iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: VII Month of publication: July 2023

DOI: https://doi.org/10.22214/ijraset.2023.54651

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VII Jul 2023- Available at www.ijraset.com

Fruit Freshness Evaluation using a Real-Time Industrial Framework for Deep Learning Ensemble Approaches

N. Ramakrishna[1], Sai Anusha[2], N. Abhigna[3], S. Sangeetha[4]
Dept. of ETE, GNITS Hyderabad, INDIA

***Abstract:** Consumers give a high value on fruits' freshness, and manual visual grading presents challenges due to labor effort and inconsistent results. This research suggests an effective machine vision system for automating a visual assessment of fruit freshness and attractiveness based on cutting-edge deep learning algorithms and ensemble methodologies. The suggested architecture enables the non-destructive and economical detection of fruit defects by utilizing convolutional neural networks (CNNs). To attain high classification accuracy, which acts as the performance metric, the system utilizes ensemble deep learning models. Fruit photographs are used to train the algorithm, enabling precise fruit quality assessment. This framework revolutionizes the inspection process by using computer vision in real-time for industrial applications in fruit freshness detection.*

***Keywords:** Artificial intelligence ,local respective fields,pooling,*

I. INTRODUCTION

Machines will be able to interact with the world in the same way that people do by employing computer vision.The pattern recognition algorithms and extensive visual data training, computer vision replicates how the human brain recognizes visual information. Mainly through deep learning, convolutional neural networks (CNNs)[1] have transformed the science of computer vision.. Using deep learning techniques, we attempt to solve the issue of creating an automated ensemble model for classifying fruit images as fresh or rotten

Convolutional neural networks (CNNs) are deep neural networks that are known for their usefulness in computer vision. In comparison with standard neural networks, which have each layer fully connected, a CNN only has the last layer fully connected. CNNs utilize local receptive fields [2] to connect discrete input neuron regions to hidden layer neurons. For the purpose to produce feature maps, these localized receptive fields are moved all over the image. Incorporating shared weights and biases, allowing for the detection of associated features, permits neurons in a feature map [3] to utilize the same filter weights and biases. For the purpose of image classification using the SoftMax function [3]; fully connected layers, connect the final hidden layer to the output layer while activation functions and pooling reduce dimensionality. Every layer in ANNs is fully connected, as illustrated in figure 1, which means that every neuron in each layer is linked to every neuron of next layer.

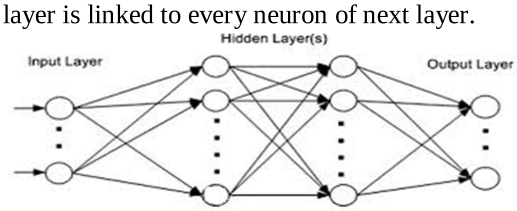


Figure 1: ANN architecture

ANNs are not appropriate for image processing since the size of the pictures causes over-fitting in these networks. Think of a picture that is [32x32x3] in size. This image must be flattened into a vector of 32x32x3 = 3072 rows so as to be input into an ANN. As a consequence, the ANNs require 3072 weights in the initial layer in order to process this input vector, resulting in a need a more powerful processor. In contrast to conventional ANNs, just a small percentage of the input layer neurons in a CNNs layer are connected to the neurons in the hidden layer. As indicated by figure 2, these regions are termed as local receptive fields. (3X3 little area of the source picture) and feature maps indicated in figure 3.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VII Jul 2023- Available at www.ijraset.com

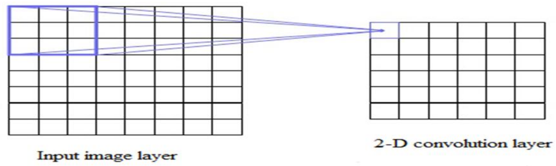


Figure 2: Receptive (3X3 small region) connected to neurons in the convolution layer

