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Deep Learning based Apple Fruit Disease Detection using Dense Net Recursive Convolutional Neural Network (DNRCNN)

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Abstract:. *Every year, fruit diseases cost the apple industry a lot of money. It can be challenging for growers to identify various apple infections because the symptoms of various illnesses are often similar and may overlap. In this study, we suggest a deep learning-based method for identifying and categorizing apple diseases. Dataset generation, which includes data collection and data labelling, is the first stage of the investigation. On the prepared dataset, we then trained a deep learning-based Dense Net Recurrent Convolutional Neural Network (DNRCNN) model for automatically classifying apple diseases. The end-to-end learning algorithm DNRCNN is appropriate for a range of tasks including image classification, object detection, and segmentation because it automatically extracts complex features from source images and learns them directly. Initialize the parameters of the proposed deep model using transfer learning. To avoid over-fitting, data augmentation techniques like rotation, translation, reflection, and scaling are also used. On the prepared dataset, the proposed Dense Net Recursive Convolutional Neural Network (DNRCNN) model achieves promising results, with an accuracy of about 96%. Some of the intricate and helpful image characteristics for detection are captured by the suggested model for classification. The model can learn the higher-order features of two adjacent layers that are not in the same channel but have a high correlation more effectively than existing techniques. High training and validation accuracy have been achieved when training and validating the suggested model. The findings support the method's usefulness in categorizing different apple diseases and show that it can be useful for farmers*

Keywords: Diseases, apple, farmers, image, transfer learning, Dense Net Recursive Convolutional Neural Network (DNRCNN), accuracy, classification

I. INTRODUCTION

Harvesting any culture involves farming to a significant extent. In actuality, agriculture is fundamental to human civilization. To meet good production goals, regular field extensions and soil moisture management are essential. The quantity and quality of production are significantly impacted by plant and fruit diseases. Diseases are widespread today, and the biggest obstacle is injuriousfaces like pesticides. Diseases associated with picking fruit were investigated. Image processing technology analyses how fruit trees are ageing. An extensive analysis of filter technology for distortion detection is conducted. The proposed system takes into account issues with fruit images. To show the dataset's value for research, it is taken from the UCI website.

This research uses machine learning (ML) and Deep Learning to build an automated fruit classification system using a set of data about each fruit. The system chooses the fruits that are healthy for us and provides information about each fruit's characteristics. A system like this aids in educating kids and introducing them to fruits. These systems can also be used to teach robots how to determine the best benefit for the user.

The suggested system makes use of standard feature extraction, convolution, and image sharpening filters. Individual colour channels are enhanced for segmentation after feature extraction. Convolutional neural networks are used to segment data using K-means clustering, which enhances the classification process that results. Data is ingested into segmented image pixels by convolutional neural network mechanisms, which then produce a range of results based on classification accuracy. This outcome has been contrasted with the prior outcome.

When it comes to fruit image detection, DNRCNN is more accurate than conventional techniques. Additionally, this method sorts fresh fruit more quickly. In this study, using a new dataset made up of 100 data sets from Apple fruit types, retrain the model to recognize fruits. The dataset is unique in that all of the data is gathered with a smartphone camera. The study's accuracy rate of 96% is encouraging. Additionally, the results of this study, which is carried out in real-world circumstances, are contradictory. This project's goal is to expand the system to include additional objects and useful applications.

II. RELATED WORK

A system that uses deep learning to distinguish between unripe, partially ripe, and ripe strawberries, as well as from overgrown or diseased strawberry varieties. Add three different modules to the convolutional encoder-decoder network that is being proposed. To detect objects of different sizes, one is used to adaptively control the network's receptive field size. The second is used to control the computational complexity of the architecture and the second is used to control the flow of crucial features (information) to the deeper layers of the network [1].A significant factor in the decline in citrus production is citrus diseases. Therefore, developing an automated system for citrus plant disease detection is crucial. Utilizing deep learning techniques in the task of identifying, using an ensemble approach to propose a model. Deep learning techniques have recently demonstrated encouraging results in a variety of artificial intelligence problems. The proposed CNN model is intended to distinguish between fruit and leaf samples that are in good health and those that have common citrus diseases like black spot, canker, scab, green spot, and black spot. To extract complementary discriminative features, the proposed CNN model combines multiple layers [2].

