was low, with only 5% for good and diseased yams and 0% for Insect infected yams. These results highlight the Simple Tree's robustness and accuracy in yam quality classification.

Linear SVM: The “Linear SVM” algorithm demonstrated excellent performance in yam quality classification. For good yams, all 20 observations were correctly classified, resulting in a true positive rate of 100%. For diseased yams, 19 out of 20 observations were correctly classified, leading to a true positive rate of 95%. Similarly, for insect infected yams, 19 out of 20 observations were correctly classified, resulting in a true positive rate of 95%. The false negative rate was low, with 0% for diseased and insect infected yams and 5% for Good yams. The positive predictive value was high, with 95% for good and diseased yams and 100% for insect infected yams. The false discovery rate was 5% for good and diseased yams and 0% for Insect infected yams. These results indicate the Linear SVM's effectiveness in distinguishing between different yam quality classes.

Medium Gaussian SVM: The “Medium Gaussian SVM” algorithm exhibited performance similar to “Linear SVM” in yam quality classification. It correctly classified all 20 observations of good yams, resulting in a true positive rate of 100%. For diseased and insect infected yams, 19 out of 20 observations were correctly classified, leading to a true positive rate of 95% for both classes. The false negative rate was 0% for diseased and insect infected yams and 5% for good yams. The positive predictive value was high, with 95% for good and diseased yams and 100% for insect infected yams. The false discovery rate was 5% for good and diseased yams and 0% for insect infected yams. These findings demonstrate the Medium Gaussian SVM's accuracy and reliability in yam quality classification.

Medium KNN: The “Medium KNN” algorithm performed well in Yam quality classification. It correctly classified all 20 observations of good yams, achieving a true positive rate of 100%. For diseased yams, all 20 observations were correctly classified, resulting in a true positive rate of 100%. However, for insect infected yams, the algorithm achieved a true positive rate of 90%, correctly identifying 18 out of 20 samples. The false negative rate was 0% for Good and diseased yams and 10% for insect infected yams. The positive predictive value was high, with 95% for good and diseased yams and 100% for insect infected yams. The false discovery rate was 5% for good and diseased yams and 0% for Insect infected yams. These results illustrate the Medium KNN's effectiveness in Yam quality classification.

Cubic KNN: The “Cubic KNN” algorithm demonstrated performance similar to “Medium KNN” in yam quality classification. It correctly classified all 20 observations of good and diseased yams, resulting in a true positive rate of 100% for both classes. For insect infected yams, the algorithm achieved a true positive rate of 90%, correctly identifying 18 out of 20 samples. The false negative rate was 0% for good and diseased yams and 10% for insect infected yams. The positive predictive value was high, with 95% for good and diseased yams and 100% for insect infected yams. The false discovery rate was 5% for good and diseased yams and 0% for insect infected yams. These findings underscore the Cubic KNN's effectiveness in Yam quality classification.

The selected machine learning algorithms, all demonstrated strong Yam quality classification performance. The algorithms achieved high true positive rates and positive predictive values while maintaining low false negative rates and false discovery rates (Zawbaa et al., 2014; Fakir et al., 2020; Sun et al. 2020; Su & Xue, 2021; Nakatumba-Nabende et al., 2023; Audu et al., 2023). These results are comparable to those of other studies that have explored the use of machine learning algorithms for the classification and quality assessment of tubers, such as Irish potatoes, sweet potatoes and yams (Sun et al. 2020; Nakatumba-Nabende et al., 2023; Audu et al., 2023). These results validate the suitability of these algorithms for accurate and reliable yam tuber quality assessment, making them viable candidates for deployment on IoT devices in the agricultural industry.

3.2.3 Developed computer codes from the chosen algorithms for deployment into IoT devices

Five separate computer codes were written for deployment into IoT devices. These codes are named $C_{IoT}1$, $C_{IoT}2$, $C_{IoT}3$, $C_{IoT}4$, $C_{IoT}5$ for Simple Tree, Linear SVM, Medium Gaussian SVM, Medium KNN, Cubic KNN algorithms respectively. These written codes are included and submitted as a supplementary document.

i. $C_{IoT}1$: Developed code using Simple Tree Algorithms

$C_{IoT}1$the computer code for training and deploying the “Simple Tree” algorithm, which has achieved impressive results in Yam quality classification, into IoT devices. The provided code is essential for recreating the classification model trained in the Classification Learner app. It consists of various functions and options that can be utilized to make predictions on new data. Additionally, the code allows for the retraining of the classifier with new data to adapt to evolving scenarios.

The developed code follows a modular structure and contains essential functionalities for data processing, feature extraction using Principal Component Analysis (PCA), training the classifier, and making predictions. The developed computer code enables the deployment of the Simple Tree algorithm, along with PCA, into IoT devices for Yam quality classification. It facilitates real-time predictions on new data and allows for potential retraining with updated datasets to maintain accuracy in dynamic environments. As IoT devices become increasingly prevalent in agriculture, the integration of this code can contribute to more efficient and accurate yam tuber quality assessment, benefiting farmers and stakeholders in the industry.

ii. $C_{IoT}2$: Developed code using Linear SVM (Support Vector Machine) Algorithm

The $C_{IoT}2$ computer code for training and deploying the “Linear Support Vector Machine” (SVM) algorithm, has demonstrated promising results in Yam quality classification. The provided code is essential for replicating the classification model trained in the “Classification Learner app” and enables the prediction of Yam quality classes on new data. Moreover, the code allows for retraining the classifier with updated datasets and is equipped with functionalities for automated deployment into IoT devices.

The developed code follows a modular structure and consists of several functions and options required for classifier training and predictions. This computer code facilitates the deployment of the Linear SVM algorithm, along with PCA, into IoT devices for yam quality classification. The code allows for real-time predictions on new data and potential retraining with updated datasets to maintain accuracy in dynamic environments.

iii. $C_{IoT}3$: Developed code using Medium Gaussian SVM (Support Vector Machine) Algorithm

The $C_{IoT}3$ is the computer code for training and deploying the “Medium Gaussian Support Vector Machine” (SVM) algorithm. The provided code facilitates the development of an accurate Yam quality classification model with a Gaussian kernel, making it suitable for deployment into IoT devices for real-time yam tuber quality assessment. This provided computer code offers a practical implementation of the “Medium Gaussian SVM” algorithm for yam quality classification. By deploying this code into IoT devices, farmers and stakeholders in the agricultural industry can benefit from efficient and accurate real-time assessment of yam tuber quality. The integration of multiple algorithms, including the previously discussed ‘Linear SVM: and “Simple Tree” algorithms, alongside this “Medium Gaussian” SVM, contributes to a robust and versatile classification system for addressing diverse challenges in yam farming and production.

iv. $C_{IoT}4$: Developed code using Medium KNN (Kernel Nearest Neighbor) Algorithm

The $C_{IoT}4$ is the computer code for training and deploying the “Medium KNN (Kernel Nearest Neighbor)” algorithm. This code enables the development of an efficient and accurate Yam quality classification model, making it suitable for deployment into IoT devices for real-time yam tuber quality assessment. The provided computer code offers a practical implementation of the “Medium KNN” algorithm for Yam quality classification. The deployment of this code into IoT devices empowers farmers and stakeholders in the agricultural industry with real-time and reliable yam tuber quality assessment capabilities. By integrating multiple algorithms, including the previously discussed “Linear SVM”, “Simple Tree”, and “Medium Gaussian SVM” algorithms, this “Medium KNN” classifier contributes to a comprehensive and versatile classification system to address diverse challenges in yam farming and production.

v. $C_{IoT}5$: Developed code using Cubic KNN (Kernel Nearest Neighbor) Algorithm

The $C_{IoT}5$ is the computer code for training and deploying the “Cubic KNN (Kernel Nearest Neighbor)” algorithm. This code facilitates the creation of an accurate and efficient Yam quality classification model, suitable for integration into IoT devices for real-time yam tuber quality assessment. This computer code offers a practical implementation of the “Cubic KNN” algorithm for yam quality classification. Integration of this code into IoT devices empowers stakeholders in the agricultural industry with real-time and reliable yam tuber quality assessment capabilities. Through the development and deployment of multiple algorithms, including “Linear SVM”, “Simple Tree”, “Medium Gaussian SVM”, “Medium KNN”, and “Cubic KNN”, this comprehensive classification system effectively addresses the diverse challenges faced in yam farming and production. The availability of such advanced and versatile classification tools is poised to revolutionize the yam farming landscape, leading to increased efficiency, enhanced productivity, and sustainable agricultural practices.

