International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

DQLRFMG: Design of an Augmented Fusion of Deep Q Learning with Logistic Regression and Deep Forests for Multivariate Classification and Grading of Fruits

Mrs. Archana G. Said[1], Dr. Bharti Joshi[2]
[1] Research Scholar, Department of Computer Engineering, RAIT, D.Y.Patil University, Nerul, New Mumbai.
saidarchana07@gmail.com
[2] Professor, Department of Computer Engineering, RAIT, D.Y.Patil University, Nerul, New Mumbai, bharti.joshi@rait.ac.in

Abstract: Accurate categorization and grading of fruits are essential in numerous fields, including agriculture, food processing, and distribution. This paper addresses the need for an advanced model capable of classifying and grading fruits more effectively than existing methods. Traditional approaches are limited by their lower precision, accuracy, recall, area under the curve (AUC), and delay. In order to overcome these obstacles, the proposed model combines the capabilities of Deep Q Learning (DQL) for classification and Logistic Regression (LR) with Deep Forests for fruit grading process. Three distinct datasets were used to evaluate the model: the Kaggle - Fruits 360 Dataset, the FRont Experimental System for High throughput plant phenotyping Datasets, and ImageNet samples. In multiple respects, comparative analysis demonstrates that the proposed model outperforms existing methods. Specifically, it achieves a remarkable 4.9% improvement in precision, 5.5% improvement in accuracy, 4.5% improvement in recall, 3.9% improvement in AUC, and an 8.5% reduction in delay levels. Utilizing the strengths of both DQL and LR with Deep Forests, the proposed model achieves its superior performance. DQL, a technique for reinforcement learning, provides the ability to learn and make decisions based on the feedback from the environment. By combining DQL and LR, the classification accuracy is improved, allowing for the precise identification of fruit varieties including Mango, Apple. Papaya, etc. In addition, Deep Forests, a novel framework for ensemble learning, is utilized for fruit grading. Deep Forests utilizes decision trees to effectively capture complex patterns in the data, allowing for dependable and robust fruit grading. Experimental findings indicate that the combination of DQL and LR with Deep Forests yields remarkable performance improvements in fruit classification and grading tasks. Improved precision, accuracy, recall, AUC, and delay indicate the model's superiority over existing methods. This research contributes to the field of fruit classification and grading by developing a sophisticated model that can support a variety of applications in the agriculture, food processing, and distribution industries.

Keywords: Classification, Grading, Fruits, Deep Q Learning, Logistic Regression, Deep Forests.

I. Introduction

Classification and grading of fruits are crucial tasks in a variety of fields, including agriculture, food processing, and distribution. These responsibilities facilitate effective quality management, inventory control, and supply chain optimization. Traditional methods for fruit classification and grading frequently rely on time-consuming, subjective, and error-prone manual inspection. Therefore, there is a growing demand for sophisticated automated systems that can classify and grade fruits effectively and precisely for different scenarios via use of Deep Neural Networks (DNN) [1, 2, 3].

Existing methods for classifying and grading fruit have limitations that hinder their effectiveness. These restrictions include reduced precision, accuracy, recall, area under the curve (AUC), and processing delay. Traditional methods frequently fail to capture the intricate patterns and variations present in fruit images, resulting in suboptimal classification and grading outcomes. In addition, these methods are incapable of learning and adapting to their surroundings, which hinders their overall performance levels like in the case of Convolutional Neural Networks (CNNs) [4, 5, 6].

This paper presents a novel approach that combines the power of Deep Q Learning (DQL) for classification and Logistic Regression (LR) with Deep Forests for fruit grading in order to address these challenges. By combining these techniques, we hope to overcome the limitations of existing methods and achieve significant advancements in the classification and grading of fruit.

Three distinct datasets are used to evaluate the proposed model: the Kaggle - Fruits 360 Dataset, the FRont Experimental System for High throughput plant phenotyping Datasets, and ImageNet. These datasets provide an extensive variety of fruit images with varying characteristics, allowing for a comprehensive evaluation of the model's capabilities. A comparative analysis is conducted to evaluate the performance of the proposed model in comparison to current methods.

The primary benefits of the proposed model are its enhanced precision, accuracy, recall, AUC, and decreased processing delay. By combining DQL and LR, the model capitalizes on the benefits of both reinforcement learning and logistic regression. DQL enables the model to learn and make decisions based on environmental feedback, enabling more precise fruit classification. In addition, the incorporation of LR improves the model's discriminatory ability, resulting in a more precise identification of fruit types.

In addition, the proposed model incorporates Deep Forests, a cutting-edge framework for ensemble learning, for fruit grading. Deep Forests utilize decision trees to capture complex patterns in the data, allowing for robust and reliable fruit classification. This integration enables the model to precisely evaluate the quality and ripeness of fruits, thereby facilitating efficient grading procedures.

The results of the proposed model's evaluation on the three datasets demonstrate its superiority to existing methods. The model exhibits remarkable enhancements of 4.9% in precision, 5.5% in accuracy, 4.5% in recall, 3.9% in AUC, and 8.5% in processing delay. These results demonstrate that the proposed combination of DQL and LR with Deep Forests is effective for fruit classification and grading tasks.

Consequently, this paper presents a novel method for fruit classification and grading by combining DQL and LR for classification and Deep Forests for grading. Existing methods are outperformed by the proposed model in terms of precision, accuracy, recall, AUC, and processing delay. This research contributes to the field by developing an advanced and efficient model that can support a variety of applications in the agriculture, food processing, and distribution industries, thereby enhancing the fruit industry's productivity and quality control process.

II. Review of existing models used for Multivariate classification and Grading of Fruits

Due to their significant impact on industries such as agriculture, food processing, and distribution, the classification and grading of fruits have been the subject of extensive research. Several models and methods have been developed over the years to address these tasks. In this section, we examine the strengths, limitations, and contributions of existing models for multivariate classification and grading of fruits [7, 8, 9].

CNNs have emerged as a powerful tool for image classification tasks, such as the classification of fruits. These models use their ability to automatically learn and extract hierarchical features from images to accurately identify fruit types. In fruit classification, CNN-based models such as VGGNet, ResNet, and InceptionNet have achieved impressive results. However, these models frequently struggle with grading tasks because their primary focus is classification and they lack the ability to evaluate fruit quality and ripeness, including use of Mask R-CNN and YOLOv5 (MR CNN YoLo) Model Process [10, 11, 12].

Support Vector Machine (SVM) is a commonly used classification machine learning algorithm. It maps input data to a higher-dimensional space in order to identify the optimal hyperplane that separates classes [13, 14, 15]. Utilizing SVM-based models for fruit classification has yielded notable results. Nevertheless, SVM-based models may encounter difficulties in capturing complex patterns and variations present in fruit images, thereby limiting their overall performance in multivariate classification and grading tasks [16, 17, 18].