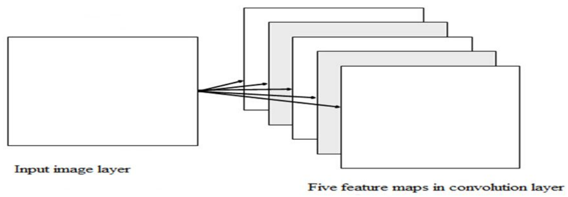


Figure 3: convolution layer feature map

The sliding window technique is employed in a convolutional layer to move filters over the entire input image. Calculated is the dot product of the filter coefficients and the input. Equation -1 gives the size of the output feature map (OUT).

$$OUT = 1 + \frac{N-F}{S} \qquad (1)$$

Where NxN is the image size, FxF is the filter size, the convolution is performed using the following equation-2.

$$[N, N, N_C] * [F, F, N_f] = \left[\left[1 + \frac{N-F}{S}\right], \left[1 + \frac{N-F}{S}\right], N_f\right] \qquad (2)$$

After convolution layer, the feature maps are subjected to the activation function. The ReLu function[3] activates neurons in the feature maps only when weights are greater than equal to zero and all negative weights are made zero. The range of F(X) is 0 to ∞.
After ReLu transformation, pooling step is applied, in which the model down samples the convolved features to save processing time and reducing the number of dimensions of the feature map, while still preserving the most critical features of images. The pooling techniques [3] are two types namely average pooling and maximum pooling. The pooling process is similar to convolve operation. In maximum pooling, for each small neighbourhood in the feature map, the maximum value is considered as output and all other values are discarded. In average pooling, for each small neighbourhood in the feature map, the average value is considering as output. The proposed work implements maximum pooling technique. Pooling operation takes two parameters: the size of the neighbourhood and stride. The stride is the distance, in pixels separating each extracted tile. Unlike with convolution, for 2X2 neighbourhood, a stride of 2 specifies that the pooling operation extracts all non-overlapping tiles from the feature map. Figure 4 shows the average pooling and max pooling.

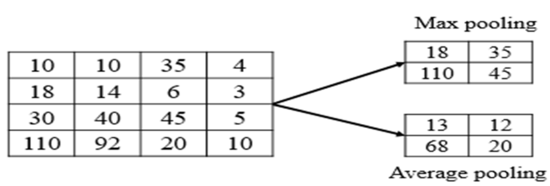


Figure 4: Max pooling average pooling

A fully connected layer scales the input X by a weight matrix W before incorporating a bias vector b. According to Equation 3, if the layer before it emits an array X of size output size is M x M x S, the completely connected layer will generate an array Z of size output size is M x S. Z = WX+b (3)
After the last fully connected layer, the SoftMax function is implemented in the model. The SoftMax function is an activation function which outputs a vector that represents the probability distributions of a list of expected image classes. A SoftMax layer uses a SoftMax function. The SoftMax activation function b(a) is given by equation – 4.

$$b(a) = \frac{e^{ai}}{\sum_{j=1}^{r} e^{aj}}$$

$$where\ 0 \le b \le 1, \quad \sum_{j=1}^{k} b = 1$$

e^{ai} is the exponential element at position i in the vector a and $\sum_{j=1}^{r} e^{aj}$ is the sum of the exponential of all elements of a vector.

The classification layer [4] at the bottom of the model generates the cross-entropy loss[11] for classes which are mutually exclusive. In the classification layer, the model employs the Categorical Cross-Entropy [4] for a 1-of-K coding scheme and the values from the softmax function to categorise each input as belonging to one of the K mutually exclusive classes.

$$\text{Categorical Cross} - \text{Entropy} = -\sum_{i=1}^{N}\sum_{j=1}^{k} t_{ij} \ln y_{ij} \qquad (5)$$

Where N is the number of samples, K is the number of classes, t_{ij} is the indicator that the i^{th} sample belongs to the j^{th} class, and y_{ij} is the output for sample i for class j, which in this case, is the value from the softmax function. That is, it is the probability that the network associates the i^{th} input with class j. The gradient descent algorithm updates the network weights by minimizing cross-entropy loss. The algorithm reduces the distance between target probability distributions and actual probability distributions.