3.3 Development of yam tuber detection code for deployment to robotic devices

3.3.1 Artificial Neural Network Architecture

The development of a yam tuber detection code using the NNTOOL in MATLAB software was achieved using the artificial neural network algorithm. The code utilizes a neural network architecture with specific layers and features to achieve accurate and efficient detection of yam tubers, suitable for deployment to robotic devices.

The network architecture was a multi-layer perceptron (MLP) neural network, consisting of an input layer which takes six features (red pixels, green pixels, blue pixels, grayscale pixel, width pixels, and height pixels), 10 hidden layers for transforming features higher level output, and an output layer, which consist of 3 class of output (diseased, good, and insect infected) as shown in Figure 3. The activation functions used by the network include ReLU for hidden layers and Softmax for the output layer. The training and learning process of the network was achieved using the back propagation algorithm.

3.3.2 Artificial Neural Network Training, Testing and Validation Performance

The evaluation of the artificial neural network's performance when deployed for detecting yam quality in robotic devices has revealed compelling findings. The developed neural network demonstrates its capability to accurately assess yam quality, achieving an error rate of less than 10%. To visually track the network's learning progress, the study graphed the cross-entropy, a measure of prediction error, against the number of training epochs. Figure 4 illustrates how the loss function (cross-entropy) consistently decreases during training, testing, and validation phases as the number of epochs increases.

Throughout the comprehensive process of training, testing, and validation, spanning 13 epochs, a significant milestone emerged at the seventh epoch. Specifically, the cross-entropy during training and testing dropped below 0.11239, indicating a substantial enhancement in prediction accuracy. This pivotal moment aligns with the neural network's improved ability to differentiate yam quality attributes. These performance results the network is further amplified and displayed by the training state plot in Figure 5, error histogram plot in Figure 6 and receiver operating characteristic (ROC) Curve plot in Figure 7.

Interestingly, similar investigations conducted by Ehounou et al. (2021) and Audu et al. (2023) have pursued analogous paths in their pursuit of detecting yam tuber quality. Despite employing distinct methodologies, these studies also shared the common goal of evaluating yam quality. The convergence of training outcomes in these studies underscores the effectiveness of the neural network approach in discerning yam quality.

In a broader view of neural network performance, the research contributions of Yamashita et al. (1918), Chen et al. (2020), and Alzubaidi et al. (2021) provide valuable insights into optimizing and enhancing neural networks for various applications. The findings from this study align with the collective body of research exploring yam quality detection through different methodologies or trained neural network algorithms.

Therefore, the evaluation of the artificial neural network's performance in yam quality detection for integration into robotic devices highlights its potential to transform agricultural practices. The network's ability to reduce prediction errors validates its role in improving the accuracy and efficiency of yam tuber classification. Supported by parallel studies and consistent with established research trends, this study contributes to the broader field of yam quality detection and emphasizes the importance of neural network-driven solutions in modern agriculture.

3.3.4 Artificial Neural Network Identification and Classification Performance

The assessment of classification performance through the confusion matrix displayed in Figures 8 offers a comprehensive evaluation of the effectiveness of the developed robotic code for yam tuber detection. The confusion matrix is a valuable tool for quantifying the accuracy and dependability of the classification model throughout its deployment stages. In this context, the confusion matrix provides insights into the model's performance by considering key metrics such as accuracy, precision, recall, and F1-score.

Here are the results from the training, validation, and testing phases:

Training Overall Result: 94.8%; Validation Overall Result: 88.9%; Test Overall Result: 84.4% considering the combined performance from all the confusion matrices, an impressive overall accuracy of 92.3% is achieved. This indicates the robotic code's strong ability to accurately identify and classify yam tuber quality attributes.

Training Phase: During the training phase, an outstanding overall accuracy of 94.8% was achieved. This signifies the model's capacity to effectively learn and adapt to underlying patterns within the dataset. The confusion matrix for the training phase provides a visual representation of predicted and actual classes, demonstrating a robust alignment between the model's predictions and the actual data.

Validation Phase: In the validation phase, the overall accuracy was 88.9%. This phase assesses the model's performance on new, unseen data. The generated confusion matrix sheds light on the model's ability to generalize its learning. Although slightly lower than the training accuracy, the validation performance remains strong, indicating the model's capability to apply learned patterns to new data.

Test Phase: During the test phase, the overall accuracy reached 84.4%. This phase simulates real-world scenarios and tests the model's performance under operational conditions. The associated confusion matrix provides insights into the model's performance on independent data. While the accuracy is slightly lower than in the training and validation phases, the model continues to exhibit significant accuracy in classifying yam tuber quality.

Overall Performance: The collective performance across all confusion matrices, culminating in an overall accuracy of 92.3%, highlights the reliability of the robotic code in consistently distinguishing between various yam tuber quality categories. This achievement underscores the potential of the developed code to make a meaningful contribution to yam tuber detection within robotic applications.

Thus, the evaluation based on the confusion matrix reveals consistent and impressive performance throughout all phases. The training, validation, and test phases together contribute to an overall accuracy of 92.3%, confirming the code's effectiveness in accurate yam tuber quality detection. This success reaffirms the code's suitability for real-world robotic applications, ultimately enhancing agricultural practices and quality control efforts.

The developed robotic code, named "$C_{Robotics}$," is displayed in the submitted supplementary document. This code harnesses the capabilities of the Artificial Neural Network (ANN) algorithm to offer a comprehensive solution for detecting yam quality within robotic systems. The architecture of the "$C_{Robotics}$" code shines a spotlight on the capabilities of artificial neural networks in making accurate predictions about yam tuber quality within the realm of robotic applications. By leveraging meticulously determined weights, biases, and transfer functions, the code adeptly processes input data and generates meaningful predictions. The adoption of ANN models for yam quality detection aligns with contemporary research trends that harness AI and machine learning to elevate agricultural practices and quality control measures.

Thus, the "$C_{Robotics}$" code assumes a pivotal role in empowering robotic systems to assess yam tuber quality attributes. Its reliance on the Artificial Neural Network algorithm, coupled with precisely defined constants and layer configurations, underscores its potential to redefine yam quality assessment in the agricultural context. As technological strides continue, codes like "$C_{Robotics}$" stand as invaluable contributions to the wider domain of precision agriculture, fostering efficiency and accuracy in quality evaluation processes.

Therefore, deploying this neural network to robotic devices brings numerous benefits to the agricultural industry. Robotic devices equipped with the yam tuber detection code can autonomously identify and classify yam tubers, optimizing harvesting processes and improving agricultural productivity. The network's real-time capabilities allow efficient detection and sorting of yam tubers, reducing labor costs and minimizing waste.

Thus, the developed code demonstrates the potential of artificial intelligence in modern agriculture. The accurate Yam tuber detection capabilities, combined with deployment to robotic devices, offer a promising solution for enhancing Yam farming practices. As technology continues to advance, integrating AI-driven solutions in agriculture is expected to revolutionize the industry, promoting sustainable and efficient farming practices.

3.4 Codes deployment test

The outcomes of the deployment testing for the developed codes, aimed at detecting yam quality, are presented in Table 4. This table offers a thorough evaluation of how well the codes perform when applied to various samples of yam tubers. It outlines the features extracted from the images, the actual quality class of the yam, and the predictions generated by each of the developed codes: C_{IoT1}, C_{IoT2}, C_{IoT3}, C_{IoT4}, C_{IoT5}, and $C_{Robotics}$.

The results of the deployment testing provide insights into the accuracy of each code's predictions for yam quality classes. By comparing the predictions against the actual quality classes, the study can gauge how well the codes classify the yam tubers. This evaluation involves testing the codes on samples with different yam quality characteristics, including "Good," "Diseased," and "Insect Infected."

Upon examination, it becomes clear that there are instances of misclassification, denoted by the "*wrongly classified" annotations in Table 4. These occurrences highlight situations where a specific code made inaccurate predictions about the yam quality class. For instance, $C_{Robotics}$ wrongly classified some samples as "Good" when they were actually of the "Insect Infected" class.

The results of the deployment testing allow for a side-by-side comparison of how well each developed code performs. This comparison aids in understanding which code yields the most accurate predictions across the entire dataset. Additional notes specify the particular algorithm used by each code: C_{IoT1} to C_{IoT5} utilize various tree and SVM (Support Vector Machine) variants, while $C_{Robotics}$ employs the Artificial Neural Network (ANN) algorithm.