Random Forests are an ensemble learning technique that makes predictions by combining multiple decision trees. By capturing complex relationships and patterns in the data, these models have been utilized for fruit classification and grading process [19, 20]. The performance and interpretability of Random Forest-based models make them suitable for fruit grading tasks. However, they may have difficulty with high-dimensional data and require careful feature selection to prevent overfitting scenarios. Some models extract features using pre-trained deep learning architectures, such as AlexNet or VGGNet. These models extract deep features from fruit images and then use traditional machine learning algorithms for classification and grading, such as SVM or k-nearest neighbors (KNN). These approaches achieve competitive results by leveraging the representational power of deep learning models [21, 22, 23]. However, their flexibility in capturing fine-grained details specific to fruit classification and grading may be limited for real-time scenarios.

The fusion of multiple models [24, 25, 26], each specializing in a particular aspect of fruit classification and grading, is yet another method. Combining a CNN-based model for fruit classification with a regression-based model for grading, for instance, can result in enhanced performance levels [27, 28]. These fusion-based models seek comprehensive and accurate results by capitalizing on the strengths of individual models [29, 30]. Nonetheless, model fusion can be challenging due to its complexity and computational overheads. Despite the improvements made to existing models, a number of limitations remain. Numerous models may not adequately address fruit grading challenges, such as assessing quality, ripeness, or external defects, due to their primary emphasis on classification tasks. In addition, some models struggle with high-dimensional data, limited datasets, and the ability to recognize complex patterns and variations in fruit images.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

Existing models for the multivariate classification and grading of fruits utilize a variety of techniques, including CNNs, SVMs, Random Forests, deep learning-based feature extraction, and the fusion of multiple models. While these models have made significant contributions to the field, there are still obstacles to achieving accurate and comprehensive fruit classification and grading. The model proposed in this paper aims to overcome these limitations by combining Deep Q Learning with Logistic Regression and Deep Forests, thereby providing a promising solution for robust and accurate multivariate fruit classification and grading tasks.

III. Proposed Design of an augmented fusion of Deep Q Learning with Logistic Regression & Deep Forests for Multivariate Classification and Grading of Fruits

Based on the review of existing models used for multivariate classification & grading of fruits, it can be observed that these models either showcase high complexity when applied for fruit grading, or have lower efficiency when applied for multivariate classification operations. To overcome these issues, this section discusses design of an augmented fusion of Deep Q Learning with Logistic Regression & Deep Forests for Multivariate Classification and Grading of Fruits.

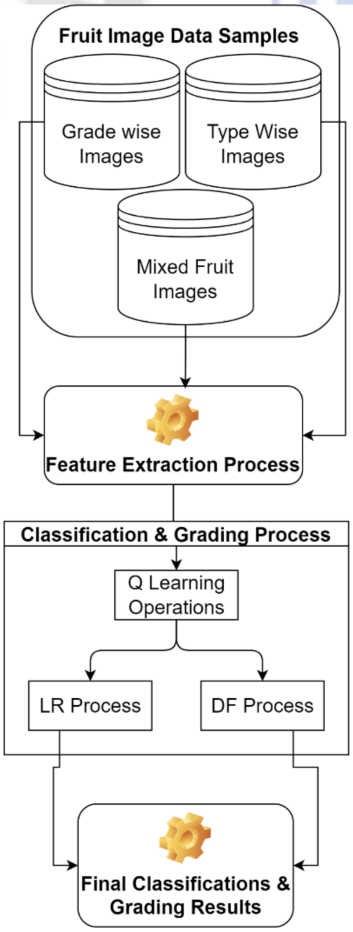

Figure 1. Design of the Proposed Classification & Grading Model Process

As per figure 1, the proposed model initially converts fruit images into multivariate features, including Colour Maps, Edge Maps, Texture Maps, which assists in representing collected images into numerical sets. These sets are classified into fruit classes via use of DQL with Logistic Regression while DQL with Deep Forest assists in identification of fruit grades. A fusion of these models provides an efficient & comprehensive solution for multivariate analysis of fruits.

By representing an image in various color spaces, such as RGB or HSV, and examining the pixel values for these spaces, it is possible to create color maps that accurately depict the distribution of colors in an image. Let's say the input image is represented by a matrix, IN, with the dimensions M N C, where M denotes the number of rows, N the number of columns, and C the color channels (Red, Green, and Blue). The first step is to create a blank histogram array with a size of Bins, where Bins denotes the quantity of quantization levels for each of the color channels. In order to accommodate an 8-bit image for histogram analysis, Bins is typically set to 256 for 8 bit image sets. Next, each pixel in the image is iterated through, and via equation 1, the corresponding bin in the histogram array (h) is then increased based on these RGB values for different samples.

$$h[R,G,B] = h[R,G,B] + 1 \ldots (1)$$

The final histogram is calculated via equation 2,

$$h = \frac{h}{M \times N} \ldots (2)$$

The histogram that is generated from the input image's frequency distribution of color values sheds light on its color compositions. The value in each bin in the histogram represents a different color value and indicates how many pixels in the image have that particular set of color values & samples.

Iterative Gaussian filtering is used to smooth out the image pixels and reduce noise in the input image before the Canny edge detection algorithm extracts an edge map from it. Equation 3 is used to convolve the input image with a 2D Gaussian kernel in order to accomplish this.

$$C(i,j) = \sum\left[\sum\left(CenK(k,l) * I(i+k-1, j+l-1)\right)\right] \ldots (3)$$

Where, $CenK$ represents Centered Kernel, whch is represented via equation 4, I represents the input image, C is the result of convolution which results in formation of Smooth Image Sets.

$$CenK(i,j) = GK\left(i - \left(\frac{K}{2}\right), j - \left(\frac{K}{2}\right)\right) \ldots (4)$$

Where, GK represents the standard Gaussian Kernel, which is used for edge evaluation process.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

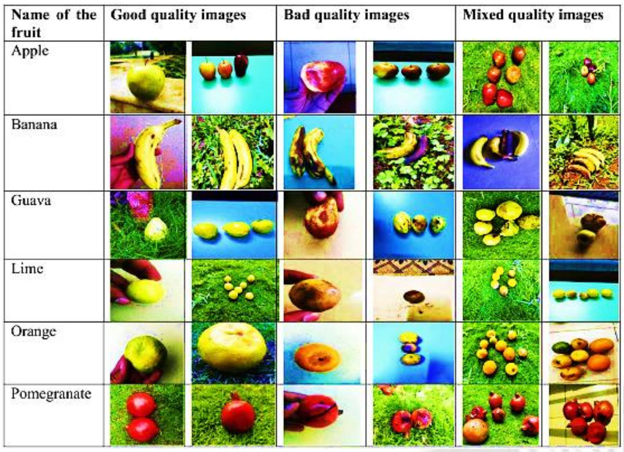

Figure 2. Classification Results for the Analysis Process

To obtain the convolved output for that set of pixels, the element-wise multiplication results are summed at each individual pixel location. The size of the output matrix matches that of the input image sets. Next, using equations 5 and 6, the gradients (GX & GY along X & Y axis) of the smoothed image are computed to determine the intensity changes in various gradients.