There are seven sections in this paper. The introduction to field of the proposed work is presented in Section I, and various methods for detecting fresh fruit are illustrated in Section II. The study's proposed approach is outlined in Section III. Section IV summarises the findings and offers a thorough analysis. The paper is concluded with a summary of the work in Section V. The goal of the proposed work is to recognize fruit freshness in images, this investigation implements an ensemble model based on transfer learning. Furthermore, Streamlit, a desktop tool, is utilized to present an integrated industrial framework. The accuracy and usability of fresh fruit detection in this study are enhanced by the combination of transfer learning and the industrial framework.

II. LITERATURE REVIEW

In the paper "Detection of freshness of fruits using electrical method" by Shweta Kammar et al [5]., the authors introduce a new approach to assess the freshness of fruits. Their method involves measuring the electrical conductivity of fruits to determine their freshness. The paper discusses the experimental setup and methodology used for measuring the electrical conductivity of various fruits. The results demonstrate a significant relationship between electrical conductivity and fruit freshness, highlighting the potential of this technique for non-destructive fruit quality assessment .The paper "A Comparative Analysis on Fruit Freshness Classification" by Diclehan Karakaya [6] presents a comparative analysis of different methods for fruit freshness classification. The author evaluates and compares the performance of various machine learning techniques and features for accurate classification. The research presented here underlines the vital importance of feature and algorithm selection. The reviewed papers highlight the effectiveness and potential of CNN-based methods for fruit freshness detection. However, limitations such as reliance on visual appearance and the need for specialized equipment are identified. To address these shortcomings, a proposed conclusion is to develop a web app-based ensemble CNN method for fresh fruit detection. This approach would leverage the power of CNNs while incorporating a user-friendly web interface for accessibility. By combining multiple CNN models and providing real-time results, the proposed ensemble CNN method offers a promising solution for accurate and convenient fruit freshness assessment.

III. METHODOLOGY

CNN is a state of art technique, because of its advantages to extract features from images without complex processing. The paper investigates the ensemble models using pre-trained CNN pre trained models, namely Vgg16 [7],Vgg19[7] Resnet50[8] ,Resent101[8] and InceptionResnetv2 [9] models to detect fruit freshness as shown in figure4.The transfer learning uses the knowledge of the pre-trained models

IV. RESULTS AND DISCUSSION

Exploratory Data Analysis (EDA) is performed on the dataset used in the present investigation are 10,342 training images and 2,708 test images entirely, taken from Kaggle[10], which also include fresh and rotten apples, bananas, and oranges. The EDA is presented using the charts as shown in Figure 5 and 6.

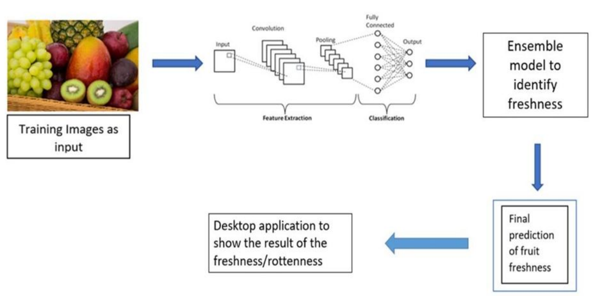


Figure4: Ensamble Learning using pre-trained cnn models.