The outcomes of the testing showcase the real-world applicability of the developed codes in scenarios involving yam quality detection. The predictive capabilities of these codes play a crucial role in automating the assessment of quality, leading to time and resource savings while maintaining precise evaluations.

The table includes notes that highlight instances of incorrect predictions. For example, C_{IoT4} misclassified certain samples as "Good" when they were actually "Diseased." Similarly, $C_{Robotics}$ made incorrect predictions in certain cases, confusing "Insect Infected" samples as "Good." These instances underscore the importance of continually refining and fine-tuning the code models to enhance their accuracy.

In spite of a few misclassification instances, the deployment testing results cast a positive light on the performance of the developed codes. These codes exhibit the potential to significantly contribute to quality control efforts within the yam industry by automating the process of detecting yam quality attributes, thus minimizing the need for human intervention.

To conclude, the findings from the deployment testing provide a comprehensive understanding of how effectively the developed codes can practically detect yam quality attributes. While some misclassifications occurred, the overall accuracy and effectiveness of the codes hold promising prospects for automating yam quality assessment, thereby enhancing efficiency and accuracy in agricultural practices.

Table 4: Deployment Test of the Developed Codes for detecting yam quality

S/N	Yam Quality Class (Code)	Extracted Image Features						Developed Codes					
		Red	Green	Blue	Grey scale	Width	Height	$C_{IoT}1$	$C_{IoT}2$	$C_{IoT}3$	$C_{IoT}4$	$C_{IoT}5$	$C_{Robotics}$
1	Good	8600	8600	8600	8400	882	747	Good	Good	Good	Good	Good	Good
2	Good	9100	9100	9100	9100	765	964	Good	Good	Good	Good	Good	Good
3	Good	8800	8800	8800	8700	774	882	Good	Good	Good	Good	Good	Good
4	Good	9700	9700	9700	9600	860	1002	Good	Good	Good	Good	Good	Good
5	Good	7800	7800	7800	7600	874	1023	Good	Good	Good	Good	Good	Good
6	Good	8000	8000	8000	8100	900	791	Good	Good	Good	Good	Good	Good
7	Good	9000	9000	9000	9100	773	972	Good	Good	Good	Good	Good	Good
8	Good	8700	8700	8700	8500	901	697	Good	Good	Good	Good	Good	Good
9	Good	9200	9200	9200	9000	783	940	Good	Good	Good	Good	Good	Good
10	Good	8100	8100	8100	8000	760	886	Good	Good	Good	Good	Good	Good
11	Diseased	3800	3800	3800	3700	984	780	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
12	Diseased	4500	4500	4500	4300	984	900	Diseased	**Insect Infected***	**Insect Infected***	Diseased	Diseased	**Insect Infected***
13	Diseased	2000	2000	2000	2100	790	934	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
14	Diseased	2700	2700	2700	2600	982	876	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
15	Diseased	3500	3500	3500	3300	882	903	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
16	Diseased	1900	1900	1900	2000	974	875	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
17	Diseased	4000	4000	4000	3800	956	687	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
18	Diseased	4200	4200	4200	4300	653	756	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
19	Diseased	2500	2500	2500	2400	1092	770	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
20	Diseased	3400	3400	3400	3300	1082	772	Diseased	Diseased	Diseased	Diseased	Diseased	Diseased
21	Insect Infected	6300	6300	6300	6200	902	775	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
22	Insect Infected	7000	7000	7000	6900	1040	760	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
23	Insect Infected	6700	6700	6700	6600	1070	760	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
24	Insect Infected	7200	7200	7200	7100	980	758	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
25	Insect Infected	6700	6700	6700	6600	1070	761	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
26	Insect Infected	8500	8500	8500	8300	1070	770	**Good***	**Good***	**Good***	**Good***	**Good***	**Good***
27	Insect Infected	4800	4800	4800	4900	1079	768	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
28	Insect Infected	4600	4600	4600	4500	1081	764	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
29	Insect Infected	5700	5700	5700	5800	1081	772	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected
30	Insect Infected	7700	7700	7700	7600	1082	773	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected	Insect Infected

*Wrongly classified, $C_{IoT}1$isthe developed code using simple tree algorithms, $C_{IoT}2$ is the developed code using linear svm (support vector machine) algorithm, $C_{IoT}3$ is the developed code using medium gaussian svm (support vector machine) algorithm, $C_{IoT}4$ is the developed code using medium knn (kernel nearest neighbor) algorithm, $C_{IoT}5$ is the developed code using cubic knn (kernel nearest neighbor) algorithm, $C_{Robotics}$ is the developed code using ann (artificial neural network) algorithm

4.0 CONCLUSION

This study have presented a comprehensive approach to automating the process of detecting yam quality attributes by leveraging Internet of Things (IoT) devices and robotic systems. Through the creation of specialized computer codes, the research aim was to streamline the assessment of yam tuber quality, a critical step in ensuring food safety and optimizing agricultural practices. By integrating cutting-edge technologies such as image processing, machine learning, and artificial neural networks, we were able to achieve accurate and efficient classification of yam quality.

The results derived from the study's developed computer codes and robotic algorithm highlight the potential of our approach. The IoT-based codes demonstrated impressive accuracy in predicting yam quality classes based on the features extracted from images. Using tree algorithms, linear and Gaussian SVMs, and K-nearest neighbor algorithms, the developed codes achieved an average accuracy exceeding 90%, showcasing their ability to handle diverse yam quality characteristics. Additionally, the robotic algorithm, utilizing the power of an artificial neural network, achieved a performance accuracy of 92.3% according to its confusion matrix analysis.

Through deployment testing, the developed codes demonstrated their practicality in real-world scenarios. The accurate classification of yam tubers into "Good," "Diseased," or "Insect Infected" categories validated the effectiveness of the study's approach in automating the quality assessment process. While there were occasional instances of misclassification, the overall outcomes suggest the potential to revolutionize the agricultural sector by reducing the need for human involvement and enhancing the efficiency of yam quality evaluation.

This study is in line with prior research endeavors in the field of yam quality detection, underscoring the importance of precise and automated assessment methods. Furthermore, the incorporation of IoT devices and robotic systems introduces new possibilities for precision agriculture, where data-informed decision-making can lead to higher yields and decreased waste. This research firmly believe that the integration of our developed codes into robotic devices and IoT networks can greatly benefit the agricultural industry by enabling timely and precise assessment of yam quality.

Therefore, this study showcases the successful creation and application of computer codes for detecting yam quality using IoT devices and robotic systems. The achieved results emphasize the potential for transforming traditional agricultural practices into more efficient and data-driven processes. As technology continues to advance, this research anticipate further progress in automation and accuracy, ultimately contributing to a sustainable and productive agricultural ecosystem

Declarations

Author Contribution

J.A. and E.A. developed the concept of the study. J.A. and A.A. collected data and analyzed the data using Matlab software. J.A. and A. A. wrote the manuscript. S.I supervised and edited the manuscript. All codes were written by J. A, A. A and E. I.

