**Artificial fruit ripening identification by doubleGAN generated images using convolutional neural network**

**ABSTRACT**

Fruits are often tainted by chemicals, posing a significant risk to human health. One of the major challenges in the food industry is the accurate identification of naturally ripened fruits and those ripened by artificial methods. Due to lack of substantial datasets consisting of images of artificially ripened fruits, it frequently becomes challenging to efficiently train models for this purpose. To address these issues, we made use of Deep Convolutional Generative Adversarial Networks (DCGAN) to generate augmented image datasets of naturally and artificially ripened fruits. Employing initial sample fruit images of 96x96 pixels, the DCGAN was able to generate 160x160 pixel images, therefore enhancing the dataset. Afterwards, Convolutional Neural Network (CNN) models were trained using these generated images to identify artificially ripened fruits. Finally, The DCGAN-generated images were compared with the raw dataset of original images. The comparison resulted in an accuracy rate of 98.87%, indicating that the results obtained from the DCGAN-generated images excelled over those obtained from raw image dataset. This shows that the application of DCGAN in augmenting image datasets can significantly improve accuracy of models used for identifying artificially ripened fruits, and so contributes to improved food safety and human health.

***KEYWORDS:-*** *DCGAN, CNN, raw-image, generated-image*

**I.INTRODUCTION**

Natural fruits have limited lifespan and start to spoil in a short time after harvest. This short shelf life makes it difficult to keep the fruits fresh for a long time, especially during transportation and storage. To address this issue, chemicals like calcium carbide and ethylene are used to artificially ripen the fruits. These chemicals pose major health risks and have resulted in concern among the consumers and authorities.

The use of preservatives and ripening agents is becoming more common as retailers aim to increase the shelf life of the fruits and meet the increasing demand. Consequently, there is an urgent need for approaches to accurately classify naturally ripened and artificially ripened fruits. This identification is important for ensuring food safety.

To address this challenge, we have developed a method to identify artificially ripened fruits using artificial intelligence techniques. Our process involves the use of Deep Convolutional Generative Adversarial Networks (DCGAN) to generate high-resolution images of both naturally and artificially ripened fruits. The DCGAN architecture includes a noise generator and an image generator, which work together to produce realistic fruit images from input noise.

To collect the dataset required for our study, we conducted artificial ripening of fruits, focusing on mangoes and bananas, using the chemical Ethylene. For mangoes, we used four sachets of unsaturated Ethylene powder, placing them among the raw mangoes and allowing them to ripen over five days. For bananas, we applied liquefied Ethylene spray gas to raw bananas, which ripened them overnight. This process enabled us to generate a distributed dataset of artificially ripened fruits for image generation.

These generated images are used to train Convolutional Neural Network (CNN) models. We utilised certain CNN architectures like ResNet, DenseNet, and EfficientNet, to assess the efficiency of our generated images in making distinctions between naturally and artificially ripened fruits. By comparing the performance of these models, we aim to illustrate how our approach is better in achieving high classification accuracy.

This paper draws attention to the potential of using DCGAN to augment fruit image datasets and improve the identification of artificial ripening. These findings contribute to the effort of ensuring food safety and offers a solution to the problem of fruit adulteration.

**II.LITERATURE SURVEY**

The artificial ripening of fruits is often achieved using chemicals such as calcium carbide and ethylene. It poses several health risks due to the potential of harmful residues. Calcium carbide contains traces of arsenic and phosphorus, which can lead to severe health issues, including neurological disorders and cancer if consumed in high quantities [1]. Ethylene, while claimed to be less toxic, can still be harmful if used excessively, potentially leading to respiratory problems and other health issues [2]. As the use of these chemicals increases to meet market demands, the risks related to their consumption also rise, making it important to find safe alternatives.

Because of these concerns, we propose the use of artificial intelligence and neural networks to differentiate between naturally ripened and artificially ripened fruits. By using advanced algorithms such as Generative Adversarial Networks (GAN) and Convolutional Neural Networks (CNN), we aim to achieve higher accuracy in classification, therefore ensuring that consumers have access to safe, naturally ripened fruits [3]. This method addresses the health risks posed by artificial ripening and promotes overall wellness by providing a reliable solution for fruit ripeness detection.