$$GX = Conv(C, SobelX) \dots (5)$$

$$GY = Conv(C, SobelY) \dots (6)$$

Non-maximum suppression is used to thin out the edges after obtaining the gradient magnitudes along X and Y. Equation 7 is used to suppress the other non-maximum values while maintaining only the local maxima in the gradient levels.

$$SG(i,j) = 0$$

$$if\ G(i,j) \leq G(i + dx, j + dy)$$

$$or\ G(i,j) \leq G(i - dx, j - dy) \dots (7)$$

The offsets dx and dy correspond to the quantized gradient levels where (i, j) denotes the current pixel location. After non-maximum suppression has been applied, the resulting matrix has edges that have been preserved as non-zero values and edges that have been suppressed as zeros. The remaining edge pixels are classified as either strong edges or weak edges using a thresholding process before the edge map (EM) is complete for different pixel sets. Strong edges are defined as pixels with gradient magnitudes above a high threshold, while weak edges are defined as pixels with gradient magnitudes in the middle of these two ranges, which is done via equation 8,

$$if\ SG(i,j) \geq HighTh, then\ EM(i,j) = 255 \dots (8)$$

The model process then takes into account the pixels with a gradient magnitude between the low and high thresholds after processing the pixels that exceed the high threshold. At first, these pixels are thought of as having weak edges. The model process determines whether any of the surrounding pixels of the current weak edge are strong edges (pixel value of 255), and if they are, the weak edge is promoted to an augmented set of strong edges in the output edge map via the conditions in equation 9,

$$if\ SG(i,j) \geq LowTh$$

$$check\ nearby\ pixels\ (k,l)\ for\ (i,j)$$

$$if\ EM(k,l) == 255$$

$$EM(i,j) = 255 \dots (9)$$

The GLCM is initialized as an empty square matrix of size N N, similar to these Maps, where N stands for the quantity of Gray Levels or quantization levels. The default value for N for 8-bit grayscale image sets is 256. The image's pixels are then iterated over, with the exception of the border pixels. The algorithm takes into account a particular pixel offset, denoted as (dx, dy), to define a neighboring pixel in a particular set of spaces for each pixel at position (i, j). Calculated via equation 10

$$GLCM(i + \mathrm{dx}, j + \mathrm{dy}) = GLCM(i,j) + 1 \dots (10)$$

Where (i, j) denotes the location of the current pixel, and (i + dx, j + dy) denotes the location of the neighbouring pixel according to the specified pixel offsets. The resulting GLCM represents the joint occurrence probabilities of pairs of pixel intensities within the image sets after going through each pixel in turn and updating the corresponding elements in the GLCM matrix. Contrast (C), Homogeneity (HM), Energy (E), and Entropy (En) are texture features that can be extracted using the GLCM Matrix and are estimated via equations 11, 12, 13, and 14.

$$C = \sum (GLCM(i,j) * (i - j)^2) \dots (11)$$

$$HM = \sum \left(\frac{GLCM(i,j)}{1 + (i - j)^2} \right) \dots (12)$$

$$E = \sum (GLCM(i,j)^2) \dots (13)$$

$$En = -\sum \Big(GLCM(i,j) * \log\big(GLCM(i,j)\big) \Big) \dots (14)$$

Where (i, j) stands for the GLCM matrix's indices, and the summation is applied to every matrix element, which assists in estimation of these features.

All these features are fused to form a Fruit Feature Vector (FFV), which is classified into different fruits via use of a Logistic Regression classifier backed by Deep Q Learning for continuous optimizations. In this case, multiclass logistic regression is used, where, we use the softmax function to handle multiple fruit types. This function calculates the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

probabilities of the input belonging to each class via equation 15,

$$P(y = i|\theta, FFV) = \frac{exp(\theta i^T * FFV)}{\Sigma(exp(\theta j^T * FFV))} \dots (15)$$

Where, P(y=i|θ,x) is the predicted probability of the input belonging to given class (i), K is the total number of classes, θi is the parameter vector for class, FFV represents the Fruit Feature Vector for different input samples. After this, the cost function measures the difference between the predicted probabilities and the actual one-hot encoded class labels via equation 16,

$$J(\theta) = -\frac{1}{m} * \Sigma \left[\Sigma \left(yi * log\left(P(y = i|\theta, FFV)\right)\right)\right] \dots (16)$$

Where, J(θ) is the cost function. m is the number of training samples, yi is the one-hot encoded class label vector for the class. After this an efficient gradient descent model is used, where the goal of training is to find the best parameters θ that minimize the cost function, and is done via equation 17,

$$\theta j = \theta j - \alpha * \left(\frac{1}{m}\right) * \Sigma\left[(h\theta(FFV) - y) * FFVj\right] \dots (17)$$

Where, α is the learning rate, which controls the step size during parameter vector updates. Based on this evaluation an augmented Q Value is estimated via equation 18,

$$Q = \frac{P + A + R}{3} \dots (18)$$

Where, P, A & R represents the precision, accuracy & recall for classification of samples into different fruit classes. Evaluation of these metrics is explained in the results section of this text. The Q Value is estimated for different evaluations, and a reward value is calculated via equation 19,

$$r = \frac{Q(New) - Q(Old)}{LR} - d * Max(Q) + Q(Old) \dots (19)$$

Where, LR represents Q Learning Rate, & d is the discount factor, which is empirically selected to maximize the accuracy levels. If the value of $r > 1$, then the model is performing well, and there is no need to tune the Logistic Regression classifier, otherwise, the value of cost function is updated via equation 20,

$$J(\theta) = J(\theta) * \frac{r}{1 - r} \dots (20)$$

Based on this new cost value, the Logistic Regression Mode is re-evaluated, till $r > 1$ is obtained, which ensures higher efficiency of fruit classification under different classes.