Millions of tonnes of date palms are produced each year in the Middle East, making them one of the staple crops. Dates are nutritious fruit that is rich in vitamins, minerals, and sugar. Additionally, it aids in the prevention of numerous illnesses like cancer and heart disease. In the data business, sorting dates is a crucial step. However, it is expensive and time-consuming for humans to carry out such tasks manually. To categories the various types of jujubes, suggest in this paper combining supervised and unsupervised deep networks. In particular, combine features learned from convolutional neural networks (VGG-F) with an unsupervised network called her PCANet using the Discriminant Correlation Analysis (DCA) algorithm. DCA efficiently performs feature fusion and dimensionality reduction simultaneously [3].

The spread of apple diseases can be controlled, and production costs can be decreased, by early diagnosis and accurate identification. However, in a complex environment, the significance of distinctive diseases of apple leaves is relatively low, and because different diseases of apple leaves have a high degree of fine-graining, traditional feature extraction techniques lose discriminative information. Suggests a multi-scale feature fusion-based classification model for apple diseases to address these issues. To achieve effective information circulation, first enhanced the traditional residual network's (ResNet) information flow and moved batch normalisation and the modified linear unit (ReLU). Second, separate the spatial projection and downsampling channels to address the serious information loss issue in ResNetdownsampling [4].

Because agriculture ensures food security, it is a crucial component of the global economy. However, it has been noted recently that plants are frequently infected with several diseases. Global agriculture suffers severe economic losses as a result of this. Utilizing automated techniques to identify plant diseases early can reduce the need for manual fruit disease inspection [5].

A deep learning strategy for continuous illness location in apple leaves in light of a changed convolutional brain organization (CNN). Utilizing information expansion and picture explanation procedures, an Apple Leaf Disease Dataset (ALDD) containing complex pictures caught in the field and the lab is first made in this review. On this establishment, another Profound CNN-based model for the identification of apple leaf sickness is proposed. This model consolidates the GoogLeNet Initiation design and Rainbow link [6]. Plant sicknesses come in a wide range of assortments and can influence a plant's capacity to typically develop. All pieces of the plant, including the leaves, stems, natural products, roots, and blossoms, are affected by these infections. The plant will commonly shrivel or could lose leaves, blossoms, and natural products on the off chance that the sickness isn't dealt with. Right determination of

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the sicknesses is essential for the successful location and therapy of plant illnesses. The investigation of plant illnesses, their hidden causes, and techniques for overseeing and controlling them is known as phytopathology. Existing techniques, nonetheless, affect individuals in the order and recognizable proof of illnesses [7].

.Deep learning-based plant infection location has drawn in a great deal of interest from researchers. Nonetheless, there hasn't been any examination concerning parts of plant conditions in reality. Contemplate diseases influence the plant's natural product, stems, and different parts notwithstanding the leaves, for example. Moreover, it has not been finished all the while identifying a few illnesses in a solitary plant organ [8]. An enormous assortment of bugs and infections, cloud-based profound learning, high information stockpiling and correspondence costs, imbalanced and deficient plantation information, and a difficult identification climate are elements of conventional vermin location innovation. The different vermin discovery strategies propose in this paper depend on Feature learning (FL) and an upgraded quick area convolutional brain organization. With the assistance of another disseminated processing model called FL, correspondence expenses can be diminished while a common model that integrates the upsides of information from all gatherings without transferring neighbourhood information is made [9].

Utilizing automated techniques to identify plant diseases early can reduce the need for manual fruit disease inspection. Used a novel technique in the article to recognize and classify diseases in apples [10].

III. MATERIALS AND METHOD

The images of apple disease that were gathered as well as the extended AFDII are all described in this section along with the tools and procedures used in the study. Also, present our suggested model and our approach to attention visualization. Using image-forming technology, a new apple fruit disease identification image (AFDII) has been created. Used image enhancement techniques to increase the dataset and simulate apple leaf disease images collected under various conditions to serve as a basis for model training to improve the generalisation performance of the model.

To get the best network depth, width, and input image resolution, Use deep network search techniques to identify the model's ideal structure. To achieve attentional integration of feature channels and spatial information, a tuned attention module is integrated into the infrastructure, which enhances the critical information models' capacity for learning.

