Journal of Autonomous Intelligence (2024) Volume 7 Issue 4
doi: 10.32629/jai.v7i4.1424

ORIGINAL RESEARCH ARTICLE

Intelligent fruit quality classification system using transfer learning

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ABSTRACT

Amidst the burgeoning demands of fruit agriculturists and grading companies for enhanced fruit quality classification, this research presents a cutting-edge approach to binary fruit quality assessment. We built a portable device for exact fruit quality inspection using transfer learning, a deep learning approach, resulting in a decrease in both human and machine labor. The performance of the system is validated and evaluated under real-time situations, with an emphasis on end-user applicability. This paper rigorously validates and assesses the system's performance in real-world scenarios, with a strong focus on its practicality for end-users. The model is trained on an online picture dataset that is divided into two categories: 'good' and 'poor' fruits. On dataset 1, our numerical findings show outstanding classification accuracies of 99.49% and 99.75% for the first and second models, respectively. Meanwhile, on dataset 2, the first and second models attain accuracies of 85.43% and 96.75%, respectively, highlighting the efficacy of our technique.

Keywords: deep learning; machine learning; image processing; feature selection; fruit quality; Internet of Things; centralized computing; transfer learning

ARTICLE INFO

Received: 8 November 2023
Accepted: 11 December 2023
Available online: 7 February 2024

1. Introduction

A significant number of practitioners in global agriculture engage in fruit growing, contributing to the world's output of 63 million tons of fruits in 2020[1]. Concurrently, the fruit industry's fruit output quality is increasing significantly. However, when it comes to meeting worldwide demand, fruit segmentation, and grading based on freshness and quality become key characteristics. Manual assessment of fruit freshness or quality by humans is labor-intensive, resulting in an increase in marketing expenses. The incorporation of technical breakthroughs in precise automatic quality grading instruments provides significant benefits to both agriculturists and industrial stakeholders.

As computational technologies evolve, a plethora of such computational tools and platforms have been developed and applied on a worldwide scale. Several studies applied advanced computer algorithms to identify form, texture, or illness in fruits[2–5].

To increase picture quality, image processing techniques such as Discrete Wavelet Transformation (DWT), Fourier Transformation (FT), segmentation, histogram equalization, and others were used. Furthermore, machine learning methods such as Support Vector Machine (SVM), Nave Bayes (NB), Decision Tree (DT), K Means

Clustering, and others were used to categorize the gathered photos[6,7]. Deep learning has been more significant in picture categorization and fruit grading in the modern day. Deep learning methods include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GNN), and others[8,9]. The optimal use of CNN can be found with high-density picture datasets, while RNN can function efficiently with time series-related workload. However, for improved accuracy on lower-density picture datasets, another enhanced deep learning approach known as Transfer Learning (TL) can be used[10,11].

Within the area of academic research, a variety of computational approaches for assessing fruit quality based on picture analysis have been developed. Notably, Stajnko et al.[3] attempted fruit grading using image processing algorithms to analyze color, shape, and texture parameters, resulting in an excellent 85 percent accuracy rate. Building on this basis, Dubey and Jalal[5] and Jadhav and Patil[12] have used image processing algorithms to incorporate enhancements for color, edge, form, and size detection, resulting in improved quality grading optimization. Sahu and Dewangan[13] used texture analysis and morphological processes within the context of image processing to classify mango fruits as defective or non-defective. Furthermore, Jayanthi et al.[14] conducted an experimental study, employing a programmed microcontroller to create a cost-effective and user-friendly system for identifying rotting fruits. This system used techniques including LVQ (Learning Vector Quantization), edge detection, and histogram-based algorithms, all of which helped to detect degraded fruit specimens.

In the age of artificial intelligence (AI) growth, the deployment of trained classification systems has become critical in fruit freshness grading, and this may be efficiently accomplished by either machine learning or deep learning algorithms, delivering the greatest levels of accuracy. Chandini and Maheswari[15] used K-means clustering for segmentation and Gray Level Co-occurrence Matrix (GLCM)-based feature extraction in fruit photos, achieving an impressive 85% accuracy using the multiclass Support Vector Machine (SVM) technique. Sidehabi et al.[16] used K-Means clustering for picture segmentation and Artificial Neural Networks (ANNs) for ripeness classification, attaining an amazing average accuracy rate of 95 percent on a constant basis. In order to count fruits precisely, a specific deep learning model called as 'DeepFruits' was built using the VGG deep neural network architecture. This model was evaluated on fruit-laden tree photos, and its accuracy rates for accuracy, precision, and recall exceeded 90%[17]. CNNs and the VGG-16 deep learning framework were used by Hossain et al.[18] for fruit categorization across two separate datasets. Case 1 had an amazing 99% accuracy rate, while Case 2 earned an accuracy rate ranging from 85 to 96 percent, despite its rather varied prediction model.

