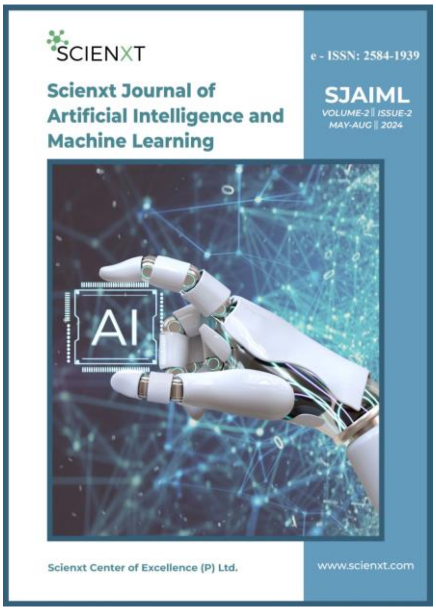

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Fruit sorting and classification of fruit using deep learning

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Abstract:

Industrial fruit sorting and packaging is a major challenge for the food sector. An innovative approach to distinguishing between several types of olive fruits was developed, by approaching the task as a picture sorting challenge. The study used 2800 fruit images of seven olive varieties. After processing the models using state-of-the-art techniques, six modeling computers were trained with these models. These models could well identify different olive species; the highest precision of 95.91% was obtained with a model called Inception-ResNetV2. Once olives are harvested, this technology has great potential for use in olive production. A staple of the Middle East, fruits are rich in vitamins, minerals and carbohydrates which are all good for health. Although manual harvesting is time-consuming and expensive, it is an important process. We present a method for segmenting dates using state-of-the-art computer networks. We use a technique called discriminant correlation analysis (DCA) to combine features from two separate computational models (PCANet and VGG-F). DCA reduces complications quickly and effectively. One of the largest datasets available, this collection of images contains 20. This dataset is available for download at https://unsat.000webhostapp.com/dataset. Our experiments show that DCA works well and that mixing features from different models increases the classification accuracy. When it comes to distribution, we've got it

Keywords:

Classification, convolutional neural network, fruit types, structure, deep learning, fruit division, growth.

1. Introduction:

With a total production of more than 8 million tonnes in 2019, it is considered one of the most important crops in North Africa and West Asia and varies in maturity depending on the season of harvest, and lies signs of immaturity, partially revealed. Ripe or mature. There are many varieties of fruits that vary in taste, color and shape from one to the next. It also has many other health benefits. It is an important source of energy due to its high sugar content. In addition, fruits contain additional nutrients such as vitamins, minerals and dietary fiber.

Fruit sorting is considered an important step in the date palm industry. That includes classifying fruit into qualities or maturity levels. Another way to accomplish this process is to divide it into several types. Such work is tedious, expensive, and time-consuming, requiring the hands of specialized employers. Consequently, there is a need for an automated accounting system that can perform this process efficiently. Examples of applications of date ordering processes in daily life include medical and business services. For example, obese and diabetic people need to know which dates are safe to consume and which ones are good for their health. Additionally, it is strongly recommended that shopping centers use their own methods of searching between dates.

Reviews of the literature have addressed the issue of date ordering over the past two decades. Generally, these courses can be divided into three distinct groups according to their objectives. The first category includes tasks that attempt to determine the state of the day. Fruits, while second-tier projects emphasize the classification of fruits based on maturity. For the third category, the included works focus on identifying varieties including a date pattern, [8 deep learning has been widely used to classify fruits instead traditional methods due to their ability to learn stability from images (CNN) will be used. Very little research has been done on the use of unsupervised depth networks for segmentation, despite the fact that most of the previous work is known to have opted for depth-based supervised structures (such as CNNs);

In this study, we present a new method based on deep learning for date change classification.

For this aim, we specifically examine supervised and unsupervised deep correlations. We use the pre-trained VGG-F as our control network because its depth allows us to extract strong local and global properties from the pod images.

Furthermore, the time required for extraction increases with the number of layers and grid structures. Consequently, the processing time becomes shorter when a shallow depth mesh is considered. For unsupervised networks, we use PCANet, which despite its simplicity exhibits robust performance in a wide range of computer vision applications. To promote individual selection by each network, by analyzing interactions with input feature forms, DCA combines feature level fusion and dimensionality reduction at low computational complexity

To help evaluate the proposed method, we are providing additional data with twenty (20) images. In terms of shift volume, our data set is the largest currently available. The empirical study confirmed the combined effect of supervised and unsupervised network effects and demonstrated the strengths of the proposed method, overcoming several related methods . . . . The contributions of the present paper are summarized as follows.