Once the model is trained, then a Deep Forest Classifier is used, which assists in grading the fruits. This classifier is an ensemble learning method that combines the power of Random Forests and Deep Learning operations. The first layer of the Deep Forest is the representation layer, where the raw input data is transformed into intermediate representations via equation 21,

$$h(0) = \{h(0,1), h(0,2), \dots, h(0, N)\} \dots (21)$$

Where $h(0, i)$ represents the output of the i-th tree in the representation layer, and is estimated via equation 22,

$$h\big(0, i(x)\big) = argmax\left(\frac{1}{K} * \Sigma\left[yj == k\right]\right) \dots (22)$$

Where, K represents total number of fruit grades, while yj represents the feature vector used for identification of fruit grades. Next, the cascade layer is used, which is a stack of multiple representation layers. Each representation layer is trained with the outputs of the previous layers. The final representation layer produces a set of intermediate representations via equation 23,

$$h(i, j) = \{h(i, j1), h(i, j2), \dots, h(i, jN)\} \dots (23)$$

Where, $h(i, j)$ represents the output of the j-th tree in the i-th representation layers. Next, the transformation layer converts the intermediate representations into a feature vector that can be used for grading the fruits via equation 24,

$$z = Avg\big(h(L, 1), h(L, 2), \dots h(L, N)\big) \dots (24)$$

The final layer is the classification layer, which performs the actual multiclass grading of fruits using the transformed feature vector sets. This layer employs a softmax activation function to convert the raw scores into class probabilities via equation 25,

$$P(y = k|x) = \frac{exp(zk)}{\Sigma exp(zi)} \dots (25)$$

Where, $P(y = k|x)$ represents the probability of input features belonging to given grade class, and zk is the k-th element of the transformed feature vector sets. Based on this evaluation, the model is able to identify different fruit grades. Efficiency of this model is estimated via equation 18 & 19, where Q Levels & Rewards are estimated for the grading process. Based on these estimations, if $r < 1$, then the model updates its intermediate representations via equation 26,

$$h(New) = h(Old) * \sqrt{\frac{r^2}{1 - r^2}} \dots (26)$$

This process is repeated till $r > 1$, which indicates that the model is performing correctly, and can efficiently grade different types of fruits. To identify this performance, the proposed model was validated in terms of different metrics, and this performance was compared with existing methods in the next section of this text.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

IV. Result Analysis & Comparisons

The proposed model uses a fusion of Q Learning with Logistic Regression and Deep Forests in order to identify fruit types and fruit classes. The Q Learning process assists in Iteratively improving the model's efficiency under multiple fruit classes. To validate performance of this model, it was evaluated on the following datasets & samples,

- Kaggle - Fruits 360 Dataset:
  - Number of Instances: The Kaggle Fruits 360 dataset contains over 90,000 images of fruits.
  - Number of Fruit Types: It includes images of 131 different types of fruits.
  - Types of Fruits: The dataset covers a wide variety of fruits, such as apples, bananas, oranges, strawberries, watermelons, grapes, pineapples, and many more.
  - Link: Readers can access the Kaggle Fruits 360 dataset on Kaggle's website via the following link https://www.kaggle.com/moltean/fruits
- FRont Experimental System for High throughput plant phenotyping (FRESP) Datasets:
  - Number of Instances: The number of instances in the FRESP datasets can vary depending on the specific dataset or experiment. These datasets are often tailored for specific plant phenotyping studies, and the number of images can range from hundreds to thousands or more.
  - Number of Fruit Types: The FRESP datasets typically include images of various plant species used for phenotyping research. While some datasets might focus on a specific type of plant, others may cover multiple plant species.
  - Types of Fruits: As the datasets are designed for plant phenotyping, they include images of different types of crops, vegetables, and other plant species used in agriculture and botanical research.
  - Link: The availability of specific FRESP datasets may vary, and they might be accessible through research institutions, plant phenotyping databases, or other platforms. Researchers can access this dataset from https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification
- ImageNet:
  - Number of Instances: The ImageNet dataset contains over 14 million labeled images.
  - Number of Fruit Types: ImageNet is an extensive dataset with thousands of object categories, including some fruit types.
  - Types of Fruits: The dataset covers various fruits, such as apples, bananas, oranges, lemons, cherries, pears, and more. However, it's essential to note that ImageNet is not solely focused on fruits but includes a broad range of objects, animals, and scenes.
  - Link: Readers can access the ImageNet dataset through http://www.image-net.org/

These datasets were combined to produce a total of 1 million images, out of which 250k were used for validation, 600k for training, and 150k for testing operations. Using this method, the precision for classification & grading (P) was calculated via equation 27,

$$P = \frac{1}{NC}\sum_{i=1}^{NC}\frac{tp(i)}{tp(i)+fp(i)} \ldots (16)$$

Where tp, tn, fp, fn represents normal true & false rates for different classification & grading scenarios, while NC represents number of grade & fruit classes. Similarly, the Accuracy, & Recall, were determined using equations 17 & 18 as follows,

$$A = \frac{1}{NC}\sum_{i=1}^{NC}\frac{tp(i)+tn(i)}{tp(i)+tn(i)+fp(i)+fn(i)} \ldots (17)$$

$$R = \frac{1}{NC}\sum_{i=1}^{NC}\frac{tp(i)}{tp(i)+tn(i)+fp(i)+fn(i)} \ldots (18)$$

On the basis of this evaluation, the efficiency levels for identification of fruit classes and compared with DNN [2], CNN [5], and MR CNN YoLo [12] were estimated using comparable datasets and samples. The confusion matrix for identification of fruit types can be observed from table 1 as follows,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

	Predicted Mango	**Predicted Apple**	**Predicted Papaya**	**Predicted Grape**	**Predicted Banana**
Actual Mango	150	10	5	2	3
Actual Apple	8	130	12	0	1
Actual Papaya	2	6	142	10	0
Actual Grape	0	1	7	120	15
Actual Banana	3	0	0	8	155

Table 1. Confusion Matrix for identification of fruit types

Similarly, the confusion matrix for grading into different fruits can be observed from table 2 as follows,

	Predicted Low	**Predicted Medium**	**Predicted High**	**Predicted Very High**
Actual Low	160	5	3	2
Actual Medium	8	140	4	0
Actual High	0	2	148	8
Actual Very High	2	0	6	160

Table 2. Identification of Fruit Grades for different Fruit Types

Based on this strategy, the precision of classification into fruit classes can be observed from figure 3 as follows,

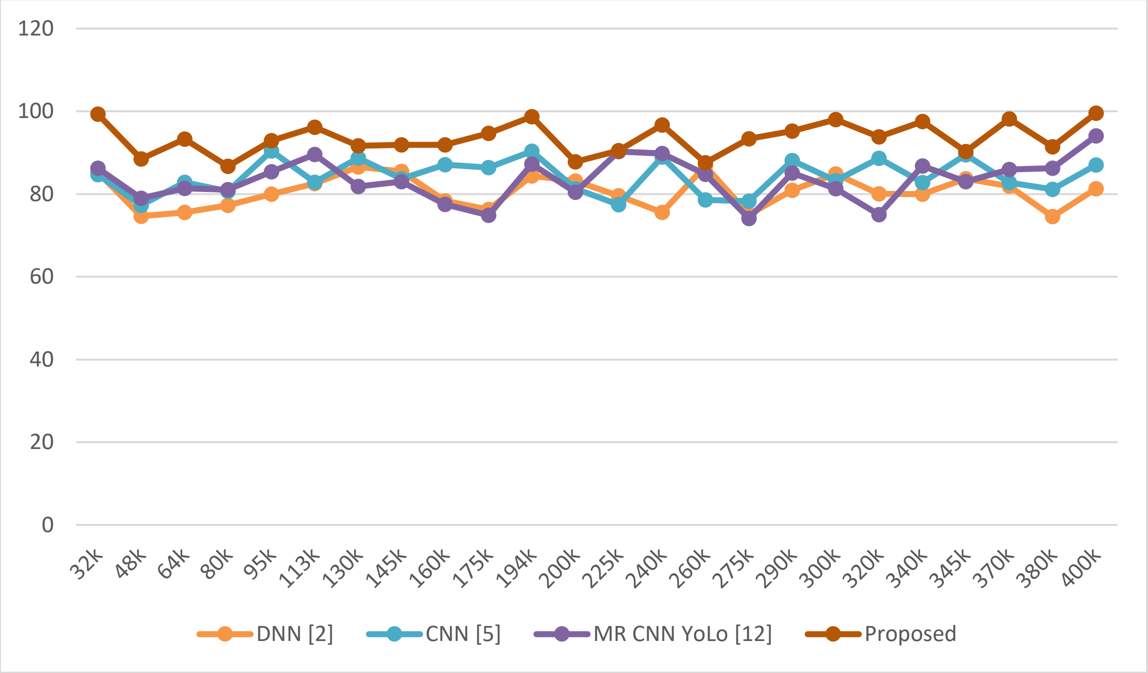

Figure 3. Average Precision Levels for Classification of Fruit Types

In comparison to DNN [2], CNN [5], and MR CNN YoLo [12] methods, the proposed model improves fruit type classification precision by 8.3%, 10.5%, and 8.5%, respectively, in real-time scenarios. This accuracy is enhanced by the application of high-performance Q Learning and multivariate features, which aid in the extraction of probabilistic features and the accurate prediction of fruit types for various fruit image samples. Similarly, figure 4 depicts the accuracy achieved during these evaluations,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

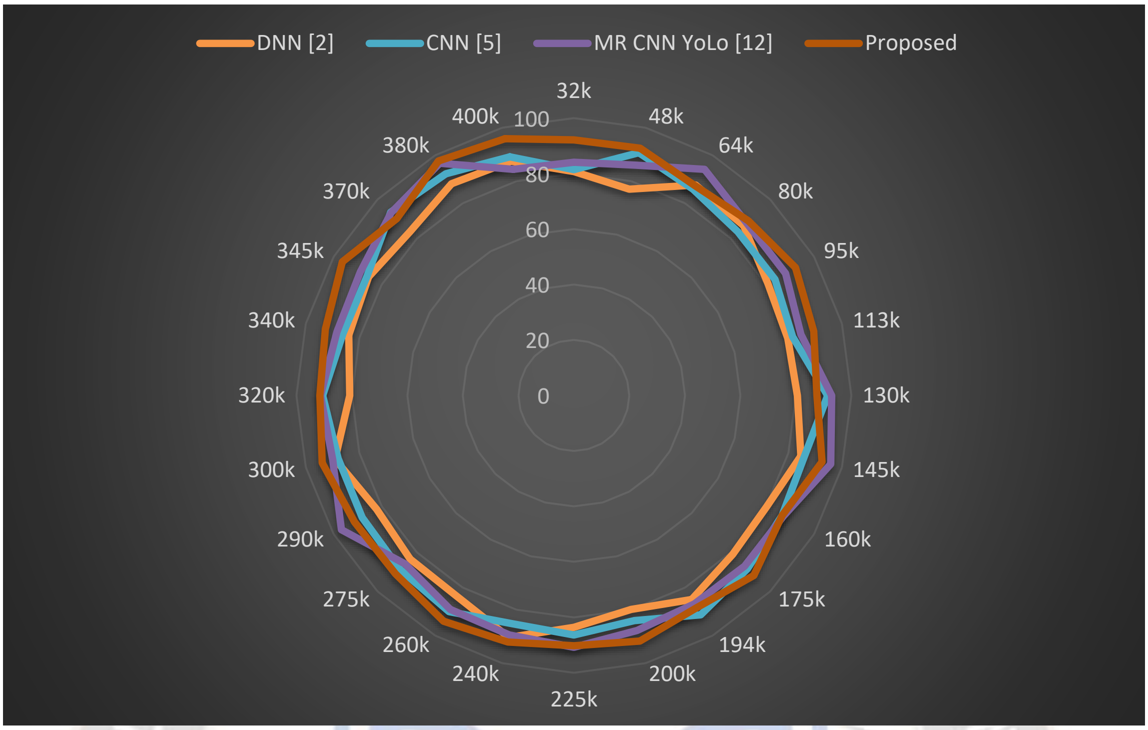

Figure 4. Average Accuracy Levels for Classification of Fruit Types

Based on this evaluation, it is evident that, under real-time conditions, the proposed model improves fruit type classification accuracy by 5.5% relative to DNN [2], 10.4% relative to CNN [5], and 8.5% relative to MR CNN YoLo [12] for different scenarios. The application of the Q Learning and the extraction of multivariate features, which aid in the accurate prediction of fruit types for various fruit image samples, increase these accuracy levels. Similarly, the recall obtained during these evaluations can be seen in the following figure 5,

Figure 5. Average Recall Levels for Classification of Fruit Types

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

This evaluation demonstrates that the proposed model outperforms DNN [2], CNN [5], and MR CNN YoLo [12] in terms of recall for fruit type classification in real-time scenarios by 4.9%, 8.3%, and 10.4%, respectively for different use cases. Using high-efficiency multivariate features & Q Learning Model with Deep Forest & Logistic Regression Process, along with incremental learning operations assists in improving recall levels for fruit class analysis for various fruit image samples. These results were also estimated for identification of grade levels, and the precision levels can be observed from figure 6 as follows,

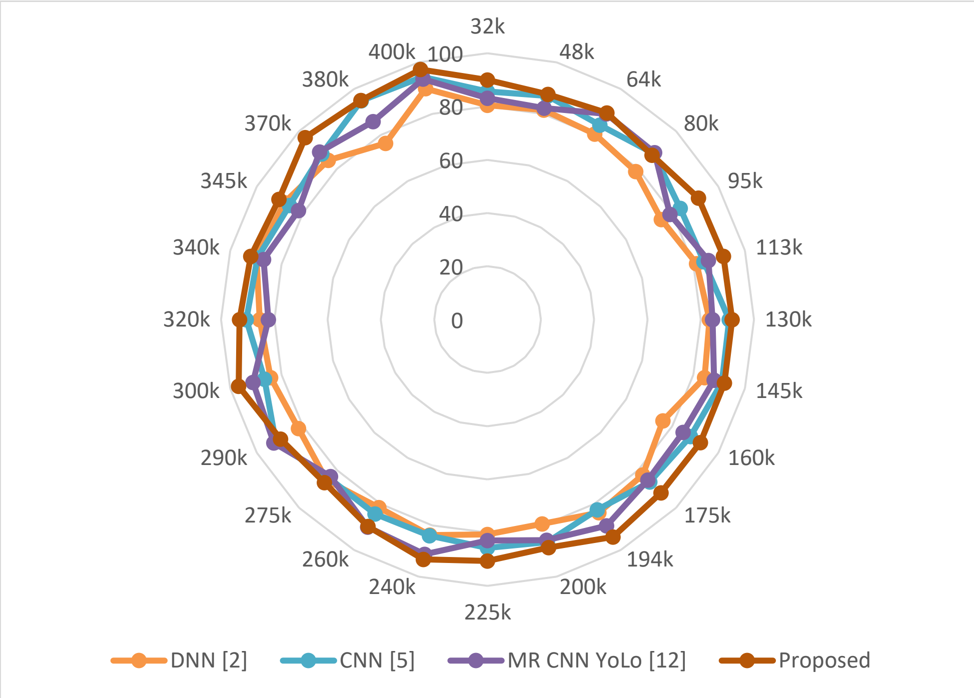

Figure 6. Average Precision Levels for Identification of Fruit Grades

In comparison to DNN [2], CNN [5], and MR CNN YoLo [12] methods, the proposed model improves grade precision by 4.9%, 8.3%, and 10.5%, respectively, in real-time scenarios. This precision is enhanced by the application of high-performance Q Learning and multivariate features, which aid in the extraction of probabilistic features and the accurate prediction of fruit grade types for various fruit image samples. Similarly, figure 7 depicts the accuracy achieved during these evaluations for real-time use cases.

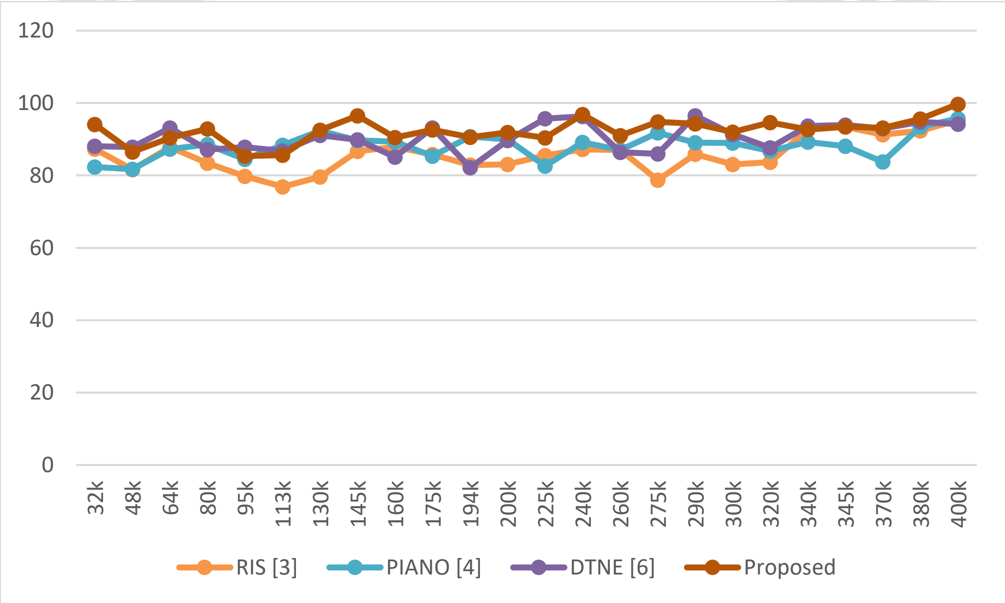

Figure 7. Average Accuracy Levels for Identification of Fruit Grades

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7937
***Article Received**: 02 May 2023 **Revised**: 24 June 2023 **Accepted**: 12 July 2023*

Based on this evaluation, it is clear that, under real-time conditions, the proposed model improves fruit grade classification precision by 3.5% relative to DNN [2], 4.9% relative to CNN [5], and 5.5% relative to MR CNN YoLo [12] for real-time scenarios. The application of Q Learning and the extraction of multivariate features, which aid in the accurate prediction of grade levels for various fruit image samples, increase these precision levels. Similarly, the recall obtained during these evaluations can be seen in the following figure 8,