Vasumathi and Kamarasan[19] trained and analyzed an SVM model for fruit data in a large big-data environment, resulting in considerable computational efficiency advantages. Zhang et al.[20] used fruit data augmentation techniques to increase the sample size, resulting in an impressive 94.94% classification accuracy utilizing a 13-layer CNN implementation. Furthermore, for fruit type classification, a hybrid technique combining an attention-based Dense-Net was used, with amazing results, obtaining an accuracy rate of 95.86%[21]. Finally, Shaikh et al.[22] trained and evaluated the Faster R-CNN model, measuring its classification skills across a variety of fruits including apple, pear, and banana. While the observed accuracy levels were usually good, they varied from 60%–75%, 85%–99%, and 80%–97% for the various fruit categories. Xiang et al.[23] conducted fruit categorization studies using a variety of deep neural network architectures, including MobileNetV2, MobileNetV1, InceptionV3, and DenseNet121, in a scholarly endeavor. Their efforts resulted in a significant training accuracy of 96%, as well as a commendable testing accuracy of 75%, coupled with low loss values close to 0.1. Furthermore, Siddiqi[24] tested VGG16 and InceptionV3 for fruit categorization, showing amazing classification accuracies ranging from 98% to 99%.

In this study, a cutting-edge Internet of Things (IoT)-based intelligent system for the exact identification and grading of fruits is described, utilizing highly optimized and extensively trained neural networks[25–28]. The training dataset contains around one thousand photos for each fruit group and has a low data density. To maximize the potential of deep learning-based transfer learning in scenarios with small dataset sizes, various algorithms have been meticulously employed to produce superior model performance, as measured by a wide range of metrics such as accuracy, precision, recall, area-under-curve, and mean square error.

In this part, we looked at a variety of approaches and factors used to evaluate fruit quality (Refer **Table 1**). The literature review demonstrates that image processing approaches, machine learning, and deep learning algorithms are useful in reaching outstanding accuracy rates in fruit quality ratings. However, there are certain practical hurdles, such as the necessity for big and diverse datasets as well as processing efficiency. To address these issues, our study employs transfer learning, a deep learning technique, to provide a cutting-edge solution to binary fruit quality evaluation. Therefore, the potential for practical application, cost savings, quality control, and integration with the wider aims of global food security and environmental sustainability drives the urgency to overcome the problems associated with dataset size, variety, and processing efficiency. Our research efforts aim to make a major contribution to these compelling aims in the realm of fruit quality evaluation.

Table 1. Fruit quality assessment results.

Reference	Methodologies and results	Assessed parameters
[12]	Enhanced quality grading through image processing algorithms.	Color, Shape, Edge
[13]	Classified mango fruits as defective or non-defectiveusing texture analysis and morphological processes.	Texture, Morphology
[14]	Developed a cost-effective system for identifying rottingfruits using LVQ, edgedetection, and histogram-based algorithms.	Color, Edge, Histogram
[15]	Achieved 85% accuracy using K-means clustering and GLCM-based feature extraction with SVM.	K-means Clustering, GLCM, SVM
[16]	Reached an average accuracyrate of 95% using K-Means clustering and Artificial Neural Networks.	K-means Clustering, ANN
[17]	A deep learning model achieved accuracy ratesexceeding 90% for fruit counting.	Deep Learning, CNN
[18]	CNNs and VGG-16 achieved high accuracy in fruit-categorization.	CNN, VGG-16
[19]	SVM model in a big data environment showedcomputational efficiency benefits.	SVM, Big Data
[20]	Achieved 94.94% classification accuracy usingCNN and data augmentation.	Deep Learning, Data Augmentation
[21]	Combined an attention-basedDense-Net for fruit type classification with a 95.86% accuracy.	Dense-Net, Attention Mechanism
[22]	Trained and evaluated the Faster R-CNN model with varying accuracy levels for different fruit categories.	Faster R-CNN, Object Detection
[23]	Used deep neural network architectures with testing accuracy of 75% and low loss values.	Deep Neural Networks
[24]	Achieved 98–99% classification accuracies using VGG16 and InceptionV3.	VGG16, InceptionV3, Classification

2. Materials and methods

This research paper is dedicated to the precise classification of high-quality fruits, with the classification process relying on a sophisticated computational model rooted in transfer learning within the domain of deep learning. The paper is organized into two distinct sections for comprehensive coverage: the first section delves into the intricacies of a centralized IoT framework, while the second section provides an exhaustive exploration of the intricately optimized learning implementations.

2.1. IoT framework

As shown in **Figure 1**, the envisioned system is based on sophisticated IoT technology and includes an artificial intelligence-driven trained model for precisely grading fruit freshness. Remote end devices collect visual data with their embedded cameras and send it to an IoT server linked to the internet, where the analytical process takes place. Notably, the IoT processing unit within the server comes pre-loaded with a pre-trained deep neural network model, a notion that will be expanded on in the next sections.