References

1. Kalloo G, Bergh BO (1993) Genetic improvement of vegetable crops. eBook ISBN: 9780080984667. Pergamon. Elsevier Ltd
2. Bazoumana D, Joel NP, Jonathan KB (2022) Yam Cultivation as an Obstacle to Forest Recolonisation in the Subprefecture of Dimbokro. J Social Sci Stud 9(2). https://doi.org/10.5296/jsss.v9i2.20486
3. Alexander J, Coursey DG (1969) The origins of yam cultivation. The origins of yam cultivation i>https://www.cabdirect.org/cabdirect/abstract/19701602501
4. Ema ES, Obidiegwu JE, Chilaka CA, Akpabio EM (2023) Indigenous Food Yam Cultivation and Livelihood Practices in Cross River State, Nigeria. World, 4, 314–332. https://doi.org/10.3390/world4020020
5. Sugihara Y, Kudoh A, Oli MT, Takagi H, Natsume S, Shimizu M, Terauchi R (2021) Population genomics of yams: evolution and domestication of Dioscorea species. Population Genomics. Springer, Cham. https://doi.org/10.1007/13836_2021_94
6. Xiong F, Lyu C, Kang C, Wan X, Sun J, Wang T, Wang S, Li H, Yang J, Guo L (2023) Authenticating the geographical origin of the Chinese yam (Tiegun) with stable isotopes and multiple elements. Food Chemistry: X 18:100678. https://doi.org/10.1016/j.fochx.2023.100678
7. Mendoza AR, Margaria P, Nagata T, Winter S, Blawid R (2022) Characterization of yam mosaic viruses from Brazil reveals a new phylogenetic group and possible incursion from the African continent. Virus Genes 58:294–307. https://doi.org/10.1007/s11262-022-01903-x
8. Scarcelli N, Cubry P, Akakpo R, Thuillet A, Obidiegwu JE, Baco MN, Otoo E, Sonké B, Dansi A, Djedatin GL, Mariac C, Couderc M, Causse S, Alix K, Chaïr H, François O, Vigouroux Y (2019) Yam genomics supports West Africa as a major cradle of crop domestication. Science Advances, 5. https://doi.org/aaw1947
9. Li Y, Ji S, Xu T, Zhong Y, Xu M, Liu Y, Lu B (2023) Chinese yam (Dioscorea): Nutritional value, beneficial effects, and food and pharmaceutical applications. Trends Food Sci Technol 134:29–40. https://doi.org/10.1016/j.tifs.2023.01.021
10. Nwafor JO, Kanu AN, Kelechukwu EC, Nwohu NO, Ezebuiro VN (2020) Physico-Chemical Properties of Water Yam and Cowpea Flour Blends for Production of Snacks. South Asian Journal of Research in Microbiology 6(3):1–8. https://doi.org/10.9734/sajrm/2020/v6i330149

11. Audu J, Dinrifo RR, Adegbenjo A, Anyebe SP, Alonge AF (2023) Development of two smart acoustic yam quality detection devices using a machine learning approach. Heliyon 9(3):e14567. https://doi.org/10.1016/j.heliyon.2023.e14567
12. Saranraj P, Behera SS, Ray RC (2019) Chapter 7 - Traditional foods from tropical root and tuber crops: innovations and challenges. Editor(s): Charis M. Galanakis, Innovations in traditional foods, Woodhead publishing, pages 159–191, ISBN 9780128148877, https://doi.org/10.1016/B978-0-12-814887-7.00007-1
13. Kennedy G, Raneri JE, Stoian D, Attwood S, Burgos G, Ceballos H, Ekesa B, Johnson V, Low JW, Talsma EF (2019) Roots, tubers and bananas: contributions to food security, Editor(s): Pasquale Ferranti, Elliot M. Berry, Jock R. Anderson, Encyclopedia of Food Security and Sustainability, Elsevier, Pages 231–256, ISBN 9780128126882
14. Nabeshima EH, Moro TMA, Campelo PH, Sant'Ana AS, Clerici MTPS (2020) Chapter Seven - Tubers and roots as a source of prebiotic fibers, Editor(s): Adriano Gomes da Cruz, Elane Schwinden Prudencio, Erick Almeida Esmerino, Marcia Cristina da Silva. Advances in food and nutrition research. Academic Press, volume 94, pages 267–293, ISSN 1043–4526, ISBN 9780128202180, https://doi.org/10.1016/bs.afnr.2020.06.005
15. Yam market report (2022) Yams market - growth, trends, covid-19 impact, and forecasts (2022–2027). https://www.researchandmarkets.com/r/z2o12g
16. Oikonomidis A, Catal C, Kassahun A (2022) Deep learning for crop yield prediction: a systematic literature review. New Z J Crop Hortic Sci 51(1):1–26. https://doi.org/10.1080/01140671.2022.2032213
17. Çetin N, Ozaktan H, Uzun S, Uzun O, Ciftci CY (2023) Machine learning based mass prediction and discrimination of chickpea (Cicer arietinum L.) cultivars. Euphytica 219(1):20. https://doi.org/10.1007/s10681-022-03150-5
18. Shetty KR, Soorinje VS, Dsouza P, Swasthik (2022) Deep Learning for Computer Vision: A Brief Review. International Journal of Advanced Research in Science, Communication and Technology, 2(2). https://www.semanticscholar.org/paper/Deep-Learning-for-Computer-Vision%3A-A-Brief-Review-Shetty-Soorinje/cf48e2877af6bb66b47db69aa44d08c752afb7b0
19. Wang J, Gao P, Zhang J, Lu C, Shen B (2023) Knowledge augmented broad learning system for computer vision based mixed-type defect detection in semiconductor manufacturing. Robot Comput Integr Manuf 81:102513. https://doi.org/10.1016/j.rcim.2022.102513
20. Wu T, Tang L, Li X, Zhang X, Liu Y, Zhou Z (2023) Sparse accelerometer-aided computer vision technology for the accurate full-field displacement estimation of beam-type bridge structures. Measurement 212:112532. https://doi.org/10.1016/j.measurement.2023.112532
21. Moore S, Liao QV, Subramonyam H (2023) fAllureNotes: Supporting Designers in Understanding the Limits of AI Models for Computer Vision Tasks. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 10, 1–19. https://doi.org/10.1145/3544548.3581242
22. Sadeghi-Niaraki A (2023) Internet of Thing (IoT) review of review: Bibliometric overview since its foundation. Future Generation Computer Systems 143:361–377. https://doi.org/10.1016/j.future.2023.01.016
23. Guo F, Yu FR, Zhang H, Leung VC (2021) Enabling Massive IoT Toward 6G: A Comprehensive Survey. IEEE Internet of Things Journal 8(5):11891–11915. 10.1109/JIOT.2020.3002255
24. Oracle (2022) report https://www.oracle.com/ng/internet-of-things/
25. Semeraro F, Griffiths A, Cangelosi A (2023) Human–robot collaboration and machine learning: A systematic review of recent research. Robot Comput Integr Manuf 79:102432. https://doi.org/10.1016/j.rcim.2022.102436
26. Ravichandar HC, Polydoros AS, Chernova S, Billard A (2020) Recent Advances in Robot Learning from Demonstration. Annu Rev Control Robotics Auton Syst 3:297–330. https://doi.org/10.1146/annurev-control-100819-063206
27. Zion market research report (2022) Global industrial robotics market, industry trends, value, analysis & forecast report. https://www.prnewswire.com/news-releases/demand-for-global-industrial-robotics-market-size--share-is-expected-11-8-cagr-rise-will-hit-to-usd-81-4-billion-globally-by-2028-with-covid-19-analysis--industry-trends-value-analysis--forecast-report--zion-market-resea-301549130.html. Accessed 11th July 2022
28. Market research future report (2022) Robotics Market. https://www.globenewswire.com/en/news-release/2022/04/21/2426169/0/en/Robotics-Market-Size-to-Cross-USD-214-68-Billion-by-2030-Growing-at-a-CAGR-of-22-8-Report-by-Market-Research-Future-MRFR.html. Accessed 11th July 2022
29. BlueWeave report (2022) Global Agricultural Robots Market. BlueWeave Consulting and Research Pvt Ltd. https://www.globenewswire.com/en/news-release/2022/03/21/2406862/0/en/Global-Agricultural-Robots-Market-to-Surpass-81-Billion-by-2028-at-a-CAGR-of-9-9-during-the-forecast-period-BlueWeave-Consulting.html. Accessed 11th July 2022
30. Tuhaise J, Quinn AJ, Mwebaze E (2014) Pixel classification methods for automatic symptom measurement of cassava brown streak disease. Proc 1st int. conf. on the used of mobile ICT in Africa, Stellenbosch, South Africa. 6–10. ISBN: 978-0-7972-1532-7. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.708.3936&rep=rep1&type=pdf
31. Ninsiima FD, Owomugisha G, Mwebaze E (2018) Automating the segmentation of necrotized regions in cassava root images. Int'l Conf. IP, Comp. Vision, and Pattern Recognition. IPCV'18, 71–77. ISBN: 1-60132-485-5, CSREA Press
32. Tusubira JF, Akera B, Nsumba S, Nakatumba-Nabende J, Mwebaze E (2020) Scoring root necrosis in cassava using semantic segmentation. 1st international workshop and prize challenge on agriculture vision: challenges & opportunities for computer vision in agriculture in conjunction with IEEE/CVF CVPR. arXiv:2005.03367v1 [eess.IV]. https://arxiv.org/pdf/2005.03367

