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Spoilage detection of tomatoes using a convolutional neural network

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Abstract: With the increasing productivity in agriculture, it has become extremely essential to look for an advanced technique that will help to minimise losses. Recently, deep learning has outperformed the task of recognition and classification of fruits and vegetables automatically from images, finding applicability in this study. This work, thus, attempts to develop an automatic spoilage detection CNN model for tomatoes. In this work, a deep learning-based CNN model is trained and validated on a self-prepared dataset for classifying tomatoes as edible and spoilt is proposed. The dataset consisted of 810 images, out of which 572 images were considered for training and 238 images for validation. The model is also trained iteratively with varying epoch and batch sizes to evaluate the model in giving the highest classification accuracy. The highest accuracy of 99.70% was achieved at epoch 20 and batch size 32. Further evaluating the performance of the developed model using a confusion matrix, a precision, recall and accuracy of 100%, 87% and 95%, respectively, was obtained for the spoilage detection of tomatoes. Also, on establishing Pearson's correlation between the predictive model and the sensory evaluation results, a Pearson correlation of 0.895 was obtained, showing that there is strong linear correlation between them.

Keywords: tomato samples; training datasets; classification models; models accuracy; images validation

The tomato is a widely grown fruit in North East India with a high demand. The tomato is bestowed with many health-beneficial properties due to the presence of several phyto-nutrients. The tomato, being rich in the antioxidant lycopene, fibre, and vitamins A and C, the demand for tomatoes has been increasing a great deal (Wan et al. 2018). However, due to its perishable nature, it suffers intense losses in the market as well as during processing. The tomato, while undergoing spoilage, entails drastic changes in colour, surface texture, flavour, etc. Also, tomatoes being sensitive are vulnerable to physical treatment, loads, vibrations etc. (Monselise 2018). In this regard, the effective spoilage detection of perishables becomes essential for processes involved in stocking and selling large quantities of such items. Recent advancements in computer imaging have made several breakthroughs in food and agriculture (Patel et al. 2020). As computer imaging is economical, accurate, and has high speed, it has replaced the manual way of food classification with automation. Manual detection is time-consuming, costly, and inefficient (Kaur et al. 2018). Overcoming these limitations, computer imaging techniques have made their way into the automatic identification, classification, sorting, grading and so on (Tu et al. 2018). Hence, this study proposes a non-destructive, rapid, and efficient spoilage detection algorithm for tomatoes based on the surface characteristics. Gradual physical and chemical changes appear in a fruit during the decay process. The physical transformations that take place are changes in the colour, texture, firmness, growth of dark spots and shrinkage. Tak-

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ing into consideration the surface characteristics as a major indicator of spoilage, spoilage classification can be modelled in tomatoes. The technique of machine learning adopted for the present work is 'deep learning'. Deep learning (DL) uses deep layers of neural networks to analyse input data, such as images, and helps in making astonishing achievements in image classification (Zhou et al. 2019). DL is advantageous for its automatic feature of learning abilities. A convolutional neural network (CNN), which is one type of deep learning that has achieved high classification accuracy in image analyses (Itakura et al. 2019). In CNNs, relevant contextual features in image categorisation problems are automatically discovered; therefore, CNNs are attracting more attention (Alzubaidi et al. 2021). The applicability of the techniques of deep learning to extract features from the images of tomatoes, captured by a mobile camera, representing the visible aspects of tomato quality for their classification, was assessed by a Python based deep learning platform. Moreover, the performance of the established model was evaluated using a confusion matrix and Pearson's correlation. Precision, recall and accuracy are also used to determine the performance of the developed model (Taner et al. 2021). A sensory evaluation was conducted by a group of semi-trained panellists through visual observation and finger tests to compare the model's prediction. A sensory evaluation was performed on the basis of the United States Department of Agriculture (USDA) defect detection standards. Also, to compare the results of the model, an instrumental analysis of the firmness of tomatoes was performed.

In most of the conducted studies, the conducted classifications are based on transfer learning or using traditional machine learning techniques. This work provides a new dimension in automatic classification of tomato images. This study, thus, involves the preparation of an image dataset containing images of edible and spoilt tomatoes. The implementation of a custom CNN architecture using Keras/Theano was used to perform the classification of tomato images. The tuning of the hyper parameters, such as batch size and epoch, to improve the classification accuracy of the CNN architecture was also undertaken. A performance evaluation of the developed model was established by using a confusion matrix and Pearson's correlation.