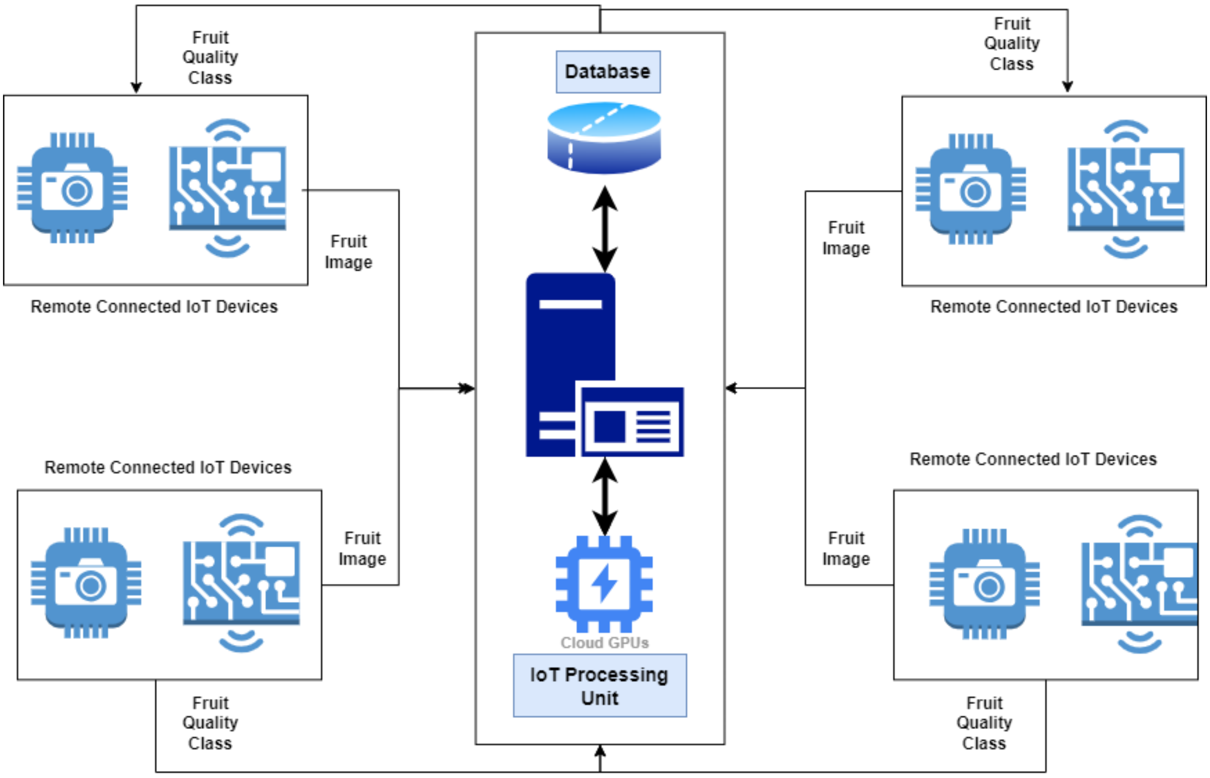


Figure 1. IoT framework

As seen in **Figure 2**, the algorithmic framework is divided into three independent phases: datacollection and pre-processing, transfer learning model selection and preparation, and class prediction using the trained model.

2.2. Phases I: Data collection and pre-processing

The major focus during this phase is on collecting distinct sets of picture data including numerous fruit species. Following that, the basic pre-processing operations are methodically carried out on the obtained dataset.

Dataset Collection - This research is devoted to a thorough examination of Indian fruit varietals. The dataset 'FruitsGB'[29] contains the top six Indian fruit categories, which are Apple, Banana, Guava, Lime, Orange, and Pomegranate. Each fruit in this dataset is divided into two unique classes: 'Good' and 'Bad,' with each class including about 1000 photos per fruit type (Refer **Table 2**). It is worth noting that these fruit photographs were recorded under a variety of settings, including different perspectives, backdrops, and lighting conditions, resulting in a diversified and realistic portrayal. This inquiry focuses on five popular fruits found in the Indian market: apple, banana, guava, lime, and orange. Equations used for splitting: Allow 'N' to represent the total number of photos in the dataset (Refer Equations (1)–(3)). The dataset is divided into three parts: training, validation, and test, with 80%, 10%, and 10%, respectively.

$$N\_train = 0.8 \times N \tag{1}$$

$$N\_val = 0.1 \times N \tag{2}$$

$$N\_test = 0.1 \times N \tag{3}$$

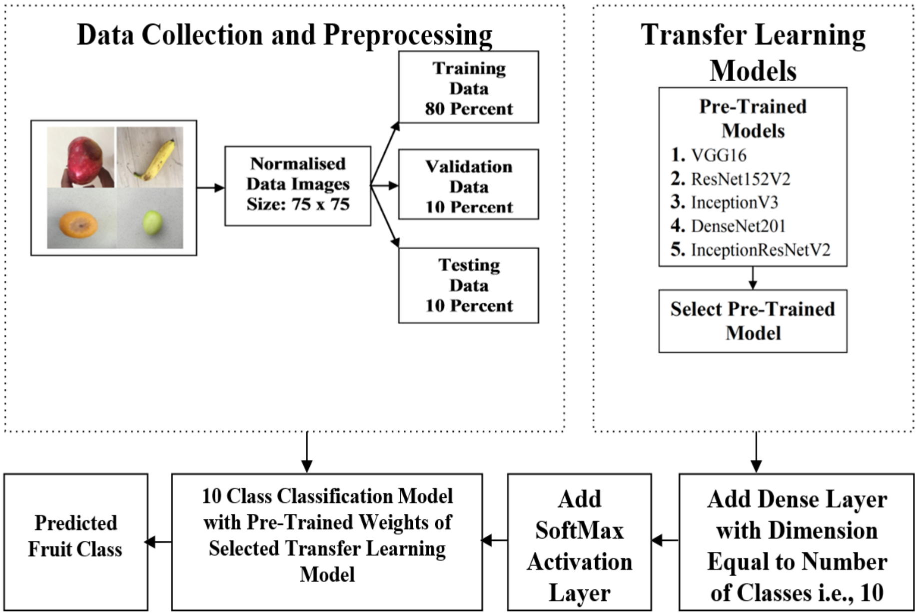


Figure 2. Overall process.