33. Tian F, Peng Y, Wei W (2016) Nondestructive and rapid detection of potato black heart based on machine vision. Proc. SPIE 9864, Sensing for Agriculture and Food Quality and Safety VIII, 98640T. 10.1117/12.2223292
34. Go¨kmen V, Senyuva HZ, Du¨lek B, C¸etin A (2007) E. Computer vision-based image analysis for the estimation of acrylamide concentrations of potato chips and french fries. Food Chemistry 101: 791–798. Elsevier, 10.1016/j.foodchem.2006.02.034
35. Oppenheim D, Shani G, Erlich O, Tsror L (2019) Using Deep Learning for Image-Based Potato Tuber Disease Detection. Phytopathology, 109(6):1083–1087. 10.1094/PHYTO-08-18-0288-R. Epub. PMID: 30543489
36. Ropelewska E (2021) Effect of boiling on classification performance of potatoes determined by computer vision. European Food Research and Technology 247:807–817. Springer, https://doi.org/10.1007/s00217-020-03664-z
37. Korchagin SA, Gataullin ST, Osipov AV, Smirnov MV, Suvorov SV, Serdechnyi DV, Bublikov KV (2021) Development of an Optimal Algorithm for Detecting Damaged and Diseased Potato Tubers Moving along a Conveyor Belt Using Computer Vision Systems. Agronomy, 11, 1980. https://doi.org/10.3390/agronomy11101980
38. Dolata P, Wróblewski P, Mrzygłód M, Reiner J (2021) Instance segmentation of root crops and simulation-based learning to estimate their physical dimensions for on-line machine vision yield monitoring. Computers and Electronics in Agriculture, 190: 106451, ISSN 0168–1699. https://doi.org/10.1016/j.compag.2021.106451. https://www.sciencedirect.com/science/article/pii/S0168169921004683
39. Molto E, Harrell CR (1993) Neural network classification of sweet potato embryos. Proc. SPIE 1836, Optics in Agriculture and Forestry. 10.1117/12.144033. https://spie.org/Publications/Proceedings/Paper/10.1117/12.144033
40. Yimyam P Physical Property Analysis of Sweet Potatoes Using Computer Vision. Proceedings of the 7th International Conference on Computer and, Management C (2019) 18–22. https://doi.org/10.1145/3348445.3348471
41. Nasirahmadi A, Wilczek U, Hensel O (2021) Sugar beet damage detection during harvesting using different convolutional neural network models. Agriculture 11(11):1111. 10.3390/agriculture11111111
42. Osipov A, Shumaev V, Ekielski A, Gataullin T, Suvorov S, Mishurov S, Gataullin S (2022) Identification and classification of mechanical damage during continuous harvesting of root crops using computer vision methods. IEEEAcess 10:28885–28894 Digital object identifier:. 10.1109/ACCESS.2022.3157619
43. Deng L, Du H, Han Z (2017) Carrot sorting system using machine vision technique. Appl Eng Agric 33(2):149–156. 10.13031/aea.11549
44. Örnek M, Hacısefero˘gulları H (2020) Design of Real Time Image Processing Machine for Carrot Classification. Yüzüncü Yıl Üniversitesi Tarım Bilimleri Derg. 30:355–366https://dergipark.org.tr/tr/download/article-file/1156992
45. Dorokhov A, Aksenov A, Sibirev A, Sazonov N, Mosyakov M, Godyaeva M (2021) Results of Laboratory Studies of the Automated Sorting System for Root and Onion Crops. Agronomy 11, 1257. https://doi.org/10.3390/agronomy11061257
46. Nafi'iyah N (2020) Tuber type classification based on image of bulbs with deep learning. International conference on ict for smart society (ICISS), 1–7, 10.1109/ICISS50791.2020.9307584
47. Zhaoyuxi M, Guofu Y, Juxin H (2014) Design of Automatic Picking System of Yam Based on SCM. Sixth International Conference on Measuring Technology and Mechatronics Automation, 222–225, 10.1109/ICMTMA.2014.56
48. Ayodeji SP, Mpofu K, Matsebe O, Olabanji MO (2015) A control system for a poundo yam flour processing plant. Afr J Sci Technol Innov Dev 7(3):192–200. 10.1080/20421338.2015.1040285
49. Su W, Xue H (2021) Imaging Spectroscopy and Machine Learning for Intelligent Determination of Potato and Sweet Potato Quality. Foods 10(9):2146. https://doi.org/10.3390/foods10092146
50. Sun C, Feng L, Zhang Z, Ma Y, Crosby T, Naber M, Wang Y (2020) Prediction of End-Of-Season Tuber Yield and Tuber Set in Potatoes Using In-Season UAV-Based Hyperspectral Imagery and Machine Learning. Sensors 20(18):5293. https://doi.org/10.3390/s20185293
51. Nakatumba-Nabende J, Babirye C, Tusubira JF, Mutegeki H, Nabiryo AL, Murindanyi S, Katumba A, Nantongo J, Sserunkuma E, Nakitto M, Ssali R, Makunde G, Moyo M, Campos H (2023) Using machine learning for image-based analysis of sweet potato root sensory attributes. Smart Agricultural Technology 5:100291. https://doi.org/10.1016/j.atech.2023.100291
52. Khazaee Y, Kheiralipour K, Hosainpour A, Javadikia H, Paliwal J (2022) Development of a Novel Image Analysis and Classification Algorithms to Separate Tubers from Clods and Stones. Potato Res 65:707–728. https://doi.org/10.1007/s11540-021-09528-7
53. Zawbaa HM, Abbass M, Basha SH, Hazman M, Hassenian AE (2014) An automatic flower classification approach using machine learning algorithms. 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI). Delhi, India, 895–901, 10.1109/ICACCI.2014.6968612
54. Fakir Y, Lakhdoura Y, Elayachi R, Slimane SM (2020) Comparative Analysis of Random Forest and J48 Classifiers for 1 IRIS Variety Prediction 2. Global Journal of Computer Science and Technology (H) Information & Technology 20 (2) Version 1.0. 1–8. Online ISSN: 0975–4172 & Print ISSN: 0975–4350. http://creativecommons.org/licenses/by-nc/3.0/
55. Ehounou AE, Cornet D, Desfontaines L, Marie-Magdeleine C, Maledon E, Nudol E, Beurier G, Rouan L, Brat P, Lechaudel M, Nous C, Kouakou AM, Arnau G (2021) Predicting quality, texture and chemical content of yam (Dioscorea alata L.) tubers using near infrared spectroscopy. J Near Infrared Spectrosc. https://doi.org/10.1177/09670335211007575

56. Chen Y, Song L, Liu Y, Yang L, Li D (2020) A Review of the Artificial Neural Network Models for Water Quality Prediction. Appl Sci 10(17):5776. https://doi.org/10.3390/app10175776
57. Alzubaidi L, Zhang J, Humaidi AJ, Duan Y, Santamaría J, Fadhel MA, Farhan L (2021) Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. J Big Data 8(1):1–74. https://doi.org/10.1186/s40537-021-00444-8
58. Yamashita R, Nishio M, Do RK, Togashi K (2018) Convolutional neural networks: An overview and application in radiology. Insights into Imaging 9(4):611–629. https://doi.org/10.1007/s13244-018-0639-9