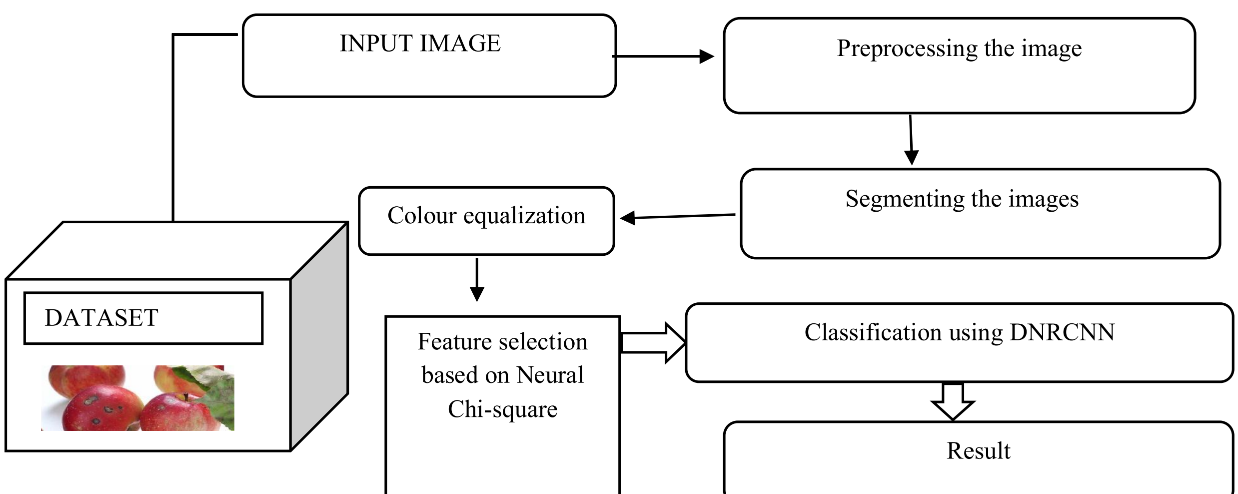

Figure 2: Proposed block diagram

Figure 2 defined the proposed block diagram for apple fruit disease detection based on deep learning approaches, Initialize the fruit images to reduce the noise and irreverent corners and proposed image for entering to segmentation process, using these images for analysis of the pixel-based segmentation and equalizing the colours for images. Then extracting and selecting the features using Chi-square extraction for good features evaluation. Finally classified the result using DRCNN to better result.

3.1 Fruit Image Preprocessing

Fruit Images' are used for preprocessing to a grayscale range using the weighted averaging method to produce the desired effect of image enhancement. To lessen image grayscale abrupt transitions and noise, bidirectional filtering is used in this paper after grayscale processing. A non-linear filter called a bilateral filter enhances correlation between pixels, preserves edge features, and maintains spatial distance relationships between pixels during sampling. The output pixels of this bidirectional filter are weighted by their surrounding pixels.

$$C(a,b) = \frac{\sum_{d,f} x(d,f) w(a,b,d,f)}{\sum_{d,f} w(a,b,d,f)}$$

$$X(a,b,d,f) = \exp\left(-\frac{(a-d)^2+(a-f)^2}{2\sigma_f^2}\right)$$

Image data depending using bilateral weights function

$$w(a,b,d,f) = \exp\left(-\frac{(a-d)^2+(a-f)^2}{2\sigma_f^2}\right) - \exp\left(-\frac{(a-d)^2-(a-f)^2}{2\sigma_d^2}\right)$$

Throughout the training process, satisfactory results were obtained by optimising the weights and utilising bilateral filtering to lower noise. It safeguards Apple's vast external data.

3.2 Image Segmentation

The next step is image segmentation, which involves gathering three images into clusters. There are R, G, and B images. Fruits in Cluster 3 are vibrantly coloured. The fruit's flawed portion is shown in Cluster 1 Image. Cluster 2 displays the whole fruit image without the background. Clustering methods for image segmentation are more effective and simpler to use. The algorithm separates the data into regions or groups of pixels that share similar traits. Based on the cluster centres that are close to the data points, all of the data points are assigned to clusters. This method will produce good results if the cluster centres are accurately estimated. Usually, the amount of noise in the image determines it.

Steps for segmentation

Input

Set of image elements $E = \{I1, I2, \ldots Sn\}$

Number of preferred clusters

Output

C- Set of clusters

Assigning input values (v1, v2 ...vm)

Repeat

Assign each weight $t1$

Calculate the new of each clusters weights

Until image weights of union criteria

The maximum distance between data points can be used to define initial parameters when using clustering algorithms.