Table 2. 'FruitsGB' dataset details and examples.

S. No.	Fruit name	Class name	Number of images	Image good class	Image bad class
1	Apple	Good + Bad	1000 + 1000		
2	Banana	Good + Bad	1000 + 1000		
3	Guava	Good + Bad	1000 + 1000		
4	Lime	Good + Bad	1000 + 1000		
5	Orange	Good + Bad	1000 + 1000		

Dataset Pre-processing - The fruit picture dataset was divided into different sets for training, validation, and testing, with 80%, 10%, and 10% distributions, respectively. The photos were transformed to a standardized format of 75 pixels in width and 75 pixels in height as part of the data pretreatment phase. Following that, the enlarged data was rescaled to fractions, allowing for more simplified and efficient algorithmic implementation.

2.3. Phases II: Transfer learning models

Transfer learning is a more sophisticated variation of deep learning in which pre-trained models are used as the foundation for training on fresh datasets. This method combines newly obtained training data with information extracted from an existing well-trained benchmark model, resulting in higher accuracy and lower loss rates. Several transfer learning models, including but not limited to VGG16, ResNet152V2, InceptionV3, DenseNet201, and InceptionResNetV2, are available. Deep learning models used in transfer learning are often based on pre-trained architectures such as VGG16, ResNet, and others. For classification, the output of the pre-trained model is sent via a densely connected layer and a Softmax layer as in Equation (4).

$$\text{Output} = \text{Softmax}(\text{Dense}(\text{Features\_Pretrained\_Model})) \tag{4}$$

For the implementation of deep learning algorithms, we used the capabilities of TensorFlow and Keras in our research project. We integrated pre-trained weights from transfer learning models to improve model performance, complementing them with a densely linked layer to enable the mapping of outputs into 10 unique classes. A Softmax layer was also added to forecast class labels based on the Softmax threshold. **Table 3** contains detailed descriptions of the applied transfer learning models and layer configurations.

Table 3. Utilized transfer learning models.

VGG16		
Layer (type)	**Output Shape**	**Param #**
vgg16 (Functional)	(None, 512)	14,714,688
dense (Dense)	(None, 10)	5130
Total params: 14,719,818	-	-
Trainable params: 14,719,818	-	-
Non-trainable params: 0	-	-
ResNet152V2		
Layer (type)	**Output Shape**	**Param #**
resnet152v2 (Functional)	(None, 2048)	58,331,648
dense_1 (Dense)	(None, 10)	20,490
Total params: 58,352,138	-	-
Trainable params: 58,208,394	-	-
Non-trainable params: 143,744	-	-
DenseNet201		
Layer (type)	**Output Shape**	**Param #**
densenet201 (Functional)	(None, 1920)	18,321,984
dense_2 (Dense)	(None, 10)	19,210
Total params: 18,341,194	-	-
Trainable params: 18,112,138	-	-
Non-trainable params: 229,056	-	-
InceptionResnetV2		
Layer (type)	**Output Shape**	**Param #**
InceptionResnetV2 (Functional)	(None, 2048)	23,851,784
dense_2 (Dense)	(None, 10)	39,210
Total params: 23,851,784	-	-
Trainable params: 23,817,352	-	-
Non-trainable params: 34,432	-	-

2.4. Phases III: Predicating classes using trained model

The analytical workflow has been rigorously partitioned into three main groups in this concluding phase:

A. Machine Learning Algorithms for Analysis

This phase involves the use of a variety of machine learning algorithms to conduct a thorough assessment of fruit quality and freshness. A thorough evaluation of the efficacy and performance of these algorithms in the context of our fruit categorization job is carried out.

B. Deep Learning Algorithms for Analysis

Within this area, our emphasis moves to the use of deep learning algorithms, which have been rigorously designed to handle complicated data structures and sophisticated patterns. Several deep neural network designs and configurations are used to test their usefulness in fruit quality classification. The third category digs into our system's real-time applicability. It examines the practicality and efficiency of our approach in dynamic, real-world circumstances, assessing its ability to complete fruit quality classification tasks quickly and accurately. Each of these areas is thoroughly examined, leading to a full evaluation of the system's capabilities and possibilities in a variety of practical scenarios.

3. Results

In this section detailed results have been analyzed in sections including "Analysis with Machine and Ensemble Learning Algorithms", "Analysis with Transfer Learning Algorithms", "Analysing Impact of Optimizers on Transfer Learning Algorithms", and "Real-Time Testing Results". The experimental setup for this paper included Intel i5 processor, 16 GM of RAM, Nvidia RTX 1650 GPU with 4 GB of Memory, Python Programming version 3.7, Tensorflow v2.14.0 and Keras 3.

3.1. Case 1: Analysis with machine and ensemble learning algorithms

In this case, a comprehensive examination of major machine learning and ensemble learning algorithms was performed to select the best approach for the previously stated precisely created dataset. **Table 4** provides a complete comparison of the employed machine learning techniques on the dataset. Notably, the results show that the Extra Trees and Histogram Gradient Boosting approaches consistently produced the top performance scores, obtaining a stunning accuracy, precision, recall, and F1-Score of 0.82.

Table 4. Result analysis with machine learning algorithms.

Classification algorithm	Accuracy	Precision	Recall	F1-score
Quadratic Discriminant Analysis	12	12	12	11
Ada Boost	26	27	26	22
Logistic Regression	28	30	28	25
Gaussian Naïve Bayes	31	30	31	26
Support Vector Machine	55	57	55	54
Decision Tree	58	58	58	58
K Neighbors Classifier	66	68	67	63
Voting	67	67	67	66
Random Forest	79	78	79	78
Extra Trees	82	82	82	82
Histogram Gradient Boosting	82	82	82	82

3.2. Case 2: Analysis with transfer learning algorithms

In this context, we implemented deep learning algorithms based on transfer learning principles, using a dataset of fruits as input. We used deep learning models based on VGG16, DenseNet201, ResNet50, and InceptionResNetV2, followed by a thorough comparison study, the findings of which are painstakingly reported in **Table 5**. The results demonstrated that the VGG16-based model was unsuitable for predicting fruit quality. The paper mentions accuracy, precision, recall, and F1-Score. The applied transfer learning models trained on 10 Epoch's. These can be calculated using the following Equations (5)–(8):

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \tag{5}$$

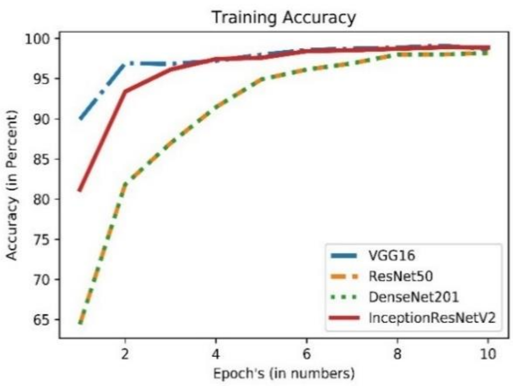
$$\text{Precision} = TP / (TP + FP) \tag{6}$$

$$\text{Recall} = TP / (TP + FN) \tag{7}$$

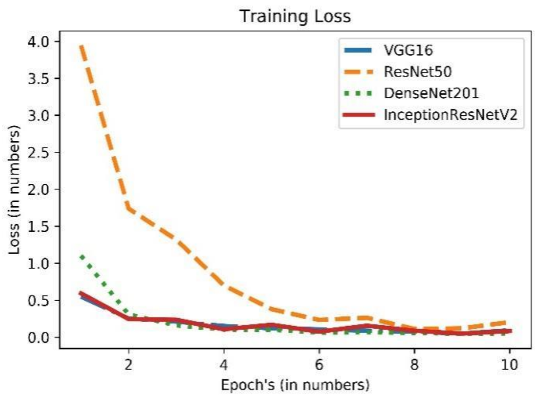
$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{8}$$

Table 5. Result analysis with 10 Epoch's trained model.

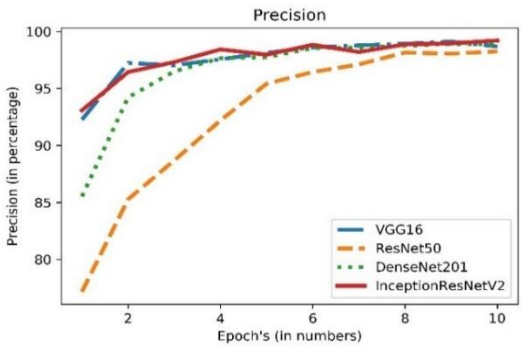
Model	**Training**		**Validation**				
	Accuracy	**Loss**	**Accuracy**	**Loss**	**Precision**	**Recall**	**Area under Curve**
DenseNet20-1	99.906	0.01	99.417	0.03	99.906	99.91	99.97
InceptionResNetV2	99.844	0.02	97.917	0.55	99.844	99.83	99.98
ResNet50	99.917	0	97.333	0.43	99.917	99.92	99.99
VGG16	8.104	2.49	8.333	2.49	0	0	49.99



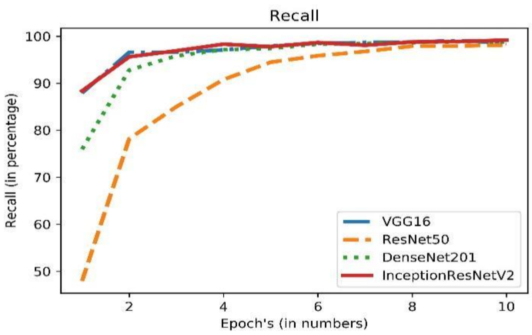
(a) Training accuracy.



(b) Training loss.

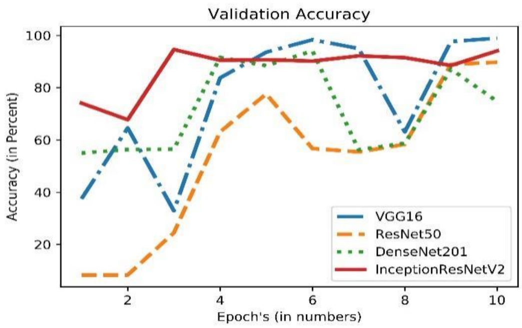


(c) Precision.

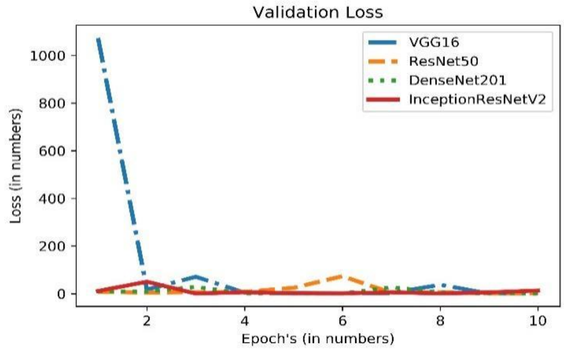


(d) Recall.

Figure 3. (*Continued*).



(e) Validation accuracy.



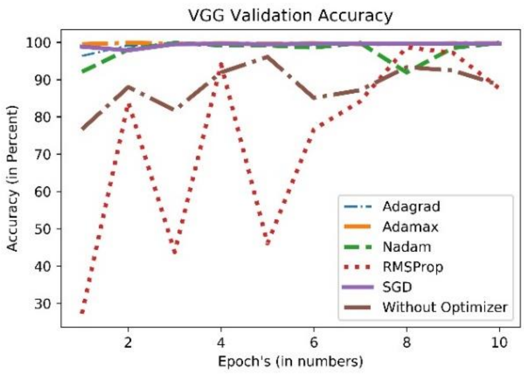
(f) Validation loss.

Figure 3. Result analysis with 10 Epoch's trained model.

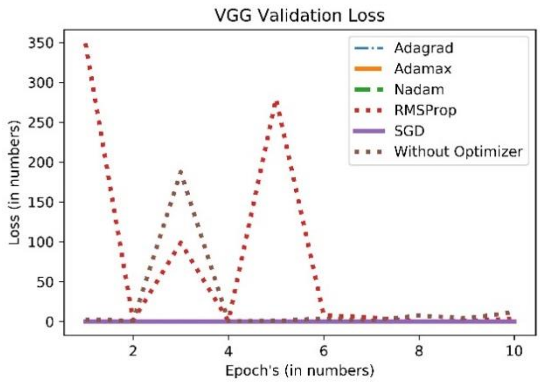
The DenseNet201, ResNet50, and InceptionResNetV2 based models, on the other hand, consistently produced remarkable results, exceeding the 99 percent accuracy criteria and excelling in terms of precision, recall, and area under the curve after just 10 training epochs. **Figure 3** depicts these results visually, demonstrating that, in comparison to the other deep learning models, VGG16 exhibits a dramatic performance fall, finally converging to zero after 40 epochs. Furthermore, the results of Case 2 significantly surpassed those of Case 1, indicating a significant improvement in the system's predictive skills.

3.3. Case 3: Analyzing impact of optimizers on transfer learning algorithms

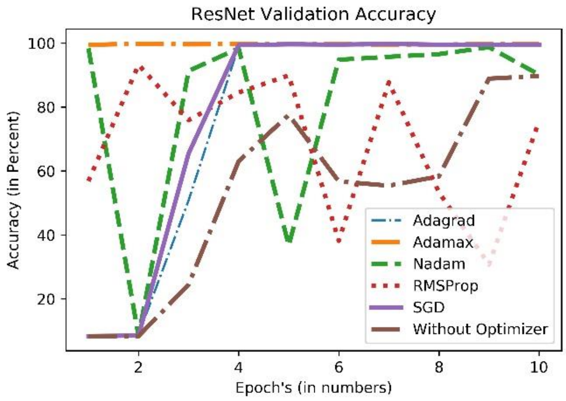
In this regard, **Figure 4** depicts a complete evaluation of transfer learning algorithms, including VGG16, DenseNet201, ResNet50, and InceptionResNet, with respect to widely used optimizers, such as Adagrad, Adamax, Nadam, RMSprop, and SGD. Notably, the SGD and Adamax optimizers outperformed the Adagrad, Nadam, and RMSprop optimizers in terms of impacting the performance of these transfer learning techniques.



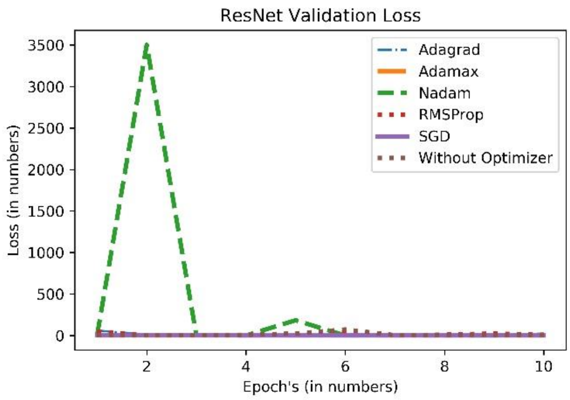
(a) VGG validation accuracy.



(b) VGG validation loss.