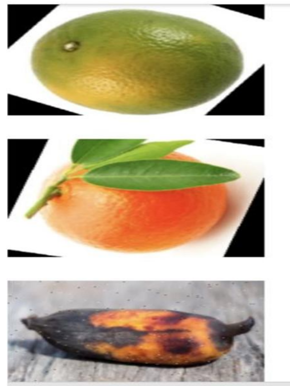


Figure 5: Sample Images of the dataset

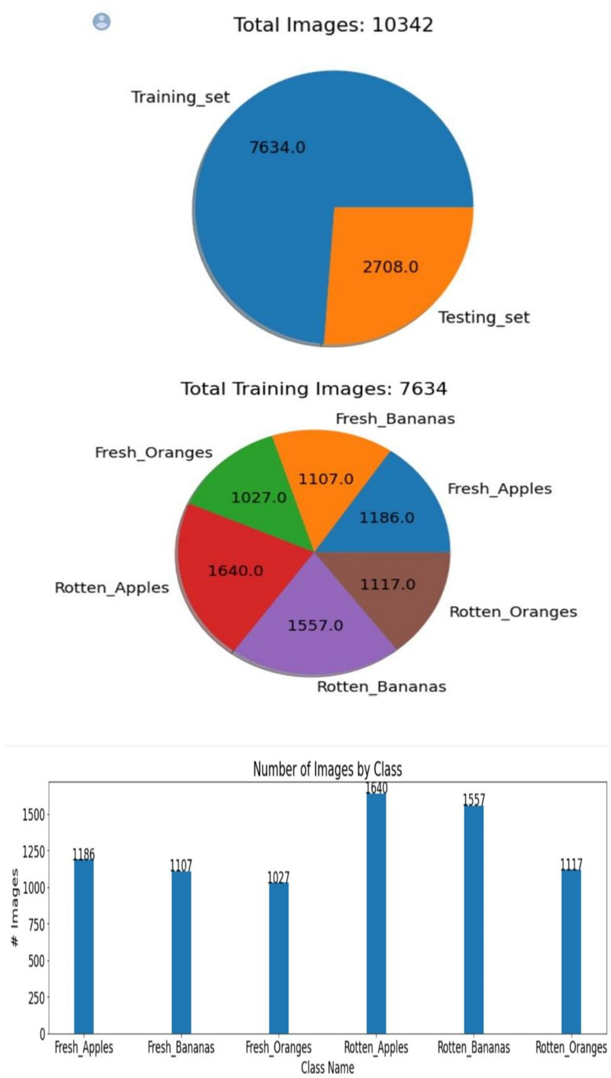


Figure 6: Graphical representation of the dataset

In this paper, Following steps are used implementing transfer learning with VGG16 and VGG19:

1) Use weights from ImageNet to the pre-trained VGG16 or VGG19 model, except the top layer.
2) To stop the layers of the already trained model from millions ImageNet dataset, freeze them.
3) Prepare your dataset by normalizing the pixel values of an input image with a size of (224, 224, 3).

4) The fresh fruit and rotten image data consist of the 6 classes namely fresh oranges, fresh apples, fresh bananas, rotten oranges, rotten apples, and rotten bananas, and divide the dataset into training and testing sets.
5) Two dense layers each containing 64 units and ReLU activation are used
6) To handle multi-class classification, present an output layer with six units (one for each class) and a softmax activation function.
7) Build the model and train the model using the training dataset for 10 epochs, using a batch size of 32.
8) Evaluate the model's performance on the test dataset, calculating accuracy.
9) Save the trained model for future use or deployment.

An ensemble model that combines the predictions of the multiple pre-trained models to obtain greater accuracy in following steps
a) Load the training weights for the pre-trained models separately.
b) Get your test dataset ready.
c) Using both models make predictions on the test dataset and record the probabilities or class labels.
d) Utilise a voting scheme to combine the multiple models' predictions. Each model provides predictions, and the class that receives the highest number of votes is chosen as the final prediction.