- That is, unsupervised deep networks (PCANet) can complete the sorting test with less computational cost than current deep networks.

- A minimum depth control device (i.e. VGG-F) may be used to complete the installation process.

This study also highlights the convergence of supervised and unsupervised networks combined with -DCA algorithm. The implementation cost of this algorithm is low and consists of dimensionality reduction and fusion.

- Unlike previous studies, which examined a limited number of species, this study provides a new dataset with twenty (20) additional seasons.In terms of the number of studies, this dataset can be the s s s s added.

- Conduct in-depth experiments to evaluate the effectiveness of the proposed method. Our approach went beyond the standard artificial complex numbers.

That is how the rest of the letter is written. We investigate classification tasks in Section 2. The data we collected are shown in Section 3. We describe the proposed method in Section 4.

Section 5 presents the results of the study. Section 6, devoted to some conclusions and considerations, is the penultimate section.

The different algorithms to be used 128 will be roughly divided into four groups: estimation based on fault detection, 129 frequency-domain-based, model-based, and learning 130 the advantages and disadvantages of such methods are shown in Table 1. By technical staff, domestic and foreign, 126 new checks were made on fault detection systems

The pod size is small, but the number of samples is large (132), and there is still considerable similarity between surface defects (133), making it difficult to distinguish between 134 defects.Conventional machine vision technology includes the manual extraction of 135 poor features, which can easily generate 136 incomplete features and influence de detection outcomes.Disadvantages of manual feature extraction are overcome with deep learning 137 technology.139 Fault features Layers that can be removed dataset using deep learning networks using automatic convolutional. This paper combined the advanced WideResNet 144 deep learning model with machine vision 145 technology to develop a multi-index classification of green 146 plum surface sinfects. This was done to meet the requirements of a domestic fruit 141 processing plant (Nanjing Longlijia Agricul-142 tural Development Co.,Ltd. (China)) to identify 143 1800plumsperhour in a dynamic manner.

The results of this paper are as follows: a) clustering of fruit surface defects in several indexes; b) a self-made photograph of a fruit enjoyment device; c) 150 Adam W optimizer and weighted cross-entropy (Wce) loss 151 implementation of fruit fault detection networks based on WideResNet networks, ensuring that the network can 153 correctly detect fruit surface faults and generate the network classification efficiency is very effective.

2. Overview of CNN architectures:

In the present work, CNN is used as an image classification problem to solve the machine learning problem of olive-fruit segmentation. Indeed, the adoption of deep learning as a dominant technique has increased in many fields, with computer vision being one of the most useful, provided by CNNs they get amazing results. The-artistic advantages.

Advances in designing and building integrated circuits with specific structures for parallel computing, and the emergence of standard frameworks such as CUDA have made GPUs more efficient and inexpensive general-purpose processing frameworks. The types of data available to the public for study have also increased over the past decade or so. As a result, other projects such as ImageNet and CIFAR-10, among many others, have provided incredibly high quality data.

Advances in designing and building integrated circuits with specific structures for parallel computing, and the advent of CUDA and other standard frameworks have made GPUs more efficient and inexpensive general-purpose processing frameworks. The amount of data available with free machine learning algorithms has also increased over the past decade or so. As a result, much better information has been made available in other projects, such as ImageNet and CIFAR-10, among many others. This is without a lot of privacy from major players in technology like Amazon, Baidu, Facebook, Google and Microsoft, who far from being complete outsiders to this trend, are now pushing for deep learning and delivery handle the application.

Despite advances in computing and data acquisition, traditional neural network approaches have met the challenge of identifying and generating a collection of meaningful mathematical expressions to feed networks. Consequently, CNN is essentially a deep neural network in which the raw data from the original image is transformed layer-by-layer into top-level features that are then used to derive classification. Consequently, convolutional layers that use high-level features obtained by convolution and down-sampling to segment images, use filters or kernels as feature detectors and convolve local regions of the input pooling layers, which reduces on the spatial dimensionality of the convolved features (also called activation maps) obtained after the convolution phase

Researcher interest in the application of CNNs and related literature has increased due to proven advantages, including broken complexity, rapid model training, ability to capture local information, sample size requirements small, or low over-tinging probability, and among others. To be interviewed for in-depth study, has exploded in recent years.