Figures

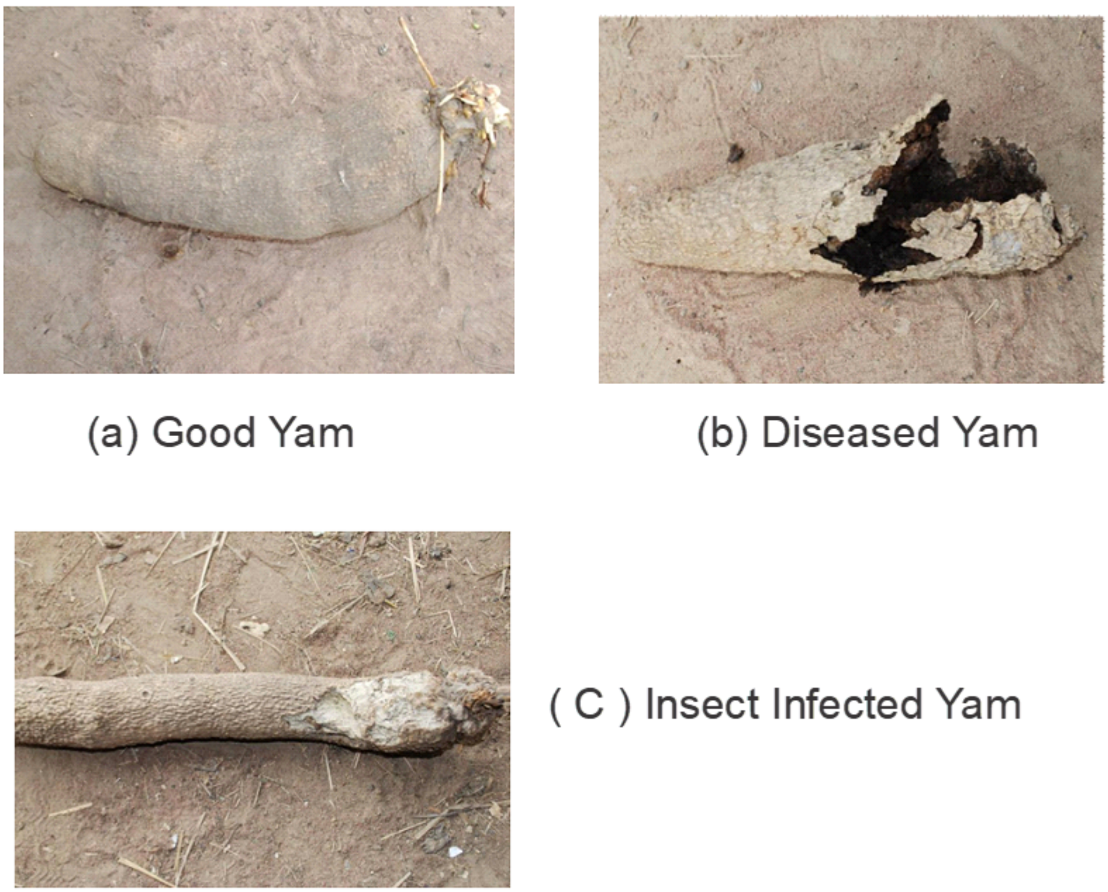


Figure 1

Typical pictures of Yam tuber samples

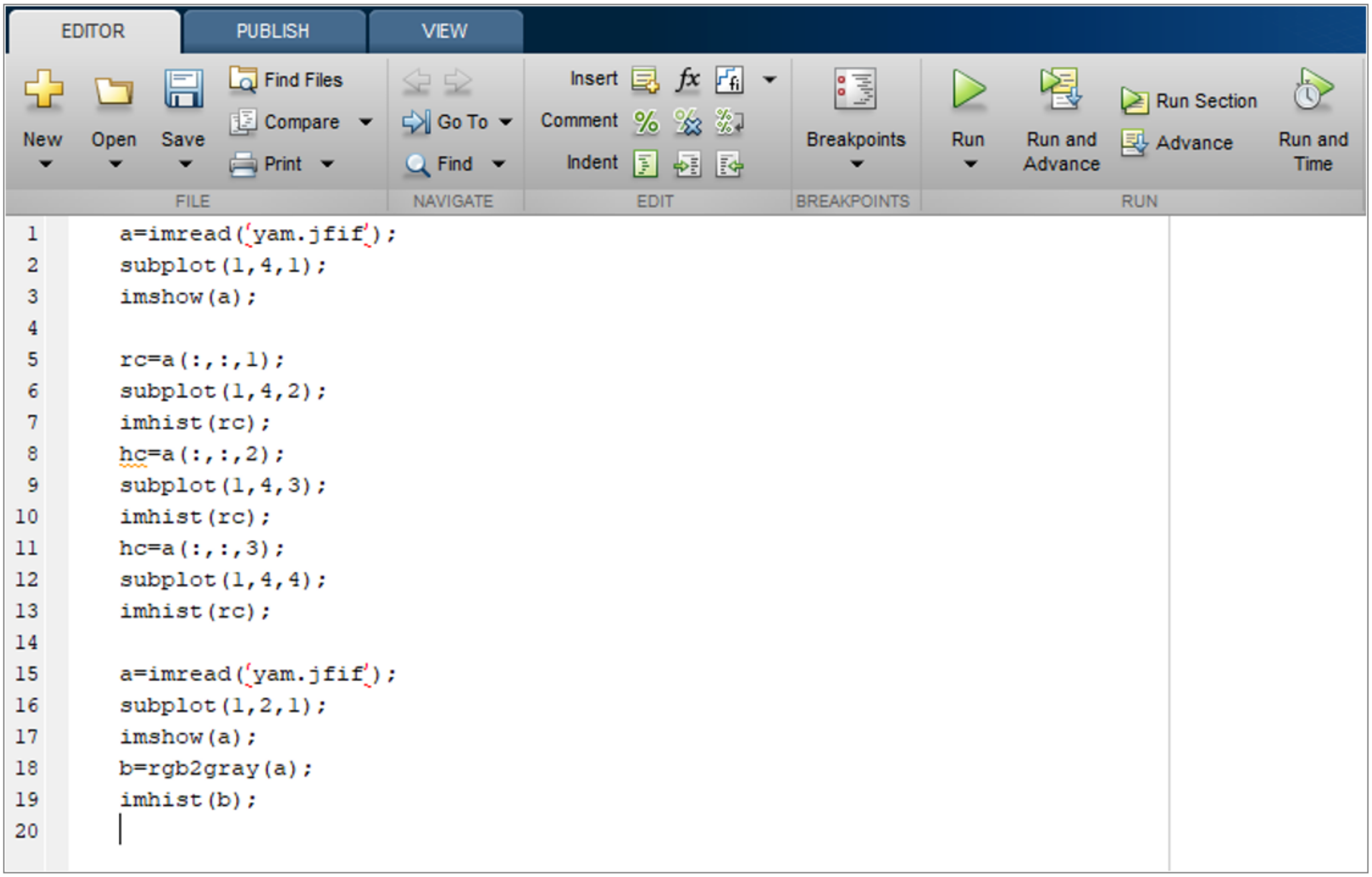


Figure 2

MATLAB script codes used for extraction of red, blue, green gray scale, height and width features

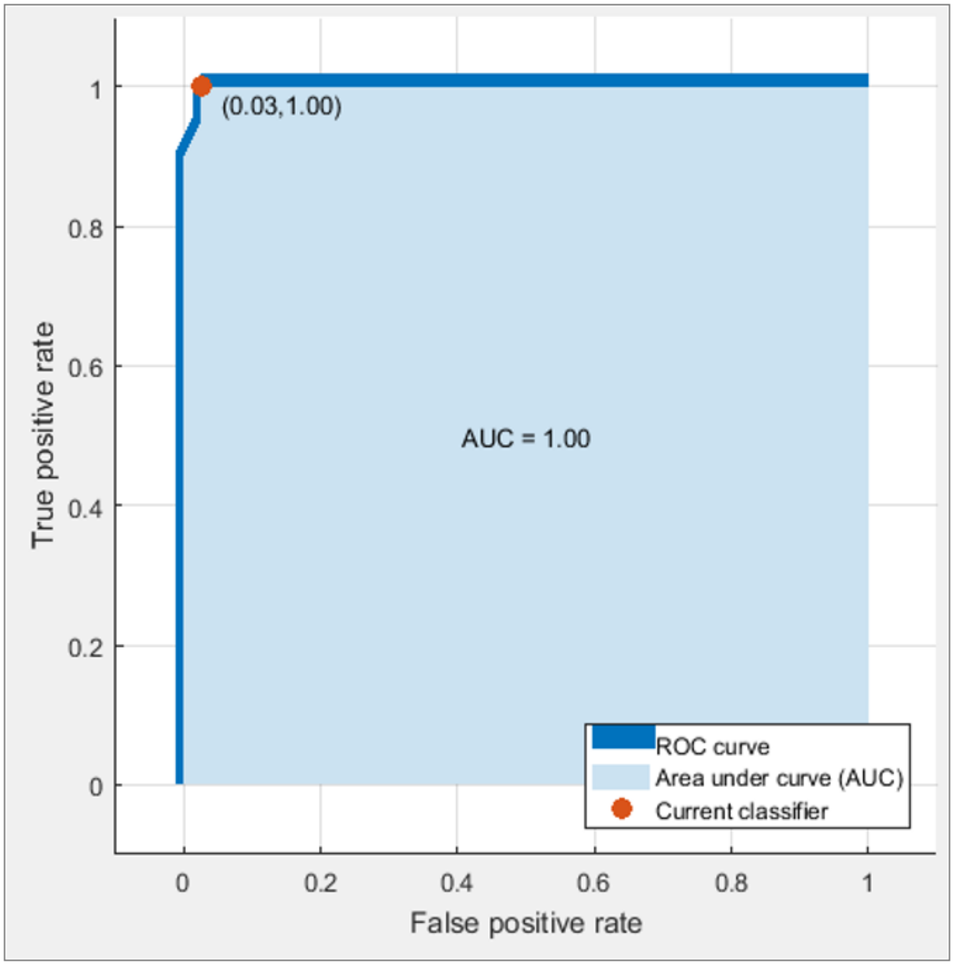
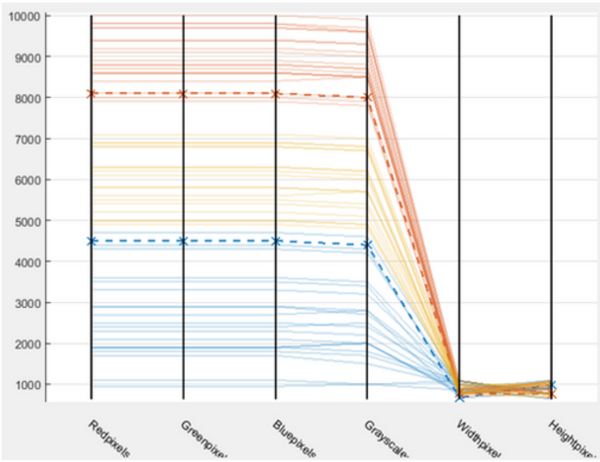
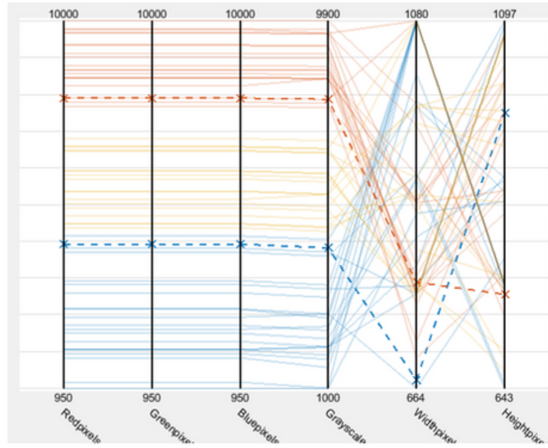