3.3 Color equalization

This regulates the appearance and behaviour of the image. Hue and saturation components should be kept when converting a colour image to an HSV image. Plot the values in the graph after extracting them. The HSI image matrix is used to generate the intensity matrix. Utilizing a histogram equalisation intensity matrix, this matrix is updated.Moments of colour Color indexing benefits greatly from the use of colour moments. Applications for image restoration only consider the first three colour moments to be featured. The colour of the two images can be used to compare them.Features of HSV Color, colour intensity, and lightness are all described by hue-saturation value (HSV). As a result, can search based on colour level and colour purity using a colour detection algorithm. It's employed to locate the pixels.

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3..4 Feature extraction based on Neural Chi-square Algorithm

Fruit colour, texture, and shape are traits that can be extracted. Apple diseases are grouped based on these characteristics. For apple diseases to be correctly identified, colour and texture are crucial. Initialization: Neural chi-square performs introduction utilizing a cluster of people known as the populace. The image is set to 30, the number of potential arrangements. The image is set to 500. This implies the calculation performs to assess the wellness capability. The change rate and the hybrid rate were set to 0.02 and 0.7, separately. Determination: The main move toward masochist hand-squaring is to choose the best features.

$$W = \frac{x_i}{\sum(xi)}$$

$$x_i = \exp\left(-y_1 \times \frac{s_p}{w_t}\right)$$

$y_1 - selected\ features, s_p - weighted\ features,$

Create a feature set $f_s = \{\emptyset\}, C = 0$

Selecting the best feature based on weights

$$a^+ = \arg\ \_max_a + \in_a [f(f_s + a^+)]$$

If $f(f_s + a^+) > f(f_s)$

Update $f_{a+1} = f_s + a^+$

$f = f + 1$

Go back to step 2

End

The chi-square algorithm begins by generating an empty set. It also adds great features to the feature set. As features add to the overall classification performance, they continue to be added to the ensemble until performance improves. Maximizing performance works well together and preserves the best features for classification.

3.5 Classification using Dense NetRecursive Convolutional Neural Network (DNRCNN)

The deep Learning model for quality recognition on the same dataset compares the performance of the proposed DNRCNN-based framework on Apple quality recognition. In this model, global mean pooling takes the place of the fully connected layers to simplify the computation.

Begin

Using feature selection set = { }

For all features in the training, set Do

Randomly pick features from dataset Fs

Find $f_s \in f$ such that $D(x, fs) = mini_a(x, fs)$

If a class (a)$\neq class\ (fs)$

$f := fs \cup x$

End if

End for

Until Not

End CNN

DNRCNN→ calculate the predictive values $\hat{p}(f+1)$

$$\hat{p}(f+1) = w(\widehat{p}(f)).N(f)$$

End

A key contribution of DNCRNN is the inception module. DNCRNN is the most classical and standard model of DNCRNN net and consists of 10 initial modules. Increase the depth and width of the network and decrease the parameters of the inception block to improve the model accuracy. Inception's framework consists of convolution functions with 1 × 1, 3 × 3, and 5 × 5 convolution kernels and pooling functions associated with 3 × 3 filters, which are adapted to network scaling.

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IV. RESULT AND DISCUSSION

To classify image data, first, create a folder with a different name and store the image data corresponding to the folder name. Second, each collected image information is transformed by the fruit representation code of the DNNCRNN model. Image learning is complete. Finally, consider the DNCRNN model retrained.