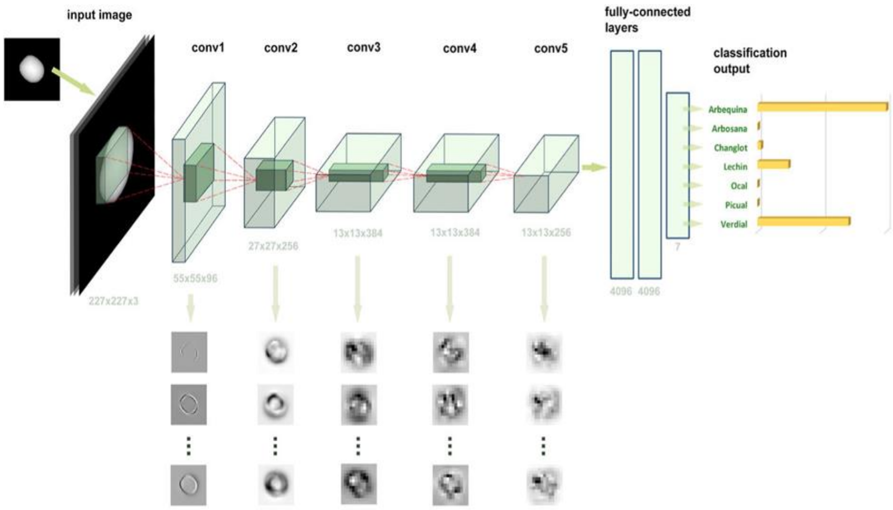


Figure. 1:

Fig. 1: shows a schematic representation of how a CNN with five convolutional layers performs when identifying the type of olive fruit. An image of a fruitthat was produced by the pre-processing mentioned in section IV-A is the input. Convolutional layers, which model the item from its grossly distinctive traits to its subtler ones as it gets deeper in the image, receive the image as input and process it. Ultimately, a fully connected layer processes the retrieved data

to produce a likelihood that the object falls into one of the classifications under consideration. Fruit in this instance is categorized as Arbequina.

We have leapt in recent years into deeper analysis. It is thought that some important CNN architectures discovered in recent years will serve as a summary of examples for the classification of olives and fruits briefly below.

According to AlexNet, improvements have been made in image recognition. Its eight-story architecture consists of three fully integrated layers and five revolving layers. Thus modeling neuronal output of the network by Rectified Linear Unit (ReLU) than other, traditional activation functions such as sigmoid or tanh, deeper than generality at that time, also helped to obtain a much faster training set for CNN.

GoogLeNet, also known as InceptionV1, sets rotation in the network and determines the global average pooling as the last fully connected neurons compared to AlexNet, the very deep Inception architectural iteration has 22 levels a total of 22 characters.

Factoring convolutions reduces the number of parameters in the InceptionV3 network. This is accomplished by reducing the filter diameter and adding more layers without sacrificing functionality—about 42 in all.

ResNet proposes a paradigm shift, which proposes the skip (or shortest path) link. The composition of one layer does not depend solely on the results of the preceding layer. This is an important issue in gradient-based learning methods, to deal with missing/missing gradients. Its design is improved by a bottleneck process that allows complexity reduction with minimal loss of performance. In this case, there are different approaches to the depth of the network: ResNet-101 has 101 layers, ResNet-152 has 152 layers, and ResNet-50 has 50 layers.

Based on the Inception framework but driven by ResNet, the remaining connections are trained with Inception-ResNetV2, which accelerates the process.

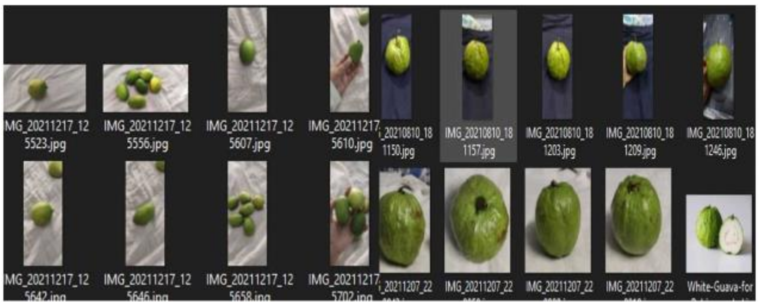


Figure.

3. Fruit dataset collection:

We provide an additional data requirement of 1619 images from twenty (20) different dates to evaluate the effectiveness of the proposed method. These varieties are called Tarmount, Tanslit, Tant Bucht, Tekbeh Tati, Tivisyouin, Ajina, Adam Deglet Noor, Bayd Hamm, Bouarous, Deglet, Deglet Kahla, Deglet Ghabia, Degla Bayda, Dfar Lgat, Dgaul, Ghars, Litima, Loullou, Hamraya , and Tinisin. Table 1 shows the number of samples available of each type. Date samples were collected from a local market in the Tougourt region of southern Algeria. Keep in mind that some varieties are only available during certain months of the year and may not always be available. For example, the Tantbucht is only available in September and October of each year. The images were captured using a camera with a resolution of 4128 x 3069 pixels. These varieties can differ from each other in taste, hardness level, growth rate, size, shape and color. However, some species—litima and baydhamam, for example—have many features in common, making them difficult to distinguish. Typical models for each variety are shown in Fig. 1, and the growth stages of several varieties are shown in Fig. 2.

- Fig. 1:Sample images of various fruits of FIDS-30 dataset-I.

  Algeria. Keep in mind that some varieties are only available during certain months of the year and may not always be available. For example, the Tantbucht is only available in September and October of each year. The images were captured us,

- Fig. 2: Sample images of different fruits of the custom dataset-I

3.1. Proposed method:

The overall date fruit sorting pipeline, and the block diagram in Figure 4 illustrate the proposed method.

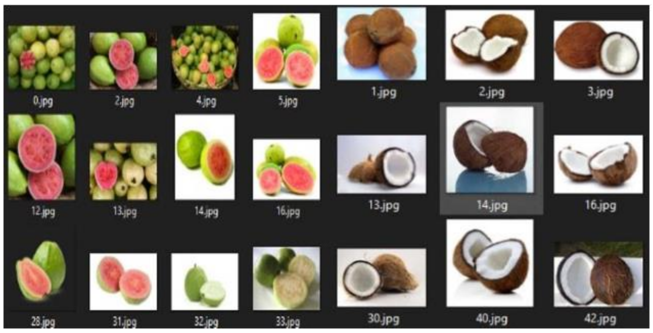


Figure. 3:

Fig. 3 shows the division of our proposed method into two phases: training and testing. Using unsupervised and supervised deep networks (PCANet and VGG-F), we first extract features from date images to improve the classification results and then perform the analysis using discriminant correlation analysis (DCA). . . . . A combination of both types. To perform classification, K-nearest neighbor classi er (KNN) is used for classifiers. Hereafter, we provide details of the proposed method.

3.2. Supervised convolutional neural network architecture:

Pre-trained CNNs have been widely used in various computer vision tasks due to their outstanding result. In the literature, there are several pre-trained architecitures of CNN which have been trained on large-scale picture databases. Specifically, the dominant CNN designs like VGG-16, VGG-19, ResNet, GoogleNet, etc. have been trained using ImageNet, which offers 1000 distinct classes. In reality, every one of these architectures has specific requirements, such as the quantity and type of layers, as well as the arrangement of the layers. Previous research on sorting date fruit take into account two techniques for taking advantage of trained networks. The initial tactic is to fine-tune the network using the dataset being classified's training portion. In the second, characteristics are taken out of the final layers and supplied into a traditional classifier. States that a key element when assessing the caliber of classification outcomes is CNNdepth. Consequently, we choose to use VGG-F, since its depth is sufficient to extract representative features from images of dates.An further rationale for this network's selection is that a CNN with a shallow width takes less processing time than one with a deeper depth. In Table 2, the VGG-F architecture is displayed.

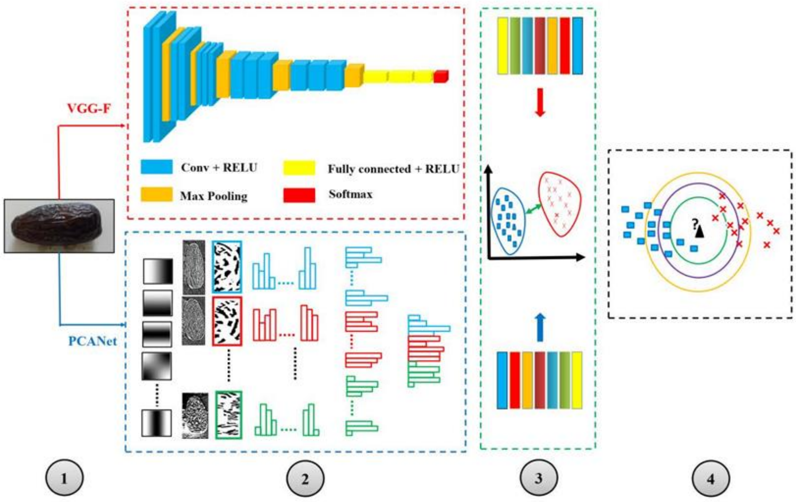


Figure. 3:

Fig. 3. The general flowchart of the proposed method: 1) input fruit image, 2) features extraction using supervised network (VGG-F) and unsupervised network (PCANet), 3) features fusion using DCA and 4) classification using KNN classifier.

3.3. Unsupervised deep neural network architecture:

We use the computationally quick and effective PCANet approach as an unsupervised deep network. This architecture is capable of producing dependable representations from date fruit photos. PCANet consists of multiple groups, with layer bank creation being the basic layer. And ending by block-wise histograming. Hereafter, we give more details on this method by explaining each of its steps separately.

4. Description of image processing algorithm flow:

Real image:

Initially, a picture is retrieved from the computer's memory. Basically, image processing, analysis, visualization, and chosen image. The image that was called from

Fig. 2: Original image

Figure. 3: block diagram

4.1. Enhancement of images:

In order for the output result to be compatible with a specific program, image enhancement is a crucial procedure to improve the visual look of a picture from a camera [5]. Numerous algorithms are used in picture enhancement, including noise reduction, histogram equalization, gamma correction, contrast enhancements, and image sharpening. The project use the histogram equalization algorithm for improving the input photos. Basically, the purpose of this method is to alter the contrast so that the intensity contrast value appears more evenly dispersed on the histogram. To put it succinctly, histogram equalization might help an image appear better. Fig. 3 illustrates the histogram equalization-based image improvement.

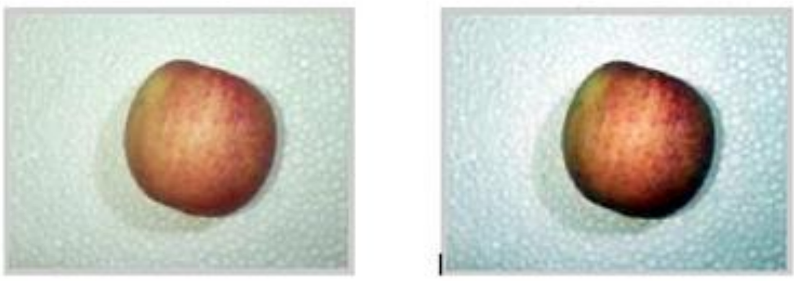


Figure.

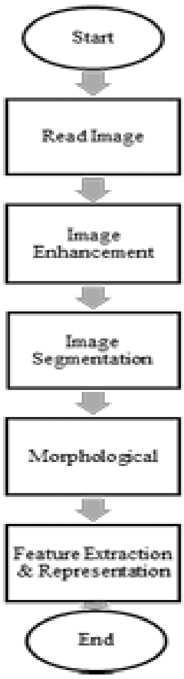


Figure. 3: Images Before and After Image Enhancement Process

4.2. Segmenting images of original images:

The technique of dividing a digital image into multiple parts is known as image segmentation [6]. In computer vision, segmentation is used to remove irrelevant data. Using feature extraction techniques, items derived from a segmented image can be displayed, examined, and categorized. Prior to extracting features from the image, thresholding and whole filling techniques are used in this session. The thresholding and picture complement algorithms are displayed in Figures 4 and 5.

Figure 3: Images Before and After Image Enhancement Process

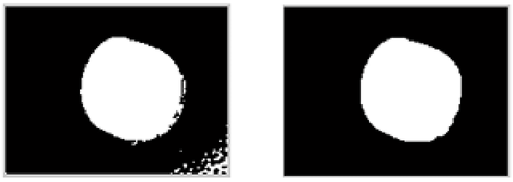
4.3. Image segmentation image:

Segmentation is defined as a process of partitioning a digital image into multiple segments [6]. Segmentation in computer vision is used to eliminate the unwanted information. Once an image has been segmented, the resulting objects can be represented, analyzed and classified with the feature extraction techniques. In this session, thresholding and holes filling technique are applied before undergoing image feature extraction. The Figure 4 and Figure 5 show the methods of thresholding and image complement.

Figure 4: Images Before and After Thresholding

4.4. Processing biologically:

An operation related to the morphology or shape of features in an image is known as morphological image processing. Grayscale images are essentially subjected to morphological procedures. Specifically, noise distorts the binary places generated by basic thresholding in computer vision, segmentation is used to remove irrelevant data. Using feature extraction techniques, items derived from a segmented image can be displayed, examined,



4.5. Segmenting images:

The technique of dividing a digital image into several parts is known as image segmentation. In computer vision, segmentation is used to remove irrelevant data. Using feature extraction techniques, items gathered from a segmented image can be displayed, examined, and categorized. Prior to extracting features from the image, thresholding and whole filling techniques are used in this session. The thresholding and picture complement techniques are displayed in Fig. 4 and 5.

4.6. Morphological processing:

Morphological image processing is an operation that is relevant to the shape or morphology of features in an image. Morphological operation is basically applied to grayscale images. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Noise may contain numbers of imperfections that may influence the analysis result. The binary regions produced by simple thresholding are distorted by noise and texture. Noise may contain numbers of imperfections that may influence the analysis result Thus, morphological technique is able to remove the imperfections by probing the structure of an image. The Figure 6 shows the image that undergoes the morphological image processing technique.

4.7. Feature deletion:

The technique of identifying and expressing specific interesting characteristics in an image for additional processing is known as feature extraction [8]. The indicator that displays the data transitioning from pictorial to non-pictorial is this procedure. The outcomes can then be used as an input for various methods of pattern recognition and categorization. But the technique has also been used in a number of other applications, like traffic signs.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \qquad (1)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \qquad (2)$$

4.8. Fruit sorting experiment:

Fig. 6: Images Before and After Morphological Processing Using Machine Vision Technique. The purpose of this experiment is to assess how well the intended image processing method performs. Various image processing techniques, including image enhancement, image segmentation, and picture extraction, are employed in this session.

The Adam optimization method is the foundation for the optimization of Adam optimization algorithm. Ever since the Adam optimization approach was introduced in 2014, it has gained widespread usage in deep learning models, including picture classification and scene identification. It was discovered through experiments that the Adamopti-mization algorithm had some convergence issues, including sluggish model convergence and non-convergence.In addition, the experimental findings in some models do not match the effect of the SGDplus Momentum method.Later, and different, enhanced versions of Adam surfaced. Among these, the Adam optimization algorithm introduced a regular term to the Adam loss function, computed the gradient of the total loss function to update the parameters, and significantly increased the training pace and decreased overtting. Consequently, the Adam-Woptimization technique was utilized in this paper to train the green plum defect classification model.As proven by formulas (1) and (2), changing parameters in.

The AdamW optimization algorithm adaptively lead to varied learning rates.

The Adam optimization algorithm takes a regular term and applies it to the loss function of the algorithm. It updates the parameters by calculating the slope of the overall loss function with the regular term whenever the model parameters are updated.As a result, Adam's optimization technique can effectively prevent overwriting during training and has a faster training time.The loss function using Adam's regular term is displayed in formula :

$$\theta_t = \theta_{t-1} - \eta\left(\alpha\hat{m}_t / \left(\sqrt{\hat{v}_t} + \zeta\right) + \omega\theta_{t-1}\right)$$

The Adam optimization technique exhibits a faster overall convergence time and less excess fitting when the parameters, ds and t, are regular terms to the algorithm's loss function. The Adam algorithm has the ability to rectify issues with poor convergence speed, high loss

$$c_n = \frac{mean\,\{a_n\}_{n=1}^{N}}{a_n}$$

$$a_n = \sum_{i=1}^{Q} 1\,(y_i = n)$$

function fluctuations, and learning rate disappearance in other optimization algorithms.