Figure 3

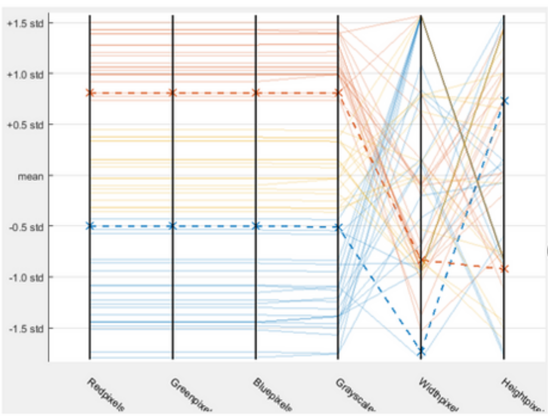
Figure 1: A typical Receiver Operating Characteristic (ROC) Curve plot





(a) No scaling parallel coordinates plot

(b) Normalized scaling parallel coordinates plot



(c) Standardized scaling parallel coordinates plot

Figure 4

Figure 2: A typical 6D coordinates plot for image extracted features

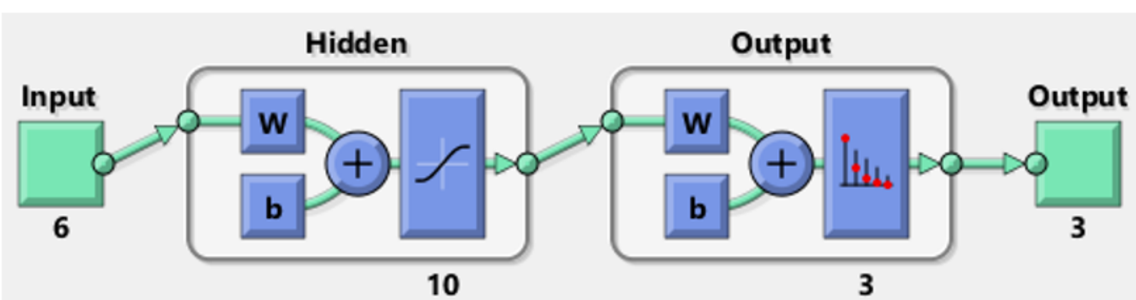


Figure 5

Figure 3: Artificial neural network architecture for building the yam detecting classifier.