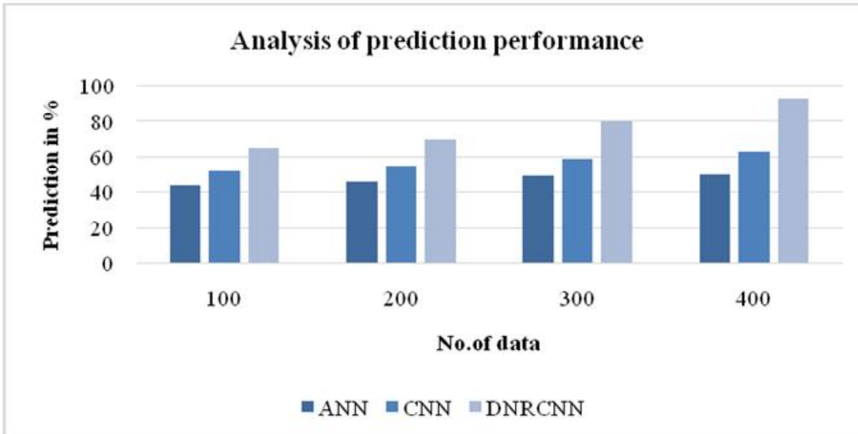

Figure 3: Analysis of prediction performance

Figure 3 shows an analysis of the proposed algorithm's Recurrent Neural Network's prediction level performance (RNN). The proposed algorithm Dense Net Recursive Convolutional Neural Network (DNRCNN) produces the highest prediction performance of 92%, outperforming the existing system Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Artificial Neural Network (CNN) by 55% and 64%, respectively.

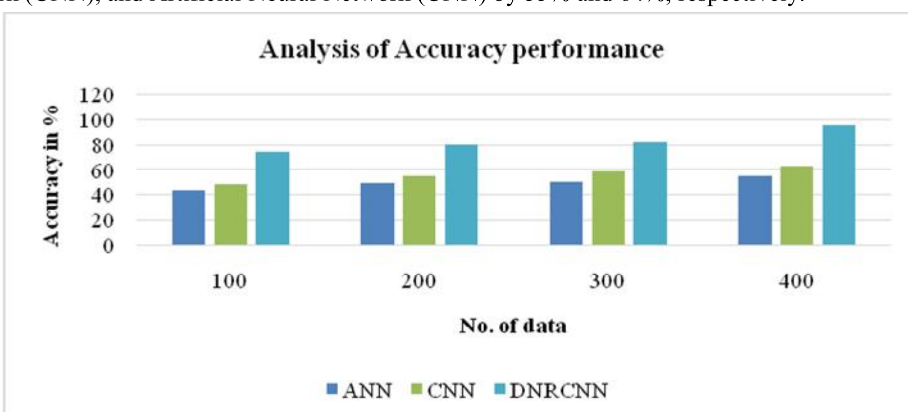

Figure 4: Analysis of accuracy performance

Figure 4 depicts an analysis of the Recurrent Neural Network algorithm's accuracy performance (RNN). The proposed algorithm Dense Net Recursive Convolutional Neural Network (DNRCNN) offers 96% accuracy performance compared to the existing system's 55%, 63%, and 55% for Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), respectively.

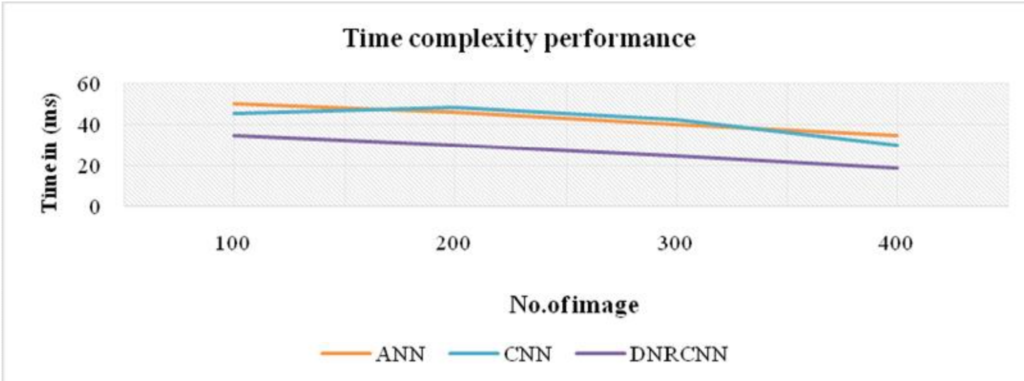

Figure 5: Analysis of Time complexity

Figure 5 displays how well the suggested technique, Dense Net Recursive Convolutional Neural Network, performs in terms of time complexity (DNRCNN). The proposed algorithm Dense Net Recursive Convolutional Neural Network (DNRCNN) has the lowest time performance of 19 (ms), beating out the existing system Artificial Neural Network (ANN), DNRCNN is 39 (ms)%.