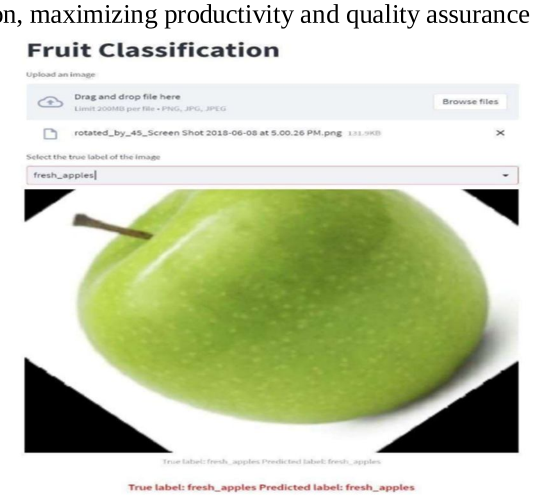
TABLE 1: Summary Of Model Results

S.No	Pretrained model	Test Accuracy (%)
1	Vgg16	**97.82%**
2	Vgg19	**96.31%**
3	InceptionResNetV2	**98.49**
4	ResNet50	**64.48%**
5	ResNet101	**61.63%**

The transfer learning is implemented using pretrained models namely Vgg16,Vgg19, Resnet50 ,Resent101 and InceptionResnetv2 models .The individual models are trained and tested on same Image dataset and their accuracy values are presented in table1.The prosed work utilize all these models to develop ensemble model using voting schemes . The proposed model produced better results on unseen data .The desktop tool stream lit app results are presented in figure7.

V. CONCLUSIONS

Convolutional neural network (CNN) ensemble techniques enable reliable classification of fruit freshness assessment. They are integrated with a desktop tool like Streamlit and offer real-time monitoring, evaluation, and user-friendly interfaces to enhance business frameworks and client inspection, maximizing productivity and quality assurance in the processing of fruit.



International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VII Jul 2023- Available at www.ijraset.com

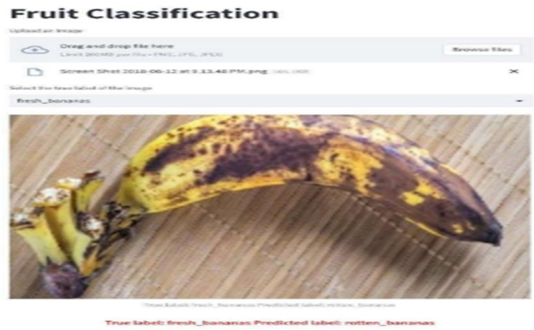


Fig 7 : Results of ensemble model on unseen images

REFERENCES

[1] M. Jogin, Mohana, M. S. Madhulika, G. D. Divya, R. K. Meghana and S. Apoorva, "Feature Extraction using Convolution Neural Networks (CNN) and Deep Learning," 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 2018, pp. 2319-2323, doi: 10.1109/RTEICT42901.2018.9012507.

[2] https://towardsdatascience.com/understand-local-receptive-fields-in-convolutional-neural-networks-f26d700be16c

[3] Alzubaidi, L., Zhang, J., Humaidi, A.J. et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data 8, 53 (2021).

[4] A. Ajit, K. Acharya and A. Samanta, "A Review of Convolutional Neural Networks," 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, 2020, pp. 1-5, doi: 10.1109/ic-ETITE47903.2020.049.

[5] Shweta Kammar, S.B.Kulkarni, U.P.Kulkarni, Ramesh.K, Ravindra.Hegadi"Detection of freshness of fruits using electrical method", International Journal of Engineering Trends and Technology (IJETT), V23(2),90-92 May 2015. ISSN:2231-5381. www.ijettjournal.org. published by seventh sense research group