MATERIAL AND METHODS

Raw material

As this work involves the classification of tomatoes into edible and spoilt classes, the first step involved the collection of raw tomatoes. Tomatoes of the hybrid variety 'PUSA 120' were collected from a local farm in Meghalaya, India. Fresh and firm tomatoes were collected, washed and kept in laboratory conditions for the image acquisition. In total, 160 tomatoes plucked on the same day were selected after visual inspection for any damage due to transportation or pests. A total of 150 tomatoes having a uniform shape, size and colour were manually selected. The selected tomatoes were labelled properly for further analysis.

Self-designed image acquisition set-up

After the collection of the raw materials, the second step involved capturing images of the tomatoes and then preparing a dataset. The images of the collected tomatoes were captured both in *(i)* a self-designed wooden box and *(ii)* open conditions. The self-designed wooden box has dimensions of 71.6 × 61 × 61 cm. The inner walls of this self-designed image processing chamber were pasted with white chart paper sheets. On the upper surface, a slit was made in order capture images using a camera. In order to illuminate the target object, two light sources (Phillips tube light with 18 Watts) were used inside the chamber. For placing the sample inside, a small bench covered with white chart paper was prepared which has the dimensions of 30.3 × 20.5 × 18.5 cm. A mobile camera (onboard camera in smartphone Vivo Y51L) with an 8 Megapixel resolution was used for capturing the images.

Instruments, hardware and software tools

For the measurement of the texture (firmness), a texture analyser (TA.XT Plus, Stable Micro System) was used. A flat plate compression test was performed to evaluate the firmness of the tomato - whole fruit (Constantino et al. 2021). The fruit was compressed at the equatorial region by means of the flat plate until it deforms 5 mm of the surface. Flat plate used had a diameter 150 mm and was fastened to a load cell with a capacity of 50 kgF. For this analysis, the test speed was set at 5 mm/s. Newtons (N) were used to record the firmness measurements. The image processing and machine learning task were performed

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using a Lenovo E49 series laptop with the following hardware configurations: Intel Pentium processor CPU M330 @ 2.30GHz, 3.05 GB RAM, and 240 GB SSD. Various software platforms are available that have the capability to perform deep learning on images datasets. To perform python deep learning tasks, Anaconda (version 3) was installed. For deep learning functionality, the conda package installer was used to install the Keras library in Anaconda3. Keras is a high-level software for developing deep neural networks and delegates computation at a lower-level. So, for low-level computations, Keras relies on "backend engines". There are various backend engines which are supported by Keras and changing the backends results in a change in the performance of the neural network. Theano and Tensorflow are the two most popularly used backends in Keras. In this work, Tensorflow was installed in Anaconda (version 3) to be used as the Keras backend. The prime objective of Keras is to build the CNN model and train it on the self-prepared dataset. Furthermore, the OpenCV python library was used for the preprocessing works such as image cropping and resizing. Along with these libraries, other python libraries such Numpy, Scipy, etc., were also used in various computational works. Lastly, to manage all the libraries and the development environment, the Anaconda package manager was used.

The proposed methodology for the classification of tomato images based on edible and spoilt fruit involves the following steps:

Acquisition of images. After visual inspection, images of tomatoes were acquired with the help of the specified mobile camera during the whole process. Images were captured using the self-designed wooden box and in open conditions. While capturing the images, it was ensured that the distance between the sample and the camera position (held perpendicularly with respect to the tomato) was almost invariant. However, the lighting condition was varied by clicking some images in the wooden box, some under sunlight and rest under room light. This was performed in order to train the model in different lighting conditions so that, different lighting conditions do not impact the results.