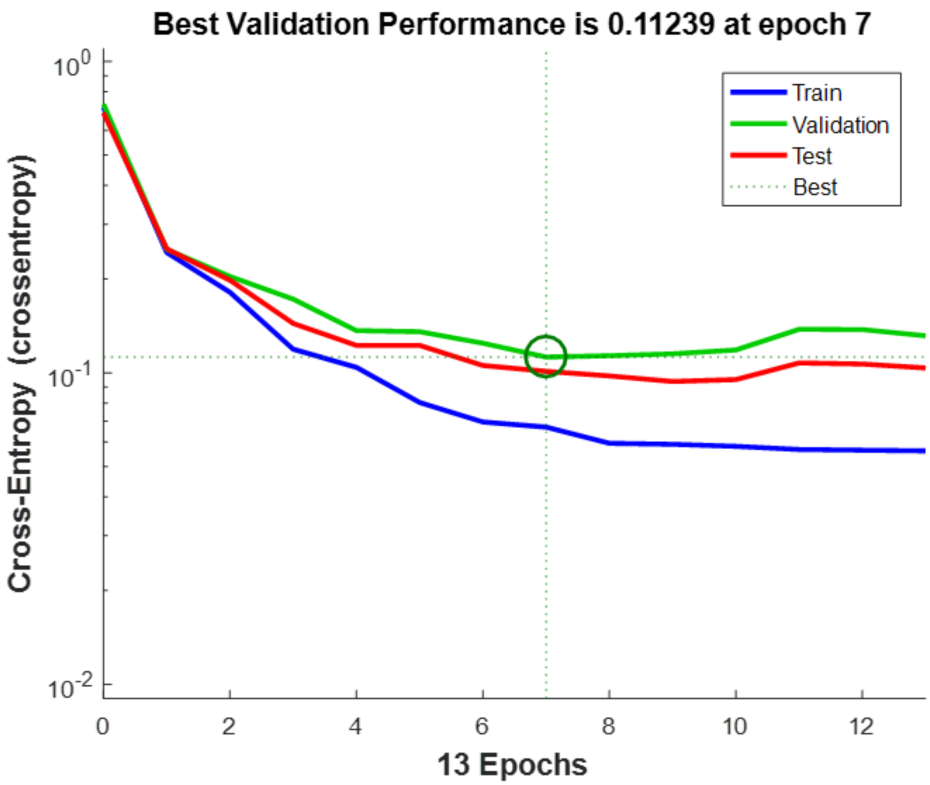


Figure 6

Figure 4: Perforce plot of the yam detection classification

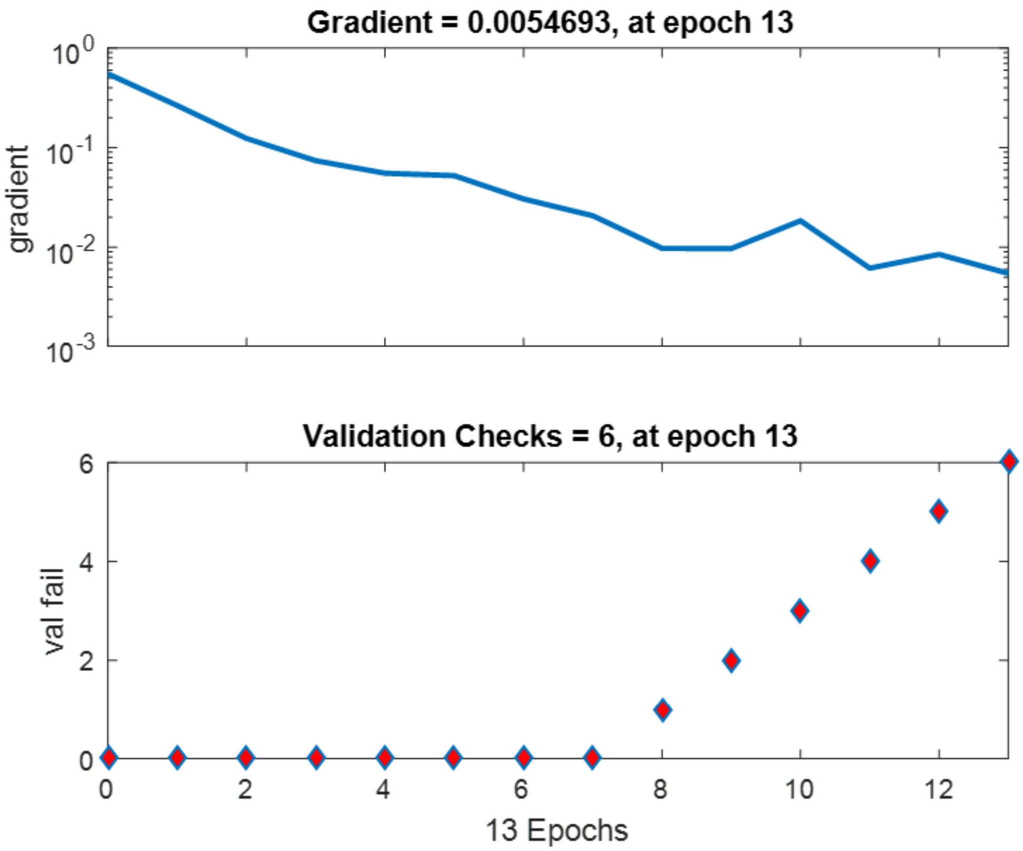


Figure 7

Figure 5: Training state plot of the neural network classification

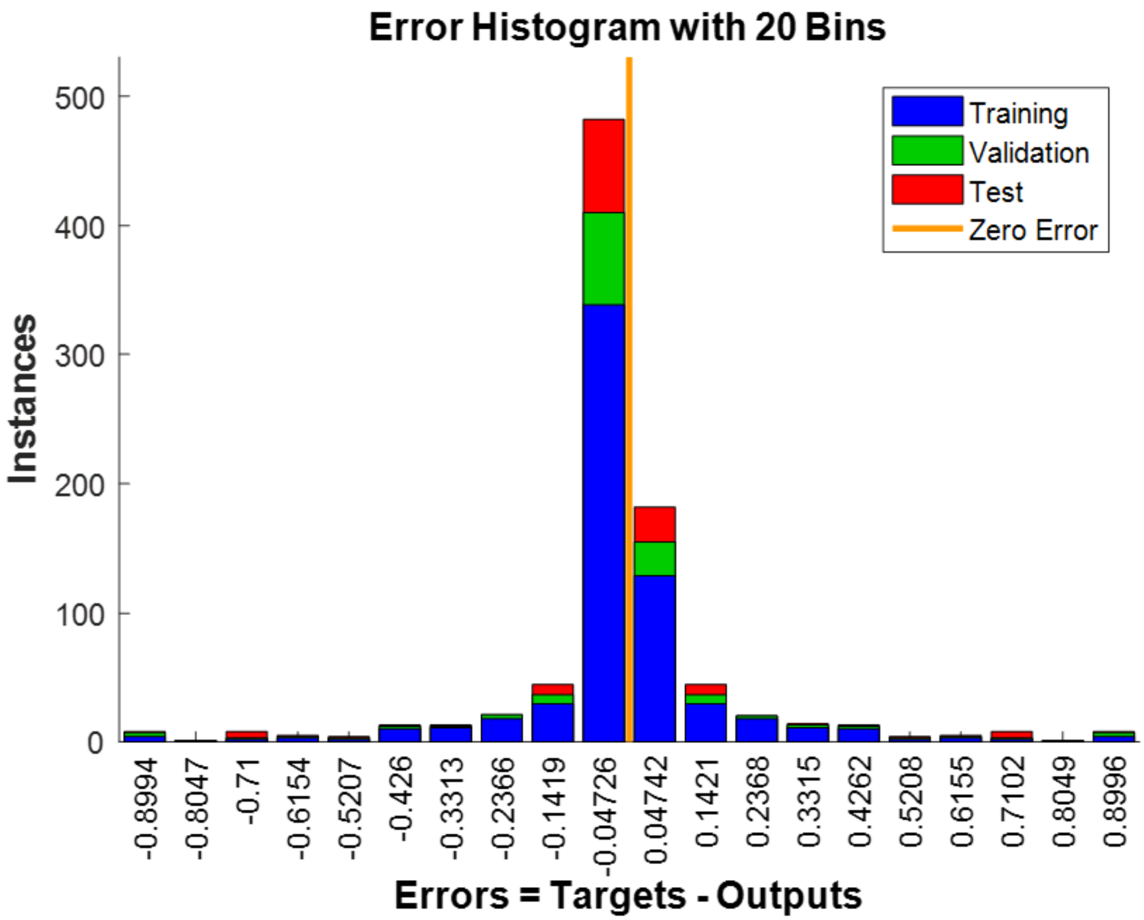


Figure 8

Figure 6: Error Histogram of the classification of the yam quality

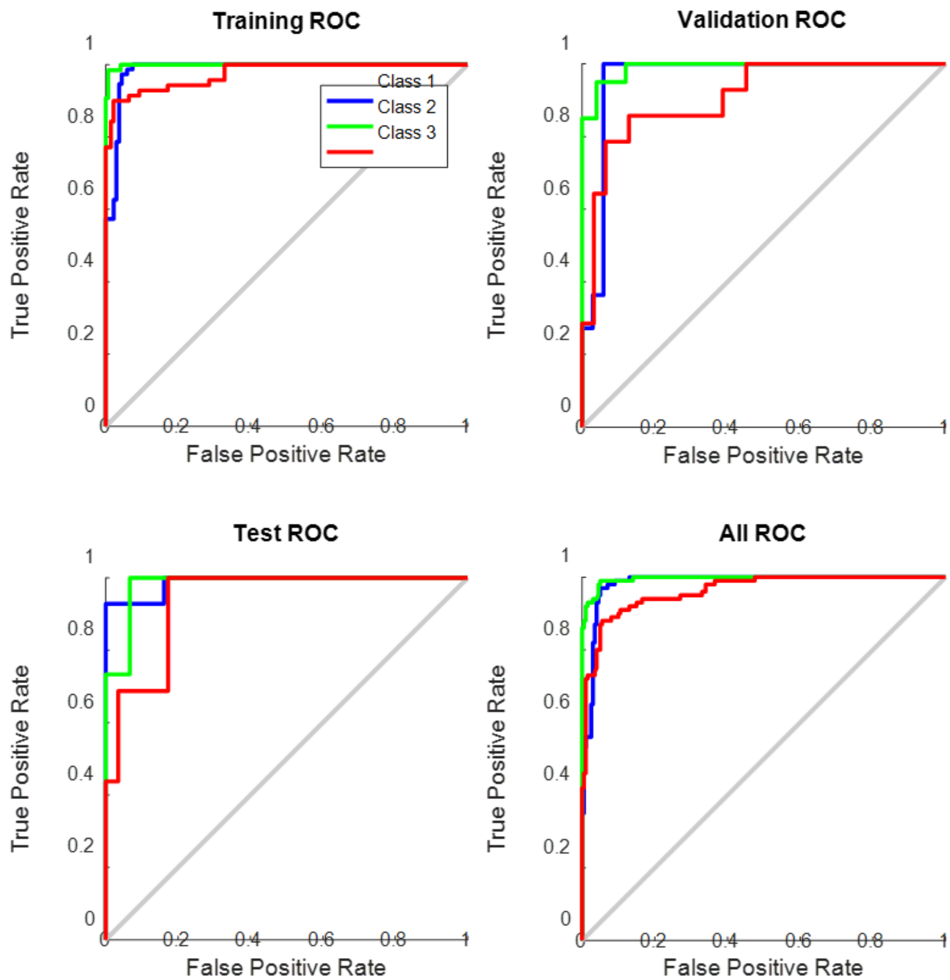


Figure 9

Figure 7: Receiver Operating Characteristic (ROC) Curve plot for the neural network yam classification

Figure 10

Figure 8: Confusion Matrix of the Neural Network Algorithms for Yam Quality Classification (1 is good yams, 2 is diseased yams and 3 is insect infected yams)

Supplementary Files

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