4.9. Weighted cross entropy loss function wideresnet:

Each sample will produce an N-dimensional array via the softmax layer following the complex network's feature extraction process. This is a distinct defect category for each dimension in the array, or the Nclassi cation issue, which can be stated as a formula.

$$O = \begin{bmatrix} P(y=1\,|x;W_1,b_1) \\ P(y=2\,|x;W_2,b_2) \\ \cdots \\ P(y=N\,|x;W_N,b_N) \end{bmatrix} = \frac{1}{\sum_n^N \exp(W_n x + b_n)} \begin{bmatrix} \exp(W_1x+b_1) \\ \exp(W_2x+b_2) \\ \cdots \\ \exp(W_Nx+b_N) \end{bmatrix}$$

The network provides an equal error loss for each sample by using the cross-entropy loss function to determine the difference between the actual and expected output.But in the real classification of green plum faults, several defects exhibit an uneven distribution. The neural network model frequently overlooks samples from a few categories and concentrates on the majority of categories in order to achieve exceptional classification performance, which results in high overall accuracy but low accuracy of samples from a few categories.Thus, the Weighted cross entropy Loss(WceLoss) function adds corresponding penalty coefficients to the error losses of different categories on the basis of the original loss function, and realizes the weightedaverageloss of different categories of errors in order to solve the distribution of imbalanced sample defect categories.The penalty coefficient can be calculated based on how several categories are balanced, which can be stated as.

5. Conclusion:

Conventional machine vision technology typically extracts features through manual means, leading to missing features and a significant influence on the detection outcomes.In order to overcome this issue, the deep learning network automatically extracts defect features from the dataset via the convolutional layer. The accuracy of defect recognition cannot be guaranteed.

The four faults of rot, crack, scar, and rainspot are not significant and share particular features because green plums are modest in size.For instance, at the decay position, some scars are created by air drying, and the two coexist.The flaw has an uneven shape and a similar color.The color of the damaged surface is similar to rot because of the oxidation of fractures generated by external force cutting; rainspots resemble rotting pits in both shape and color. These parallels could lead to erroneous identification.

Furthermore, following data augmentation, there are several photos and data of green plum surface defects that were gathered during the experiment. Traditional approaches are not able to meet the detection requirements with the same efficiency and quality, which is why using the deep learning network work model is required.With the advent of deep learning network models, each of the following network models—ResNet, DenseNet, ResNeXt, WideResNet, and others—has advantages and disadvantages when it comes to processing photos. This paper uses a self-designed image acquisition device to gather surface images of green plums in accordance with the requirements of grading and classifying green plums according to surface defects. This is done in order to meet the requirements of dynamic detection of 1800 green plums per hour in green plum processing enterprises. The Adam W optimizer and Wce Loss function were applied to the green plumbing defect classification network to establish the WideResNet50-Adam W-Wce model. This was done in response to the problem that there were numerous flaws on the green plumbing surface and their solution if it was not possible to correctly identify and classify, based on WideResNet 50. The network successfully classified green plum surface flaws, and the accuracy of the results was 98.95%.Rainspots had the greatest classification accuracy rate, at 100.00%. For precision, recall, and F1-Measure values, the established network is compared with ResNet50 SGD, WideResNet50-SGD, WideResNet50-SGD-Wce, Re-snet and WideResNet50-Adam networks.The WideResNet50-AdamW-Wcenet work can learn more about the features of a defect and has the greatest F1-Measure of any defect. WideResNet50-AdamW-Wce network's superiority over other network methods in defect classification performance is proven, and its automatic defect detection method, Greengage, is made up of these components.While not the quickest at finding a single plum surface fault, only 103 ms, is sufficient to meet the limit of 1800 per 623 hours.

This work finished building the WideResNet-based green plum surface defect classification model WideResNet50-AdamW-Wce, and it produced a better surface defect classification result based on the static classi cation of green plums sur faced faults.In dynamic conditions, it may fulfill the needs of businesses to identify 1800 pieces every hour.Multiview vision technology should be taken into consideration in the next research in order to capture the complete surface image of the green plum.Three-dimensional modeling can be utilized to obtain the three-dimensional model of the green plum, which can lessen the influence of curvature change brought about by the reduction of three-dimensional entity dimensionality into a two-dimensional image on surface defect features

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