Preparation of dataset. For capturing images, a batch of 10 tomatoes out of 150 tomatoes was randomly selected. The dataset of edible and spoilt tomatoes was prepared from the acquired images (Figure 1). The three edible tomatoes in Figure 1 are free of any external injury, catface, external discoloration, sunburn, sunken discoloured areas, internal discoloration, worm injury, scars, hail which are the standards for tomato defect detection. Out of the three spoilt tomatoes, the first and second tomato had external discoloration (scuffing), whereas third tomato had internal discolouration (microbial contamination). The tomato images were taken over the whole process under different conditions as mentioned above. The images of the tomatoes were captured both using the image acquisition set-up and under ambient conditions. Around 6 images per tomato were taken every day, starting from the second day of harvest until it was completely spoilt or rotten. The images were then transferred to the E49 series Lenovo laptop with Intel Pentium processor (2.30GHz) and 3.05GB RAM for further process-

Edible

Spoilt

Figure 1. Categorisation of the images for the dataset preparation

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ing. After transferring the images, they were renamed, cropped and resized to 100 × 100 pixels and stored in two separate directories based two conditions: edible and spoilt. Each image of the tomato contains pixel values comprising of red, green and blue colour channels, these pixel values carry information about the external features of the tomatoes. During the experiment, the images were further randomly split into training and test sets in the ratio of 7 : 3, i.e., the training set contains 70% of the images and the test dataset contains 30% of the images.

Building the Convolutional Neural Network (CNN) model. The neural network used in this work was a Convolutional Neural Network (CNN). The CNN architecture is a sequence of convolutional layers with activation functions, fully connected, pooling layers and lastly a softmax layer. Convolutional layers are accountable to the feature extraction, while the fully connected layers are accountable to the classification. The hierarchical architecture of a CNN is a way to learn visual representations of the model (Hu et al. 2015). A CNN with effective prediction accuracy must have the effective optimisation of its hyper-parameters. The parameters, such as the number of layers, number of epochs, batch size, learning rate, number of neurons in each layer, optimisation algorithm, etc., need to be set while modelling a CNN (Bergstra et al. 2011). Setting the hyper-parameters plays a key role during the experimentation and is set based on human judgment. A typical CNN architecture for image classification consists of a number of convolution layers, a maxpooling layer, and a dense layer one after another [Figure S1 in the Electronic supplementary material (ESM)]. Dropout layers are also added to overcome the problem of overfitting. To perform the targeted task of classifying tomatoes into edible and spoilt, some of the layers were configured into a customised model. Three 2-D convolutional layers with a 3 × 3 kernel size make up the created model, which is used to extract spatial features. Additionally, a rectified linear activation function (ReLU) was applied in each convolution layer. Following all the convolutional layers, there was a maxpool layer that computes the maximum, or largest, feature point in the region enclosed by the filter by sliding a 2 × 2 filter across the feature map's channels. In essence, it shrinks the feature maps produced by the convolutional layer. After the last maxpooling layer, a dropout layer with a 25% dropout rate was applied. Subsequently, a 1D feature vector was obtained by flattening the output of the dropout layer. Figure S2 in the ESM displays the several layers of the CNN model that were utilised for this study. The 1D feature vector obtained was given as the input to a dense layer having 256 neurons. The dense layer is a fully connected layer which learns the patterns in the feature vector. The dense layer uses the ReLU activation function. A dropout layer with 40% dropout was also used to prevent the model from overfitting. Another dense layer having 256 neurons and the ReLU activation function was again applied. Then again, a dropout layer with 30% dropout was applied on the output of the dense layer. Then, the output of the dropout layer was given as the input to the last layer, i.e., the output layer. In the output layer, a single neuron with a sigmoid activation function was used to classify the tomatoes images into two classes: edible and spoilt.

Training the CNN model. The next important step after building the model was to train it on the self-prepared tomato dataset. The CNN model was trained using 70% of the tomato images and with an equal number of images in each class. During the training phase, the Adam optimiser with a learning rate of 0.001 and a binary cross entropy loss function was employed. Various researchers claim that the epoch and batch size are two hyper parameters that mostly affect the accuracy of a model. In this study, the model was trained iteratively with a different number of epochs and batch sizes to test the accuracy of the model in classifying tomatoes as edible or spoilt. The number of epochs is a hyperparameter that indicates the number of iterations of the learning algorithm over the entire training dataset. Here, the model was trained iteratively setting epoch sizes 10, 20, and 30 to observe whether the model had any overfitting or underfitting issues. Batch size is the parameter that adjusts the error rate of the working model after training the specified number of samples. Batch sizes of 8, 16, 32, and 64 were set during the experimentation and the accuracy of the model during training and validation was recorded.

Physiological and sensory analysis. Most tomato samples that are spoiled are caused by fungi rather than bacteria (Khalid et al. 2024). The fruits may therefore alter in terms of flavour, aroma, ap-

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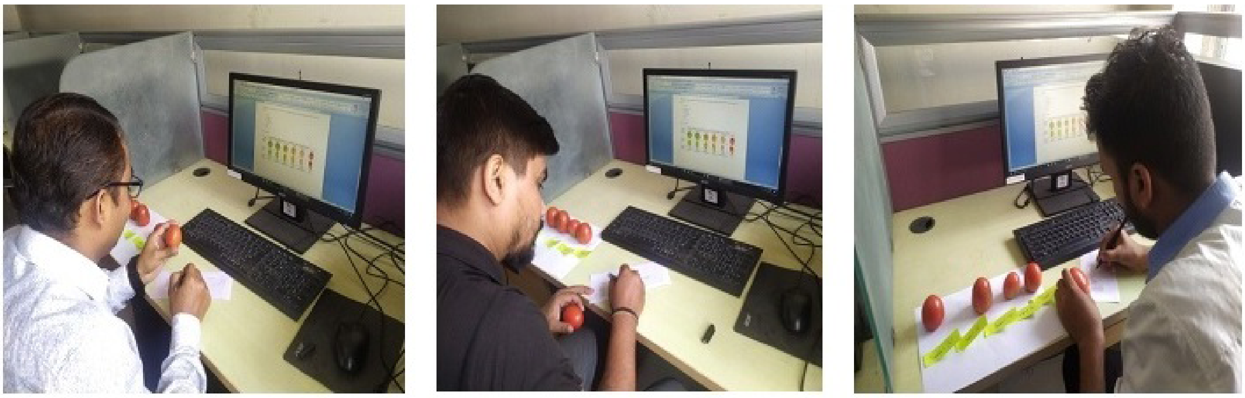

Panelist 1 Panelist 2 Panelist 3

Figure 2. Sensory analysis performed by semi-trained panellists

pearance, or texture (Ghosh 2009). Thus, the physiological parameter considered as an indicator to spoilage detection is the firmness. A sensory evaluation was carried out at the end model development to ascertain the consumer perception on the produced tomato. A group of 15 semi-trained panellists were trained for defect detection following USDA defect detection standards. This evaluation was basically performed to identify tomatoes on their spoilage in respect to the consumer's perception. The training included familiarity with the terminology, identification and categorisation of tomatoes. In addition, a Finger-Test was performed by the same group of panellists to evaluate the textural property of the given sample as an indicator of its quality (Ranatunga et al. 2008). The analysis was performed in individual booths at even lighting conditions. Isolated booths were provided with a view to eliminate any external influences (Figure 2). An even lighting condition was provided to eliminate any light interference. The panellists were provided with 20 samples labelled from 1 to 20. Every booth was provided with a computer set up to go through the USDA defect classification standards. The panellists were asked to evaluate the tomatoes for their current state as either edible or spoilt and score them accordingly. The final sensory scores were then compared with the output of the predictive model. This evaluation is, thus, used for assisting the validation of the established model. To ensure the reliability of the customised deep learning model, a correlation test was performed between both. The techniques used for the sensory evaluation: *(i)* selection of a group of 15 semi-trained panellists, *(ii)* train them for USDA defect detection of tomatoes, *(iii)* distribution of score cards to record their perception, and *(iv)* Finger-Test.

		Predicted label	
		Positive	Negative
True label	positive	TP (true positive)	FN (false negative)
	negative	FP (false positive)	TN (true negative)

Figure 3. Confusion matrix obtained during the performance evaluation

Performance Evaluation

The performance of the customised CNN model was evaluated by developing a confusion matrix and Pearson's Correlation (Figure 3). From the confusion matrix, the recall, precision, and accuracy of the model was established using Equation (1), (2), and (3), respectively. Pearson's linear correlation was conducted to establish a significant correlation between the predicted results and the sensory results. Based on the established correlation, the developed model's performance can be evaluated.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{1}$$

where: TP – true positive; FN –false negative

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

where: TP – true positive; FP – false positive

$$\text{Accuraccy} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{3}$$

where: TP – true positive; FP – false positive; TN – true

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Table 1. Classification accuracy and average time taken in each step of an epoch corresponding to different optimisers and learning rates

Cases	Learning rate	Optimizer	Average time taken per step (ms in 1 epoch)	Classification accuracy
I	0.0100	Adam	698	98.32%
II	0.0100	RMSprop	743	98.74%
III	0.0100	SGD	782	96.64%
IV	**0.0010**	**Adam**	**741**	**99.56%**
V	0.0010	RMSprop	760	99.10%
VI	0.0010	SGD	792	59.24%
VII	0.0001	Adam	769	99.25%
VIII	0.0001	RMSprop	770	99.12%
IX	0.0001	SGD	825	64.71%

negative; FN –false negative

RESULTS AND DISCUSSION

Effectiveness of various optimisers during the model training. The CNN architecture in this work is employed to predict the current condition of the tomato as either being edible or spoilt as discussed in the section above. In total, 810 images were collected during the experiment which woks as the dataset for this model. Splitting the dataset into training and testing classes is performed in a ratio 7 : 3. Out of the 810 images of the dataset, 572 images were randomly selected for training and 238 images were randomly selected for testing. The developed model was trained on the prepared image dataset using three different optimisers in order to identify the optimiser which is best suitable for the considered classification problem. Three different learning rates were set for each optimiser and the classification accuracy along with the average time taken per step (in 1 epoch) was obtained by training the model. The different cases corresponding to the learning rates and optimisers are shown in Table 1. From Table 1, it is evident that the Adam optimiser provided the highest classification accuracy among the three selected different optimisers.

The training was carried out iteratively with the varying epoch and batch sizes to evaluate the model in giving the highest accuracy. The model was trained with 10, 20 and 30 epochs and 8, 16, 24 and 32 batch numbers. The classification accuracy obtained on the test set on the varying epoch and batch sizes is presented in (Figure 4). The overall classification accuracy obtained is above 95% for the epoch between 10 and 30 as well as batch size between 8 and 64. The highest classification accuracy of the CNN model was achieved at epoch 20 and batch size 32. Thus, at the aforementioned hyperparameters, the architecture of the CNN model showed an accuracy of 99.70%. The obtained classification accuracy of the model vindicates its applicability in predicting the current condition of tomatoes as being edible or spoilt.

Figure 4 indicates that the CNN model obtains an overall classification accuracy above 95% for epoch between 10 and 30 as well as batch size between 8 and 64. This study shows that the adjustment of the hyperparameters, namely the epoch, learning rate and batch size, is an important factor in the spoilage detection of tomatoes (Letsoin & Herák 2024). The customised CNN model is thus capable of distinguishing the two classes of tomatoes under consideration paving the way for the application of the deep learning-based image processing technique for grading systems. Figure S3 in ESM and Figure S4 in ESM presents the ability of the model to distinguish between an edible and spoilt tomato.

Model evaluation. To evaluate the performance of the customised CNN model, a comparison was made between the predicted results, sensory results (actual) and physiological analysis results. From Table 2, it is seen that the predictions made by the customised CNN model are at par with the recognition made by the sensory panellists. Also, upon performing the texture (firmness) analysis on similar tomatoes, it was found that firmness

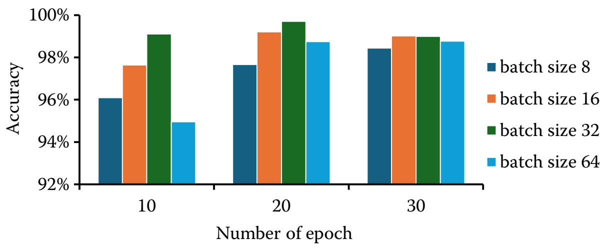

Figure 4. Classification accuracy obtained in the test set on different epoch and batch sizes

<table>
<tr><td colspan="2" rowspan="2">Confusion matrix</td><td colspan="2">Predicted</td><td rowspan="5"><u>Precision</u>
Precision = TP/ (TP + FP) = 7/(7+0) = 1
(100%)
<u>Recall</u>
Recall = TP / (TP + FN) = 7/(7+1) = 0.87
(87%)
<u>Accuracy</u>
Accuracy = TP+TN / (TP + TN+ FP + FN)
= 7+12/(7+12+0+1) = 0.95 (95%)</td></tr>
<tr><td>Edible</td><td>Spoilt</td></tr>
<tr><td rowspan="2">Actual</td><td>Edible</td><td>7</td><td>1</td></tr>
<tr><td>Spoilt</td><td>0</td><td>12</td></tr>
</table>

Figure 5. Evaluation parameters calculated from the confusion matrix

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Table 2. Comparison between the model prediction, and the sensory and physiological evaluation

Sample	Model recognized as	Sensory panelist evaluated as	Firmness value (N/mm)
S1	Spoilt	Spoilt	10.53
S2	Edible	Edible	30.42
S3	Spoilt	Spoilt	10.43
S4	Spoilt	Spoilt	5.74
S5	Edible	Edible	28.22
S6	**Spoilt**	**Edible**	9.32
S7	Edible	Edible	44.12
S8	Spoilt	Spoilt	10.28
S9	Spoilt	Spoilt	11.52
S10	Spoilt	Spoilt	19.72
S11	Edible	Edible	56.15
S12	Edible	Edible	37.62
S13	Spoilt	Spoilt	10.53
S14	Spoilt	Spoilt	3.28
S15	Edible	Edible	29.30
S16	Spoilt	Spoilt	2.81
S17	Spoilt	Spoilt	5.53
S18	Edible	Edible	69.24
S19	Spoilt	Spoilt	3.27
S20	Spoilt	Spoilt	4.42

values were less than 10 N/mm for the spoilt tomatoes. A firmness value of 1.45 N/mm is an indicator of a spoilt tomato (Batu 1995).

Model evaluation using a confusion matrix. The performance of the model was evaluated by establishing a confusion matrix based on the results obtained from Table 2. From the confusion matrix, the precision, recall and accuracy were calculated (Figure 5).

The result of the confusion matrix presumes that the customised CNN model outperforms the task of spoilage detection with a precision, recall and accuracy of 100%, 87% and 95%, respectively. A precision of 100% means that the model is 100% precise in the spoilage detection of tomatoes. From the above confusion matrix, it is seen that 12/12 images were predicted as being spoilt whereas 7/8 images were predicted as being edible giving a recall of 87%.

Model evaluation using Pearson's correlation. From the results obtained in Table 2, correlation is established between sensory panelist and model prediction. The developed model showed a Pearson correlation of 0.895, showing that there is strong linear correlation between the predictive model and the sensory evaluation results.

Comparison of the model output with the different models. The output of the model in terms of the classification accuracy is compared with a few of the research studies conducted by different researchers on defect detection of tomatoes using machine learning (ML), which is presented in Table 3.

CONCLUSION

The study undertaken develops a CNN model that can be a reliable technique for spoilage detection in tomatoes based on the surface characteristics. Spoilage detection is performed by classifying the tomatoes into two classes - edible and spoilt. The proposed model is thus trained and validated on a self-prepared dataset consisting of 810 images, out of which 572 images are considered for training and 238 images are considered for validation. Training the model iteratively with the varying epoch and batch sizes, the highest accuracy of 99.70% is achieved at epoch 20 and batch size 32. Furthermore, to assist the validation of the developed model, a sensory evaluation was performed by a group of semi-trained panellists. The sensory results obtained are analogous to the model's performance proving it to be viable solution to consumers and industrialists.

Table 3. Comparison with different models

Authors	Objective	Technique	Accuracy
Goyal et al. 2024	Shelf-life in tomato using ML	SVM, DT, RF, GBM	90.35%
Ireri et al. 2019	Defect in tomatoes using image based ML	RBF-SVM	97.09%
Semary et al. 2015	Tomato Grading	SVM classifier	92.00%
Chaturvedi et al. 2023	External defects in tomatoes	VGG19, ResNet, DenseNet, EffNet, Incepv3.	97.97%
Da Costa et al. 2020	Computer vision based detection of external defects on tomatoes using deep learning	ResNet50	94.60%

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The capability of the deep learning architecture in estimating the current state of tomatoes as either being edible and spoilt can thus be employed in large scale tomato production lines.

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