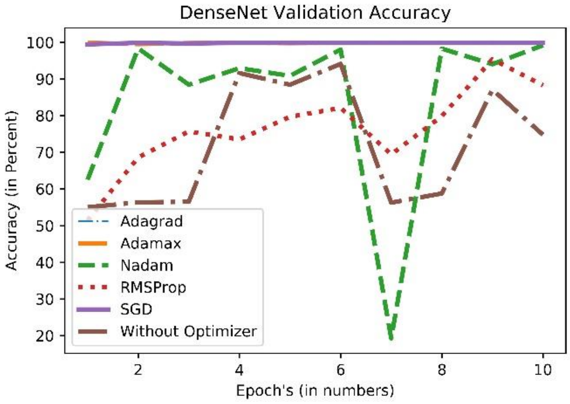


(c) ResNet validation accuracy.

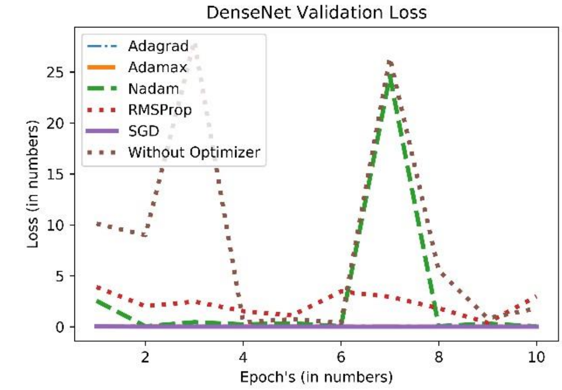


(d) ResNet validation loss.

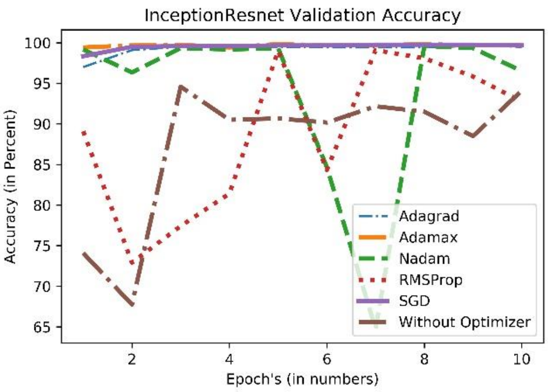
Figure 4. (*Continued*).



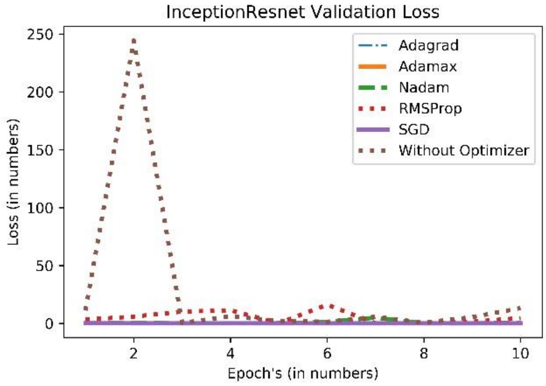
(e) DenseNet validation accuracy.



(f) DenseNet validation loss.



(g) InceptionResNet validation accuracy.



(h) InceptionResNet validation loss.

Figure 4. Result analysis with 10 Epoch's of optimized trained model.

3.4. Case 4: Real-time testing results

In this part, we rigorously tested the proposed system using a real-time dataset obtained from physical sources under actual environmental circumstances. The review included a thorough examination of the performance of ResNet50, DenseNet201, and InceptionResNetV2 trained algorithms. The trained models of ResNet50, DenseNet201, and InceptionResNetV2 consistently displayed improved accuracy, as seen in **Figure 5**. **Figure 6** depicts a confusion matrix, which provides a more complete breakdown of the categorization findings. Resulted confusion matrix explains the exact and correct number of classifications for each class. Here InceptionResnetV2 clearly represents more than 99 percent of correct class identification. A thorough parametric analysis demonstrated that the InceptionResNetV4 model attained an excellent accuracy rate close to 99 percent, outperforming the other trained models.

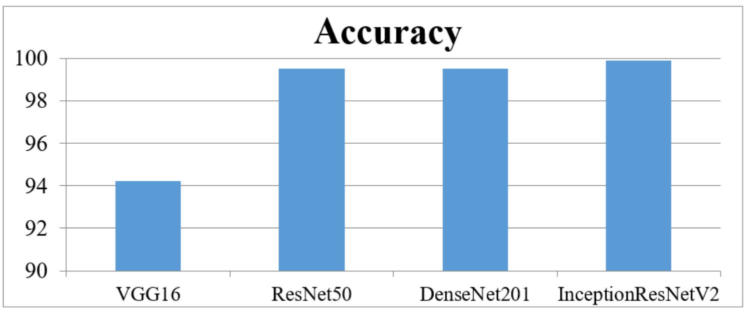
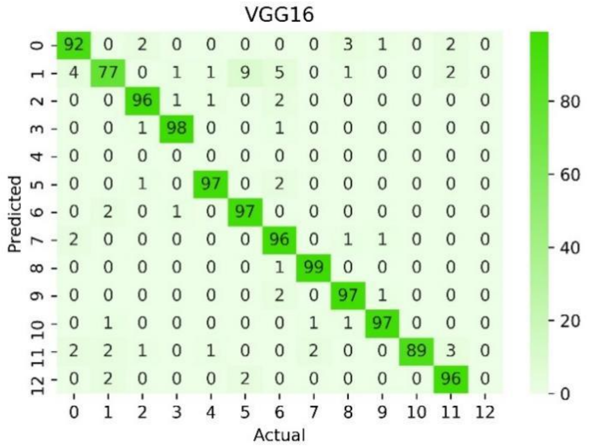
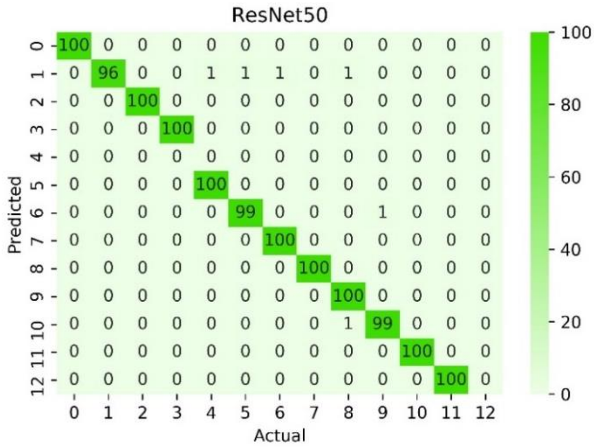


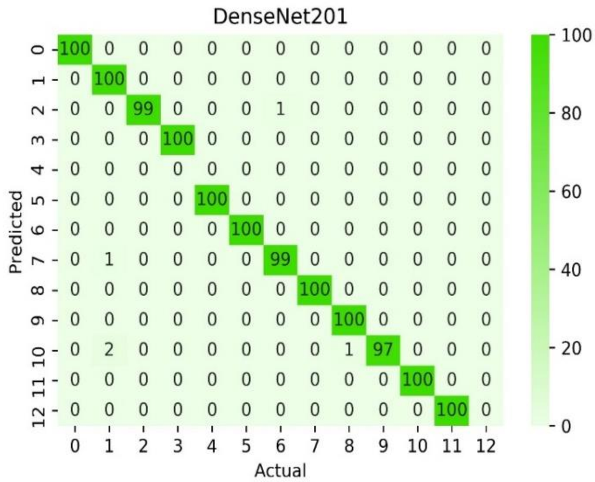
Figure 5. Real time analysis.



(a) VGG16 model.

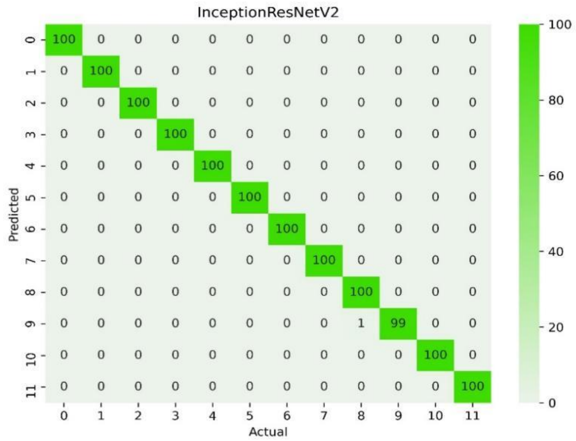


(b) ResNet50 model.



(c) DenseNet201 model.

Figure 6. (*Continued*).



(d) InceptionResNetV2 model.

Figure 6. Confusion matrix testing data.

4. Conclusion

The automation of fruit freshness categorization is a significant achievement that reduces the need for human labor. This study presents a powerful deep learning-enabled automated method for determining the freshness of fruits. The 'Fruit360' dataset, which is freely available online, was used to train a wide range of machine learning and deep learning models. Prior to model training, a thorough data preparation process that included cleaning and preprocessing was rigorously carried out. Our initial approach involved employing various machine learning models. Extra Trees and Histogram Gradient Boosting consistently demonstrated superior performance over other machine learning techniques. Equation (9), which represents the number of right predictions in proportion to the total number of test cases, proved useful in assessing real-time accuracy. In establishing the success of our automated fruit freshness assessment system, the addition of rigorous model evaluation measures, as specified by Equations (5)–(8), has been critical. Following that, the preprocessed dataset was subjected to an existing deep learning-based categorization model. Deep learning models, such as ResNet50, DenseNet201, and InceptionResNetV2, showed exceptional results, approaching the 99 percent accuracy barrier and outperforming standard machine learning methods. The adoption of SGD and Adamax optimization methods to these transfer learning algorithms significantly improved their performance in terms of validation accuracy and loss minimization. These findings show the possible use of improved transfer learning algorithms in the creation of an IoT-based framework for determining fruit quality. Furthermore, the suggested system has the potential for scaling testing inside larger real-time scenarios, proving its adaptability and application in a variety of operating situations.

Author contributions

Conceptualization, VK, HPS and MA; methodology, VK, HPS, JCP, MA and AA; software, VK, JCP, MA and AA; validation, HPS, JCP, MA and AA; formal analysis, HPS, MA and AA; investigation, JCP, MA and AA; resources, VK, MA and AA; data curation, VK and HPS; writing—original draft preparation, VK, HPS and MA; writing—review and editing, JCP, MA and AA; visualization, JCP, MA and AA; supervision, VK and HPS; project administration, MA and AA; funding acquisition, JCP, MA and AA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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