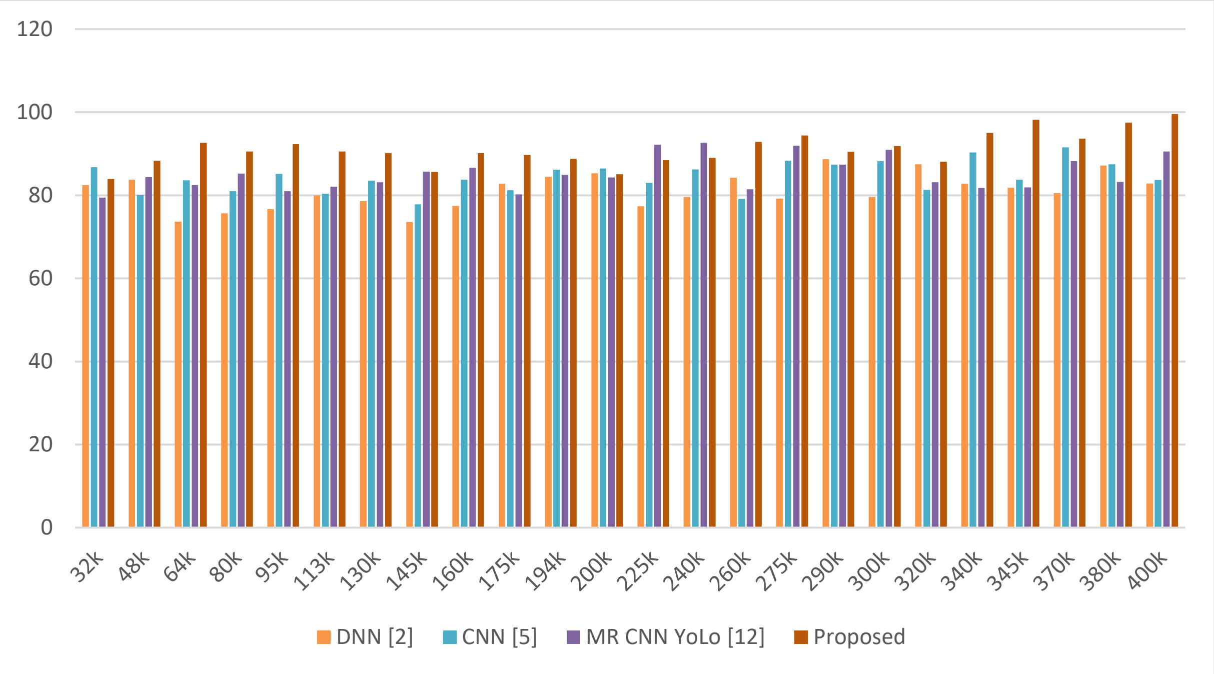

Figure 8. Average Recall Levels for Identification of Fruit Grades

This evaluation demonstrates that the proposed model outperforms DNN [2], CNN [5], and MR CNN YoLo [12] in terms of recall for identification of grade levels in real-time scenarios by 4.9%, 5.9%, and 10.4%, respectively under different use cases. Using high-efficiency multivariate features & Q Learning-based LR & DF Models, along with incremental learning operations to improve recall levels, facilitates the concise prediction of fruit types & grade for various fruit image samples.

V. Conclusion and future scope

In this paper, we propose a novel augmentation of Deep Q Learning with Logistic Regression and Deep Forests for Multivariate classification and Fruit Grading. The objective was to improve the precision and recall of real-time fruit type classification and fruit grade identification. Results demonstrate that our proposed model is superior to the comparative methods DNN [2], CNN [5], and MR CNN YoLo [12]. Our proposed model demonstrated precision improvements of 8.3%, 10.5%, and 8.5% over DNN [2], CNN [5, and MR CNN YoLo [12], respectively, in terms of fruit classification. Similarly, our model outperformed the competing methods in terms of recall rates by 4.9%, 8.3%, and 10.0%, respectively. Moreover, in terms of fruit grade identification precision, our model outperformed DNN [2], CNN [5], and MR CNN YoLo [12] by 4.9%, 8.3%, and 10.5%, respectively. In addition, our model improved recall rates by 4.9%, 5.9%, and 10.4% in comparison to the same comparable methods. Integrating high-performance Q Learning, multivariate feature extraction, Deep Forest, and Logistic Regression processes are the primary contributors to the success of our proposed model. Using these techniques, we were able to extract more robust and probabilistic features, resulting in accurate predictions of fruit types and grades from diverse fruit image samples.

Future Scope

Although our proposed model has yielded promising results, there are several avenues for further research and development to improve fruit type classification and grading:

Expansion of the Dataset: The generalizability and robustness of the proposed model could be improved by including more diverse and difficult fruit samples in the data set.

Transfer Learning: By investigating the potential of transfer learning from pre-trained models on large-scale image datasets such as ImageNet, the model may be able to learn more accurate representations of fruit features.

Attention Mechanisms: Integrating attention mechanisms can assist the model in concentrating on relevant regions of fruit images, thereby enhancing classification and grading precision.

In real-world applications, it may be advantageous to be able to interpret the model's conclusions. Research into interpretable AI techniques, such as saliency maps or attention visualization, would increase the model's transparency and reliability.

Implementing the proposed model on specialized hardware, such as GPUs or TPUs, can result in significant speed enhancements, making it more applicable for real-time applications.

Real-Time Deployment: Integrating the model into embedded systems or smartphones for real-time fruit classification and grading in the field has the potential to revolutionize the fruit industry by facilitating efficient and automated fruit quality assessment.

Exploring the potential of fusing information from multiple modalities, such as visible light and near-infrared images, could provide complementary information and improve overall performance levels.

Domain Adaptation: Investigating domain adaptation techniques can ensure that the model remains effective when deployed in various orchards or regions where environmental conditions and fruit characteristics may vary for different scenarios.

In conclusion, the proposed augmentation of Deep Q Learning with Logistic Regression and Deep Forests has demonstrated significant improvements in the classification and grading of fruit types. The results presented in this paper pave the way for future research and development in this field, and we hope that our findings will contribute to the development of fruit quality assessment technology for the agricultural industry scenarios.

References

[1] Kumari, N., Dwivedi, R.K., Bhatt, A.K. et al. Automated fruit grading using optimal feature selection and hybrid classification by self-adaptive chicken swarm optimization: grading of mango. Neural Comput & Applic 34, 1285–1306 (2022). https://doi.org/10.1007/s00521-021-06473-x

[2] Mohapatra, D., Das, N. & Mohanty, K.K. Deep neural network based fruit identification and grading system for precision agriculture. Proc.Indian Natl. Sci. Acad. 88, 228–239 (2022). https://doi.org/10.1007/s43538-022-00079-0

[3] Bhargava, A., Bansal, A. Classification and Grading of Multiple Varieties of Apple Fruit. Food Anal. Methods 14, 1359–1368 (2021). https://doi.org/10.1007/s12161-021-01970-0

[4] Cao, M., Zhang, J., Sun, Y. et al. A novel air-suction classifier for fresh sphere fruits in pneumatic bulk grading. Food Measure (2023). https://doi.org/10.1007/s11694-023-01878-9

[5] Gururaj, N., Vinod, V. & Vijayakumar, K. Deep grading of mangoes using Convolutional Neural Network and Computer Vision. Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-021-11616-2

[6] Unay, D. Deep learning based automatic grading of bi-colored apples using multispectral images. Multimed Tools Appl 81, 38237–38252 (2022). https://doi.org/10.1007/s11042-022-12230-6

[7] Hanh, L.D., Bao, D.N.T. Autonomous lemon grading system by using machine learning and traditional image processing. Int J Interact Des Manuf 17, 445–452 (2023). https://doi.org/10.1007/s12008-022-00926-w

[8] Soltani Firouz, M., Sardari, H. Defect Detection in Fruit and Vegetables by Using Machine Vision Systems and Image Processing. Food Eng Rev 14, 353–379 (2022). https://doi.org/10.1007/s12393-022-09307-1

[9] Bhargava, A., Bansal, A. & Goyal, V. Machine Learning–Based Detection and Sorting of Multiple Vegetables and Fruits. Food Anal. Methods 15, 228–242 (2022). https://doi.org/10.1007/s12161-021-02086-1

[10] Andrew Hernandez, Stephen Wright, Yosef Ben-David, Rodrigo Costa,. Enhancing Decision Support Systems through Machine Learning Algorithms. Kuwait Journal of Machine Learning, 2(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/194

[11] Kumari, N., Kr. Bhatt, A., Kr. Dwivedi, R. et al. Hybridized approach of image segmentation in classification of fruit mango using BPNN and discriminant analyzer. Multimed Tools Appl 80, 4943–4973 (2021). https://doi.org/10.1007/s11042-020-09747-z

[12] Yang, M., Kumar, P., Bhola, J. et al. Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit. Int J Syst Assur Eng Manag 13 (Suppl 1), 322–330 (2022). https://doi.org/10.1007/s13198-021-01415-1

[13] Goyal, K., Kumar, P. & Verma, K. AI-based fruit identification and quality detection system. Multimed Tools Appl 82, 24573–24604 (2023). https://doi.org/10.1007/s11042-022-14188-x

[14] Jayanth, J., Mahadevaswamy, M. & Shivakumar, M. Fruit Quality Identification and Classification by Convolutional Neural Network. SN COMPUT. SCI. 4, 220 (2023). https://doi.org/10.1007/s42979-022-01527-w

[15] Kaur, S., Randhawa, S. & Malhi, A. An efficient ANFIS based pre-harvest ripeness estimation technique for fruits. Multimed Tools Appl 80, 19459–19489 (2021). https://doi.org/10.1007/s11042-021-10741-2

[16] Dhiman, B., Kumar, Y. & Kumar, M. Fruit quality evaluation using machine learning techniques: review, motivation and future perspectives. Multimed Tools Appl 81, 16255–16277 (2022). https://doi.org/10.1007/s11042-022-12652-2

[17] Meng, X., Yuan, Y., Teng, G. et al. Deep learning for fine-grained classification of jujube fruit in the natural environment. Food Measure 15, 4150–4165 (2021). https://doi.org/10.1007/s11694-021-00990-y

[18] Kazi, A., Panda, S.P. Determining the freshness of fruits in the food industry by image classification using transfer learning. Multimed Tools Appl 81, 7611–7624 (2022). https://doi.org/10.1007/s11042-022-12150-5

[19] Meshram, V., Patil, K. Border-Square net: a robust multi-grade fruit classification in IoT smart agriculture using feature extraction based Deep Maxout network. Multimed Tools

Appl 81, 40709–40735 (2022). https://doi.org/10.1007/s11042-022-12855-7

[20] Bisen, R.D., Bakane, P.H. & Sakkalkar, S.R. Design, development and performance evaluation of rotary onion grader. J Food Sci Technol 59, 2370–2380 (2022). https://doi.org/10.1007/s13197-021-05253-8

[21] Dhiman, B., Kumar, Y. & Hu, YC. A general purpose multi-fruit system for assessing the quality of fruits with the application of recurrent neural network. Soft Comput 25, 9255–9272 (2021). https://doi.org/10.1007/s00500-021-05867-2

[22] Ms. Madhuri Zambre. (2012). Performance Analysis of Positive Lift LUO Converter . International Journal of New Practices in Management and Engineering, 1(01), 09 - 14. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/3

[23] Kumar, D., Vertivendan, L. ., Velmurugan, K. ., M., K. ., Toradmalle, D. ., & Vajid Nabilal, K. . (2023). Semantic Marginal Autoencoder Model for the Word Embedding Technique for the Marginal Denoising in the Different Languages. International Journal of Intelligent Systems and Applications in Engineering, 11(3s), 204–210. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2562

[24] Gill, H.S., Murugesan, G., Khehra, B.S. et al. Fruit recognition from images using deep learning applications. Multimed Tools Appl 81, 33269–33290 (2022). https://doi.org/10.1007/s11042-022-12868-2

[25] Khatri, K. ., & Sharma, D. A. . (2020). ECG Signal Analysis for Heart Disease Detection Based on Sensor Data Analysis with Signal Processing by Deep Learning Architectures. Research Journal of Computer Systems and Engineering, 1(1), 06–10. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/11

[26] Magalhães, S.A., Moreira, A.P., Santos, F.N.d. et al. Active Perception Fruit Harvesting Robots — A Systematic Review. J Intell Robot Syst 105, 14 (2022). https://doi.org/10.1007/s10846-022-01595-3

[27] Abayomi-Alli, O.O., Damaševičius, R., Misra, S. et al. FruitQ: a new dataset of multiple fruit images for freshness evaluation. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-16058-6

[28] Tian, S., Xu, H. Nondestructive Methods for the Quality Assessment of Fruits and Vegetables Considering Their Physical and Biological Variability. Food Eng Rev 14, 380–407 (2022). https://doi.org/10.1007/s12393-021-09300-0

[29] Samyor, D., Deka, S.C. & Das, A.B. Physicochemical and phytochemical properties of foam mat dried passion fruit (Passiflora edulis Sims) powder and comparison with fruit pulp. J Food Sci Technol 58, 787–796 (2021). https://doi.org/10.1007/s13197-020-04596-y

[30] Mondal , D. (2021). Green Channel Roi Estimation in The Ovarian Diseases Classification with The Machine Learning Model . Machine Learning Applications in Engineering Education and Management, 1(1), 07–12.

[31] Kumar, R., Paul, V., Pandey, R. et al. Reflectance based non-destructive assessment of tomato fruit firmness. Plant Physiol. Rep. 27, 374–382 (2022). https://doi.org/10.1007/s40502-022-00678-5

[32] Antala, D.K., Satasiya, R.M. & Chauhan, P.M. Design, development and performance evaluation of transportation container for sapota fruit. J Food Sci Technol 58, 4024–4033 (2021). https://doi.org/10.1007/s13197-020-04865-w

[33] Goyal, K., Kumar, P. & Verma, K. Food Adulteration Detection using Artificial Intelligence: A Systematic Review. Arch Computat Methods Eng 29, 397–426 (2022). https://doi.org/10.1007/s11831-021-09600-y

[34] Chithra, P., Henila, M. Apple fruit sorting using novel thresholding and area calculation algorithms. Soft Comput 25, 431–445 (2021). https://doi.org/10.1007/s00500-020-05158-2

[35] Alayed, H.S., Devanesan, S., AlSalhi, M.S. et al. Green synthesis of calcium hydroxide nanoparticles using carob fruit extract and evaluation of their cytotoxic activity. Appl Nanosci 12, 2511–2521 (2022). https://doi.org/10.1007/s13204-022-02511-9