V. CONCLUSION

We present a novel approach to classifying fruits that makes use of convolutional neural network algorithms. The aforementioned results were attained using 20 images for training and testing and 7 test samples taken from the actual 180. Software called Anaconda is used to code and test the aforementioned algorithms. For training and testing, a variety of fruit cultivars with various backgrounds were used. The accuracy of the suggested algorithm is 98%. A classification algorithm for fruits based on DNRCNN. Using the fruits360 dataset, accuracy vs. loss curves were produced using various hidden layer combinations. Present various computer vision-based methods and algorithms for fruit recognition and classification. DNRCNN performs better and classifies fruits more accurately.

REFERENCES

[1]. T. Ilyas, A. Khan, M. Umraiz, Y. Jeong and H. Kim, "Multi-Scale Context Aggregation for Strawberry Fruit Recognition and Disease Phenotyping," in IEEE Access, vol. 9, pp. 124491-124504, 2021, doi: 10.1109/ACCESS.2021.3110978.

[2]. Khattak et al., "Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model," in IEEE Access, vol. 9, pp. 112942-112954, 2021, doi: 10.1109/ACCESS.2021.3096895.

[3]. O. Aiadi, B. Khaldi, M. L. Kherfi, M. L. Mekhalfi and A. Alharbi, "Date Fruit Sorting Based on Deep Learning and Discriminant Correlation Analysis," in IEEE Access, vol. 10, pp. 79655-79668, 2022, doi: 10.1109/ACCESS.2022.3194550.

[4]. Y. Luo, J. Sun, J. Shen, X. Wu, L. Wang and W. Zhu, "Apple Leaf Disease Recognition and Sub-Class Categorization Based on Improved Multi-Scale Feature Fusion Network," in IEEE Access, vol. 9, pp. 95517-95527, 2021, doi: 10.1109/ACCESS.2021.3094802.

[5]. M. A. Khan et al., "An Optimized Method for Segmentation and Classification of Apple Diseases Based on Strong Correlation and Genetic Algorithm Based Feature Selection," in IEEE Access, vol. 7, pp. 46261-46277, 2019, doi: 10.1109/ACCESS.2019.2908040.

[6]. P. Jiang, Y. Chen, B. Liu, D. He and C. Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks," in IEEE Access, vol. 7, pp. 59069-59080, 2019, doi: 10.1109/ACCESS.2019.2914929.

[7]. S. S. Chouhan, A. Kaul, U. P. Singh and S. Jain, "Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach Towards Plant Pathology," in IEEE Access, vol. 6, pp. 8852-8863, 2018, doi: 10.1109/ACCESS.2018.2800685.

[8]. M. H. Saleem, J. Potgieter and K. M. Arif, "A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand," in IEEE Access, vol. 10, pp. 89798-89822, 2022, doi: 10.1109/ACCESS.2022.3201104.

[9]. F. Deng, W. Mao, Z. Zeng, H. Zeng and B. Wei, "Multiple Diseases and Pests Detection Based on Federated Learning and Improved Faster R-CNN," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-11, 2022, Art no. 3523811, doi: 10.1109/TIM.2022.3201937.

[10]. M. A. Khan et al., "Correction to "An Optimized Method for Segmentation and Classification of Apple Diseases Based on Strong Correlation and Genetic Algorithm Based Feature Selection"," in IEEE Access, vol. 8, pp. 36514-36514, 2020, doi: 10.1109/ACCESS.2020.2974161.

[11]. Subha, V., Kasturi, K. Structural Invariant Feature Segmentation Based Apple Fruit Disease Detection Using Deep Spectral Generative Adversarial Networks. *SN COMPUT. SCI.* **5**, 635 (2024). https://doi.org/10.1007/s42979-024-02994-z

[12]. Samuel, B., &Kasturi, K. (2024). A secure authentication and collaborative data-sharing model based on a blockchain network in the cloud. *Journal of Control and Decision*, 1–16. https://doi.org/10.1080/23307706.2023.2293965

[13]. Kasturi, K, Pradeep, K. Deep Learning Techniques for Rice Kernel Defect Detection and Multi Classification using Yolo-V8 Model. International Journal of Engineering Research in Computer Science and Engineering (IJERCSE), vol. 10, issue 7,pp. 1-7.

[14]. S., E. ., &Kasturi, K. . (2023). Evaluation of Linkage Between the Corporate Economic Value-Added Analysis and Information Technology Using Big Data. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(4s), 109–117. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2577