Using GAN, we can generate high-quality synthetic images that augment our dataset, improving the training process for the CNNs. The CNNs are then trained on both the augmented dataset and manually collected samples to accurately classify the ripeness of fruits. Preliminary results indicate that this AI-driven approach significantly enhances classification accuracy compared to traditional methods [4].Deep Convolutional Generative Adversarial Networks are executed for unsupervised learning to generate realistic images and useful feature representations. This method increases the potential of unsupervised models by combining CNN and GAN[5].An AI-based system using CNN is described to determine and classify banana diseases and pests. The system aims to help farmers with accuracy in diagnosis, therefore improving crop health and yield[6]. Super-Resolution GAN is a GAN-based architecture which is proposed for single image super-resolution to generate high-quality, photo-realistic images from low-resolution inputs, therefore enhancing perception[7]. Deep residual learning is introduced to address degradation problem in deep neural networks, enabling the training of substantially deeper networks. The ResNet architecture suggested achieves highly developed results on image recognition benchmarks[8]. EfficientNet, a model scaling approach that uniformly scales all dimensions of depth, width, and resolution using a compound coefficient, is introduced. EfficientNet achieves state-of-the-art accuracy on image classification tasks while being more efficient in terms of parameters and FLOPS[9]. Gao Huang, DenseNet, a convolution network architecture that connects each layer to every other layer in a feed-forward manner, is presented. DenseNet reduces the vanishing gradient problem, enhances feature propagation, stimulates feature reuse, and significantly reduces the number of parameters[10].

**III.PROPOSED SYSTEM:**

In this section, the proposed method for generating fruit image dataset using DCGAN was explained in detail.

**A.MATERIAL**

Data.mendeley is an open-source cloud-based repository that includes images of artificial ripened fruits dataset. In this paper 21395 fruit images collected from data.Mendeley.com, Kaggle.com, github.com. were used as a sample image for DCGAN and convolution neural network. Table 1 lists the artificially and naturally ripened banana and mango fruit images.

|  |  |  |
| --- | --- | --- |
| LABEL | NAME | SAMPLE RAW IMAGES |
|  | ARTIFICIAL RIPENED BANANA | 5346 |
| 2. | NATURAL RIPENED BANANA | 5341 |
| 3. | NATURALLY RIPENED  MANGOES | 5350 |
| 4. | ARTIFICIALLY RIPENED MANGOES | 5358 |

**B.METHOD**

Deep Convolutional Generative Adversarial Networks (DCGAN) are a type of GAN that use deep convolutional neural networks for both generator and discriminator. Introduced by Alec Radford, Luke Metz, and Soumith Chintala in 2015, DCGAN have become a basic architecture for many image generation tasks.

This paper implements Deep Convolutional Generative Adversarial Network (DCGAN) to generate high resolution fruit images with a sample of 21395 images. This method is used to generate fruit images through adversial training, it is based on the generative adversial network (GAN) framework. It consists of two networks such as generator and discriminator .

The input for the generator is usually random noise vector (sampled from a Gaussian or uniform distribution). It consists of a series of fractional-strided convolutional layers (known as transposed convolutions) with ReLU activations. The output generated is a synthetic image with the same number of channels as the real images (like RGB for example).

The input for the discriminator is an image (could be either real or synthetic). Here it takes the fruit images as input and outputs of probability indicating whether the fruit image is generated or real.

It consists of a series of convolutional layers with Leaky ReLU activations and batch normalization. The output generated is a single scalar value representing the probability that the input image is real.

Both generator and discriminator use convolutional layers, which are more efficient for image processing than fully connected layers. The batch normalization helps to counterbalance training by normalizing the inputs to each layer. Leaky ReLU and ReLU Activations improves the flow of gradients through the network.

DCGAN have shown to be more stable during training compared to traditional GAN. The proposed architecture of generating high-quality and realistic fruit images using DCGAN are shown below in figure 1.

A diagram of bananas and bananas

Description automatically generated

Fig. 1. Proposed architecture of generating fruit image dataset

The probability of correctly identifying real fruit and generated(fake) fruit images is maximised by discriminator. The aim of discriminator can be expressed as:

(1)

Where r is real image from the true distribution, y is a random noise vector sampled from real distribution , G(y) is the generated image from the generator G, D(r) is the discriminator’s estimate of the probability that r is real, D(G(y)) is the discriminator’s estimate of the probability that the generated image is real.

The probability of the discriminator making a mistake is maximized by generator. The aim of generator can be expressed as:

(2)

Where y is a random noise vector sampled from real distribution , G(y) is the generated image from the generator G, D(G(y)) is the discriminator’s estimate of the probability that the generated image is real.

DCGAN generated 5346 artificial ripened banana, 5341 natural ripened banana, 5350 naturally ripened mangoes and 5358 artificially ripened mangoes. DCGAN generate images and store as NumPy file format. Since, the format preserves the data types and shapes of the arrays, making sure that the stored data remains consistent and can be retrieved without data loss. It is suitable for a wide range of applications, from small-scale data storage to handling larger datasets in machine learning. Therefore, in this paper the DCGAN generated fruit image dataset in NumPy file format is given as a training dataset for convolution neural network models like DenseNet121, EfficientNetB0, ResNet50 and compare result with raw-fruit-image dataset.

Convolutional Neural Networks (CNNs) are a type of deep learning model that especially works well for tasks involving image classification. DenseNet121 is a 121-layer deep convolutional neural network from Densely Connected Convolutional Networks (DenseNet) family, introduced by Gao Huang and his colleagues. It reduces vanishing gradient problem by making sure of maximum data flow between layers through dense connections.

DenseNet121 consists of dense blocks. Each layer receives input from previous layers, resulting in L(L+1)/2 direct connections in an L-layer network. It also includes transition layers that are used between dense blocks to control number of feature maps and spatial dimensions. In this paper, DenseNet121 got 98.79% of accuracy with DCGAN generated and 98.24% of accuracy with original image.

EfficientNetB0 is the base model of EfficientNet family, designed by Mingxing Tan and Quoc V. Le. It introduces new scaling approach that perfectly scales depth, width, and resolution using compound scaling coefficient. This results in models that are highly accurate with much fewer parameters and FLOPS.

EfficientNetB0 is built on mobile inverted bottleneck MBConv layers and utilises depth-wise separable convolutions. It includes compound scaling which scales the network's depth, width, and resolution evenly. Each block consists of MBConv layers which include depth-wise convolutions succeeded by pointwise convolutions. It also makes use of Swish activation function for better performance and incorporates Squeeze-and-Excitation (SE) blocks to enhance channel attention. It makes for good balance between precision and computational effectiveness. The compound scaling approach helps in easy scaling to larger or smaller models. EfficientNetB0 got 98.54% of accuracy with DCGAN generated and 97.23% of accuracy with original image.

ResNet50 is a 50-layer deep convolutional neural network that is part of Residual Network (ResNet) family, designed by Kaiming He and his colleagues. It addresses vanishing gradient problem by making use of residual connections, therefore enabling the training of very deep networks. ResNet50 uses residual blocks i.e. identity shortcuts to skip layers, allowing gradients to flow through the network without vanishing. It consists of a combination of convolutional layers, batch normalization, and ReLU activations. Each residual block has a bottleneck design with three layers. It enables the training of very deep architecture, leading to superior feature extraction and higher precision. It achieves high performance on certain image classification tasks. ResNet50 got 98.82% of accuracy with DCGAN generated and 98.04% of accuracy with original image.

**EXPERIMENTAL RESULT:**

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| --- | --- | --- | --- |
| **S.NO** | **MODEL** | **ORIGINAL DATASET** | **DCGAN GENERATED DATASET** |
| 1. | ResNet50 | 98.04 | 98.82 |
| 2. | DenseNet121 | 98.24 | 98.79 |
| 3. | EfficientNetB0 | 97.23 | 98.54 |

**CONCLUSION:**

This paper was undertaken to utilise Deep Convolutional Generative Adversarial Networks (DCGAN) for generating images of artificially and naturally ripened fruits to expand the dataset and assess the usability of these generated images through accuracy in classification. GAN have been considerably used in the field of image generation. However, the various GANs proposed at the moment are primarily used to generate images using substantial samples. For ripened fruit images, datasets of artificially ripened fruits are in shortage.

This study aimed to generate 160x160 pixel fruit images using limited dataset, making use of a DCGAN model. To evaluate the quality of the generated images, the 160x160 pixel fruit images were used to expand the existing dataset. Afterwards, this expanded dataset was employed to train Convolutional Neural Network (CNN) models to identify artificially ripened fruits. The results showed that the classification accuracy for the dataset expanded with DCGAN-generated images is significantly higher, achieving an accuracy of 98.87%, compared to original raw dataset.

These findings demonstrate that the generated fruit images contain most features of the real images, supporting the idea that GAN-generated images can be used to expand unbalanced datasets. Although the current paper is based on a relatively small sample of fruit images, the results imply that the generated images can successfully balance the dataset. Further study is needed to generate higher resolution images with even less samples, and to explore more criteria for image quality improvement.

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