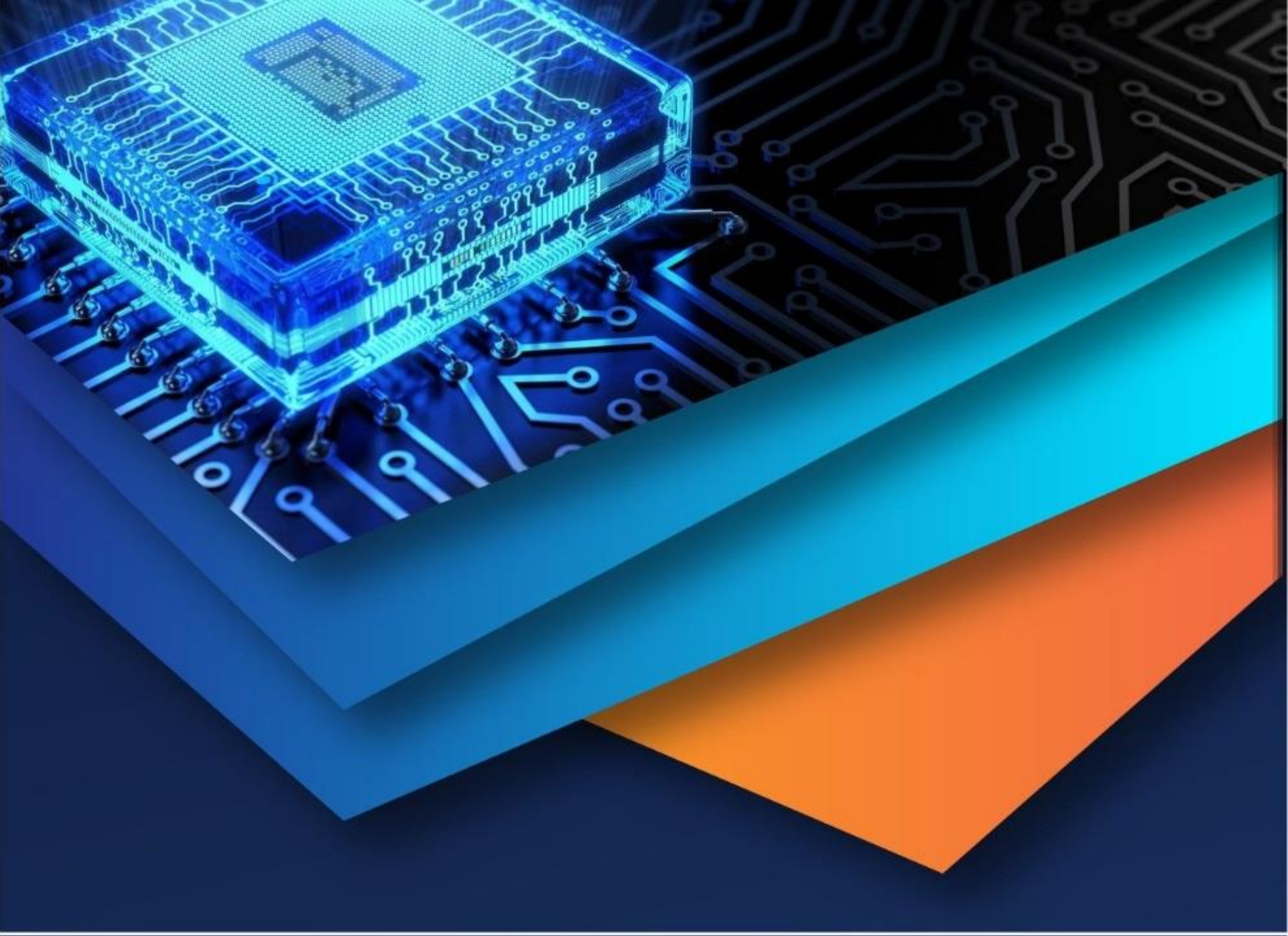
[6] D. Karakaya, O. Ulucan and M. Turkan, "A Comparative Analysis on Fruit Freshness Classification," 2019 Innovations in Intelligent Systems and Applications Conference (ASYU), Izmir, Turkey, 2019, pp. 1-4, doi: 10.1109/ASYU48272.2019.8946385.

[7] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

[8] He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[9] Szegedy, Christian, et al. "Inception-v4, inception-resnet and the impact of residual connections on learning." Proceedings of the AAAI conference on artificial intelligence. Vol. 31. No. 1. 2017.

[10] Kaggle dataset: https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for- classification



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY