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Image-Based Dimension Extraction of Flowers' and Classification with SFFFP Neural Network

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Abstract — **In the era of Automation and Big Data analysis, botanical research is incorporating in-depth machine learning techniques for expedited flower classification and identification. However, existing approaches face several challenges, such as the dependency on pre-measured datasets, which do not accommodate real-world object-based floral measurement, and the inefficiency of manual sepal and petal measurement methods. Recent techniques like Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) have shown promise in image classification but struggle with accuracy and adaptability in diverse environmental conditions. This work presents a novel method for flower species classification, addressing the limitations of manual sepal and petal measurement methods. Existing approaches often rely on pre-measured datasets, neglecting the real-world requirement for object-based floral measurement. This research proposes a deep learning model for flower species identification, applicable to flowers with three petals (tri-petal flowers) such as Iris. The model employs a segmentation technique (lightweight image processing) to isolate the flower from its background, followed by the extraction of pixel measurements for sepals and petals. These pixel values are then converted into real-world dimensions (cm) using a scaling factor obtained through external calibration. The derived dimensions serve as inputs to the subsequent model. The proposed deep learning framework utilizes a Sequential Fast Forward Feed Perceptron (SFFFP) neural network, achieving a precision accuracy of 96.67%. This method, therefore, offers an automated and robust solution for flower identification, eliminating the need for manual measurements and real-world analysis.**

Keywords — Image Processing, Flora Segmentation, Statistics, Neural Net

I. INTRODUCTION

The ever-expanding field of artificial intelligence (AI) has permeated numerous scientific disciplines, including botany. Driven by the surge in computational power and advancements in machine learning algorithms, researchers are actively exploring novel techniques for automated plant identification and classification [1]. A significant challenge in automated plant identification lies in accurately extracting meaningful features from image data [2]. Traditional methods often rely on meticulously curated datasets containing pre-measured features, which can be a laborious and time-consuming process. Furthermore, these methods often lack generalizability when applied to real-world scenarios with variations in image quality and background clutter [3].

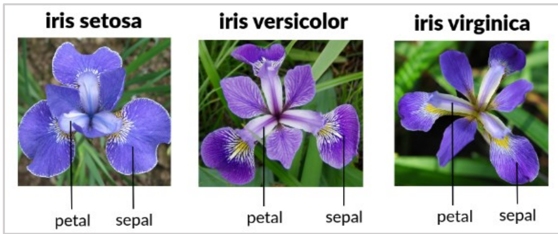


Fig 1. Variety of Iris Flower as a Test Subject for the Experimentation

This work proposes a deep learning-based approach for tri-petal species of flower classification that addresses these limitations. The model leverages the power of a Sequential Fast-Forward Feedforward Perceptron Neural Network (SFFPN) to directly analyze iris flower images for testing and experimentation to extract relevant features for classification [4]. SFFPNs, also known as Multi-Layer Perceptrons (MLPs), are a fundamental type of artificial neural network architecture consisting of interconnected layers of processing units (neurons) arranged sequentially [5]. Information propagates forward through the network, with each layer applying a non-linear activation function to transform the weighted sum of its inputs. This progressive processing allows the network to learn complex relationships between the input image data and the desired classification output [6].

In this study, the SFFPN is trained on a dataset of iris flower images as an example for tri-petal flowers. During the training process, the network learns to automatically extract features from the images, such as sepal and petal dimensions, which are then used to classify the flowers into their respective species (for eg. Iris setosa, Iris versicolor, and Iris virginica). This approach eliminates the need for manual feature extraction, circumventing the limitations of pre-measured datasets.

Error! Reference source not found. depicts the global popularity of the Iris flower dataset would be a valuable addition to this section sourced from Kaggle. Such a visualization could be incorporated after the first paragraph to illustrate the widespread adoption of this dataset as a benchmark for machine learning algorithms in botanical applications. By leveraging the capabilities of SFFPNs, this work proposes a novel and efficient solution for iris flower classification, paving the way for the development of robust and automated image-based plant identification systems.

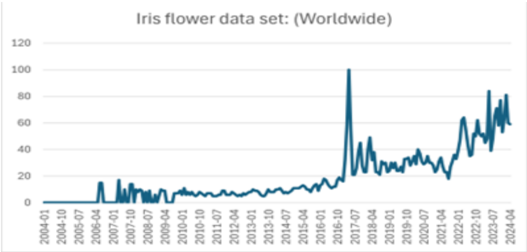


Fig 1. Trend and Case Usage of the Iris Dataset over the Years

II. LITERATURE STUDY

Advances in computer vision and deep learning, coupled with smartphone technology, enable efficient crop disease identification. Training a neural network on a dataset of 54,306 plant images achieved 99.35% accuracy, showing promise for global-scale smartphone-assisted diagnosis, vital for food security [2].

This article presents a novel image deblurring method that doesn't require blur kernel estimation. It uses paired images captured in low light: one blurred and one noisy. By extending Gaussian mixture models and employing optical flow, it achieves superior deblurring results compared to existing techniques, especially for complex blur types [10].

Deep learning in computer vision has seen remarkable progress, employing CNNs, Deep Belief Networks, and Autoencoders. Advancements include feature learning and unsupervised training, yet challenges persist in optimizing model selection and understanding efficacy in tasks [4].

The paper presents a high-precision Sigmoid activation function (AF) neuron circuit for Artificial Neural Networks (ANNs). It achieves a 1.76% error fitting the Sigmoid function in TSMC 0.18μm CMOS technology, demonstrating noise resilience and potential for large-scale systems [13].

III. METHODOLOGY

The workflow structure and implementations of the study have been mentioned below in the sections discussed in the sections ahead. The study seeks to conclude on the note of finding an optimized and efficient algorithmic structure to aid the usage of photogenic sensors to sense the Floral Dimensions. Along with this, the study leverages the concept to use the acquired dimensions to be foddered as input variables for the Artificial Neural Net Model for predictions with 150 epochs for the job. The proposed model is described in described in Fig .

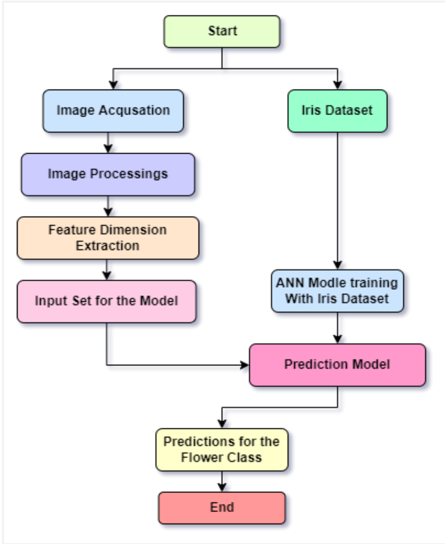


Fig 2. Workflow Algorithm of the Proposition

IV. DATA ANALYSIS

The first phase for the concept with Image is just light-weighted Image Processing which will be discussed in the Implementation section. The Iris Dataset only needed EDA for the modeling purpose. The data tested for implementation was acquired from Kaggle's repositories. Preparing the dataset for training and testing is the first stage in our process. We see the dataset called "iris_flower.csv" using the Pandas package. Loading the dataset and converting it to the float32 data type guarantees that it will work with the other procedures. Using the sci-kit-learn 'train test split' function, we divided the dataset into training and testing sets to evaluate the performance of the model. For testing, the split ratio is 20%, and for training, it is 80%. After loading the dataset, extract the pertinent species labels and features. Determine the average values for every characteristic among various species. A scattered relation distribution is visualized in Fig .

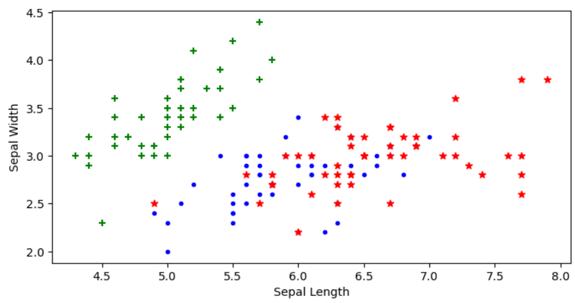


Fig 3. Numeric Distribution of the Dataset Representation

Analyzing the data is a must for every predictive modeling process. seeing data, however, encompasses much more than just seeing in the context of data mining. Examining data encompasses investigating it, organizing it, and presenting it using charts and graphs. It's common to refer to this as exploratory data analysis a sample is described in Table 1 where "L" represents the Length of the Flora and "W" means the Width. A head distribution is visualized in Table 1.

Table 1. Sample view of the Dataset

sepalL	sepalW	petalL	petalW	species
5.1	3.5	1.4	0.2	0
4.9	3.0	1.4	0.2	0
4.7	3.2	1.3	0.2	0
4.6	3.1	1.5	0.2	0

With the pre-processing and EDA done the next process to check for was the relationship matrix for the entire dataset, which in terms would describe the point of relationship of the individual variables with each other.

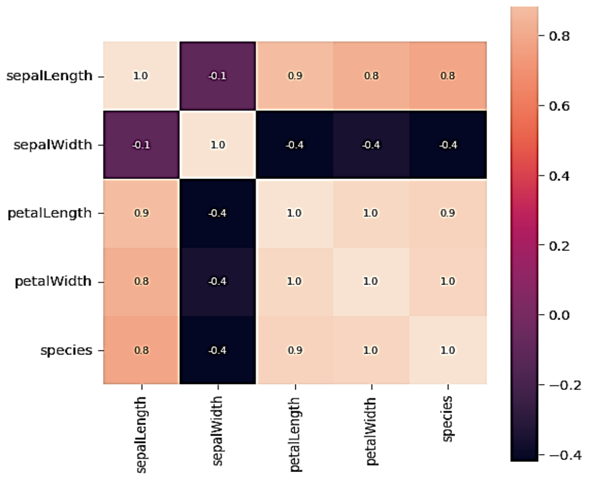


Fig 4. Correlation Heatmap Matrix of the Dataset

V. MATHEMATICAL IMPLEMENTATION

Phase 1: The modeling done for this algorithm has been mentioned by authors in [7]. The first stage after the acquisition is splitting up of the image in the spatial domain into its RGB components in which r is termed as the reflectance component and i is termed as the illumination component mentioned as follows,

$$f(x,y) = r(x,y)\,.\,i(x,y) \tag{1}$$

From equation (1) the spatial form of the image can also be termed as,

$$I(x,y,c) = f(x,y) \tag{2}$$

Where the c represents the channel frame and the (x,y) pixel coordinates, the frames of the channel c are the form vectors quantity of concatenation in linear form which is usually described as,

$$I(x,y,c) = \begin{cases} I(x,y,R) \\ I(x,y,G) \\ I(x,y,B) \end{cases} \tag{3}$$

From equation (3) $I(x,y,B)$ is selected for the operation as the hue of blue and white is highly prominent in the Blue Plane rather than the other two planes as shown in Fig. 6. Then on the Blue plane, Piecewise Linear Transformation of Intensity Level Slicing Thresholding is done as shown in Fig 4,

$$t(r1,r2) = (m\,, L-1\,) \tag{4}$$

$$w = (255-0)/n \tag{5}$$

$$\begin{cases} l_i = i * w \\ u_i = (i+1) * w \end{cases} \tag{6}$$

$$s_i\,(x,y) = t(\,I\,(x,y), l_i) \;*\; t(\,I\,(x,y), u_i - 1) \tag{7}$$

With l_i and u_i in equation (7) as [220,235], a scattered unprocessed representation is obtained Visible in Fig 4. With the resultant obtained the Convex Hull expression is applied, to obtain the area of interest shown in Fig 4.

Considering $Q = \{q_1, q_2, \dots, q_n\}$ be the points' set for the Convex Hull vertices, where the coordinates of q_i are described as $(\,x_i\,, x_i)$. For a specific edge q_i, q_{i+1} all the other points lie on one side of the straight line through q_1 and q_{i+1}, with having an interior angle of less than 180° [8].

Let $P = \{\, p_i(\,x_i\,, y_i\,)\,,\, i = 1,2,\dots n \,\}$ be a planar point set.

With it if all points' coordinates satisfy $\begin{cases} x_i < x_{i+1} \\ y_i > y_{i+1} \end{cases}$ or $\begin{cases} x_i > x_{i+1} \\ y_i < y_{i+1} \end{cases}$, p is the monotonic decreasing ordered point set, with having the property of both decreasing and increasing nature called as ordered monotonic ordered point sets.

So with that, it is to possibly define a function of straight line which would define the area and local points enclosed by the geometry of Convex Hull through the points of A and B where a factor b is introduced to be the active point on Straight Line enclosing the,

$$f(b,A,B) = 0 \tag{8}$$

Having acquired the region of interest the maximum x-coordinates and y-coordinates having formed a four-cornered polygon structure to check for the dimensions of the object say p, q shown in Fig. 7 obtained the area for Petal's Dimensions.

$$p_1, q_1 = (\textit{area of the contour convexing})_1 \tag{9}$$

Having the contoured part of the image acquired, considering the new point of action to obtain the sepal's dimensions. Laplacian of Gaussian Filter (Spatial Filter) a second order derivative mask is applied on the extracted image portion to obtain the major regions of the Sample shown in Fig 8 [9]

$$f_l\,(x_{p1}, y_{q1}) \;=\; \begin{array}{|c|c|c|} \hline 0 & 1 & 0 \\ \hline 1 & -4 & 1 \\ \hline 0 & 1 & 0 \\ \hline \end{array} \tag{10}$$

With the resultant obtained from the (10) Laplacian Operation on the image i.e the $f_l\,(x_{p1}, y_{q1})$ a reducing operation from the original Blue Plane (3) is done to highlight the major regions plausible in the image as visualized in Fig 6,

$$f_i = f_l(x_{p1}, y_{q1}) - I(x, y, B) \tag{11}$$

From the f_i obtained from (11) a Gaussian blurring [10] is applied to smoothen the resultant and on that resultant a sharpening mask [11] is applied as visualized in Fig 7. Having the image sharpened the Canny Edge Detector was applied to it as shown in Fig 10. With that it was found that the resultant image was broken in the boundary contour regions, it was repaired and filled with a $5 \times 5\{1\}$ Kernal and was filled as well as shown in Fig 9. On the Image Convex Hull (8) was applied which extracted the region of Ariel portion of the Petal say p_2 , q_2 .

So, $$\textit{Sepal Length} = \{ p_1, q_1 \} - \{ p_2, q_2 \} \tag{12}$$

But the dimensions obtained are still in pixel ration nature it has to be transformed into a real-world entity (12). That can be achieved by applying the scaling factor i.e. key is to establish a scaling factor between pixels and real-world units, if there's an object with a known real-world dimension (e.g., a ruler) in the image, you can measure its pixel length and calculate the scaling factor. Divide the real-world dimension by the pixel length to get the factor (e.g., pixels/cm) .

Real-world dimension = Pixel dimension * ***Scaling factor*** (13)

As an example,

50 cm = 100 pixels * ***(2 pixels/cm)*** (14)

Scaling Factor acquisition is really in did an excruciating task and a different point of research has been done by the authors for that part, with the integration of Hybrid Statistical and ml methodologies.

Phase 2

After having the input set prepared for the Predictive Model from (13) it was now to build the approach **"Sequential Fast Forward Feed Perceptron Neural Net".** That's described as a dense net comprised of *Sigmoid*, *Relu,* and *Softmax* Layer for classification for 3 classes. The architecture has been described in Fig 2, with '*Adam Optimizer*'.

- ReLU activation is defined as, $\sigma(x) = max\ \{0, x\}$ where x is the input feature to a neuron at any given layer of the neural network. [12]
- The Sigmoid function described as $f(x) = 1 / (1 + e^{-x})$. [13]

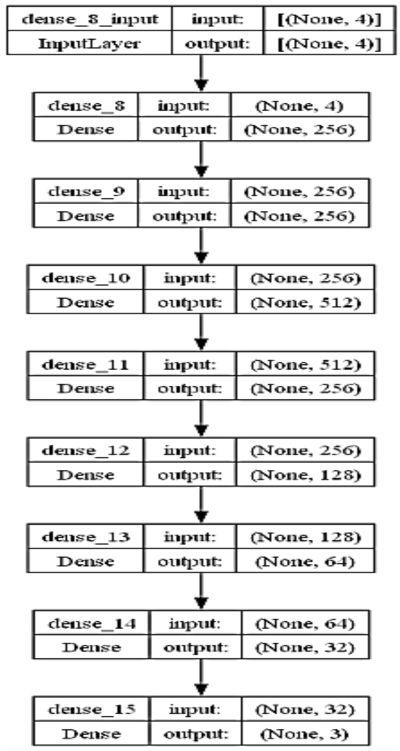


Fig 2. Architectural Composition of the SFFP

VI. RESULT AND DISCUSSION

To begin with the Image Processing phase the original image was split into the RGB plane for feature extraction ideology to choose from the prominent plane as shown in Fig 3.

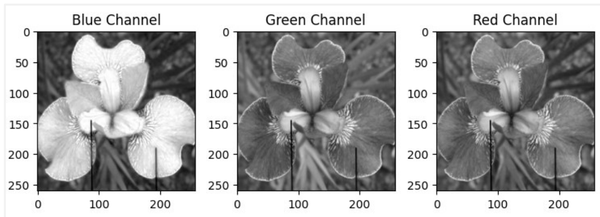


Fig 3. RGB Composition of the Image

Out of the three the "Blue Plane" was found featured enough as the properties of the Flora were visible and proper extraction could have been done. Having selected the Plane then Intensity Level Slicing as Thresholding with a range of 220, 235 was done to highlight and reveal the prominent regions of the petal as shown in Fig 4. Having the featured Image obtained Convex Hull was applied to the Image which described the Dimension (Pentagonal Dimension) including the full petal of the Flora, which resulted in the Pixel ratio dimension of Height: 134, Width: 127.

Fig 4. Threshold Convex Hulled Image Portioned

With the portion extracted the major highlight of the task is to level out the sepal region that is the bolide region of the Flower. So, to do that Laplacian Mask is applied so that the Major Areil Regions are exfoliated, which is been shown in Fig 5.

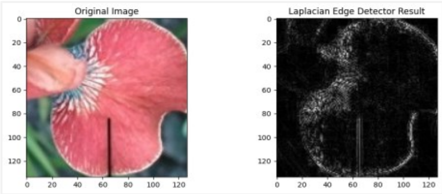


Fig 5. Laplacian Masked Image Sample

With the Laplacian Masked image having been obtained Thresholding of range 25 to 35 is applied. After that Gaussian Blur is applied to the image to dissolve the minute noise and impurities, having done so a static sharpening mask is applied, which procured the major portions of the Flora shown in Fig 7.

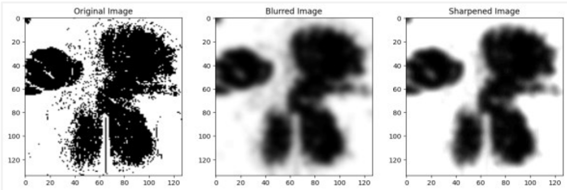


Fig 7. Gaussian Blur and Sharpening of the Sample Image

With so done the Convex hull couldn't have been applied as the proper region of the image is still in diluted form. To contour the major portions Canny Edge Detector was implemented. After applying the mask it was observed that the boundary regions were broken so the region filling and edge repairing algorithm was used to fixate the region boundaries as shown in Fig 9Fig 7.

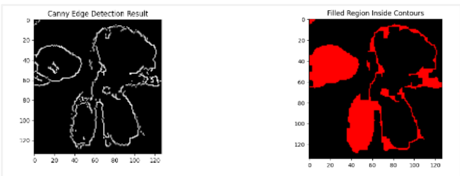


Fig 9. Canny Edge Detector with Boundary Repair Algorithm

With boundaries repaired Convex Hull was applied to the Image and it leveled bounded the ariel region of the petal, but the sepal was not bounded. That was no failure to the experiment as the ariel portion is highlighted whose Pixel ratio dimension resulted in Height: 124, Width: 91 shown in Fig 10. So to get the dimension of the sepal a simple application of deduction would be sufficient. After the dimension has been acquired scaling factor can be applied to formulate the real-life dimensions as described in (13), (14).

Dimension of Sepal = | Dimension of Petal – Dimension of Ariel Region of the Petal |

(10, 36) = | (134, 127) - (124, 91) |

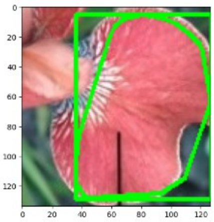
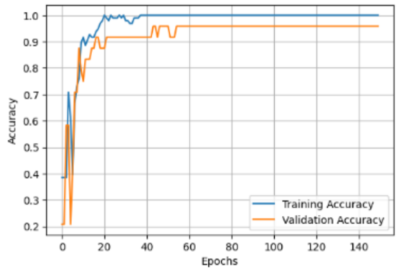


Fig 10. Convex Hull of the Areial Portion of the Petal



After thorough analysis and implementation, the **Sequential**

Fig 6. Performance of the Model

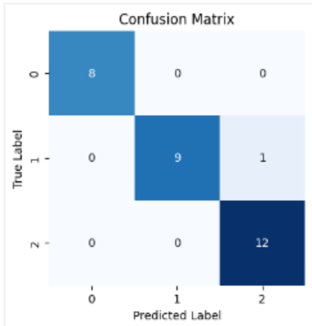


Fig 8. Performance Metrics for the Model

Fast Forward Feed Perceptron Neural Net proved to be exceptionally successful, achieving a remarkable test accuracy of 96.67%. This exceptional performance surpasses that of the models previously studied in the literature, highlighting the effectiveness and robustness of the Sequential Fast Forward Feed Perceptron Neural Net. The implementation of the Sequential Fast Forward Feed Perceptron Neural Net with 150 epochs resulted in an impressive test accuracy of 96.67%, as shown in Fig 13 and Fig 14. This level of accuracy demonstrates the superiority of the Sequential Fast Forward Feed Perceptron Neural Net over existing models shown in TABLE 2TABLE 2. COMPARISON OF THE EXPERIMENTED MODEL WITH THE STUDIED LITERATURE, opening new possibilities for practical applications.

TABLE 2. COMPARISON OF THE EXPERIMENTED MODEL WITH THE STUDIED LITERATURE

Model	Performance of Accuracy
KNN [14]	96.60
Neural Net [15]	92.45
SVM [16]	95.98
The Tested Model	**96.67**

VII. CONCLUSION

This research study has introduced a new method of iris flower classification using deep learning techniques. A Sequential Fast Forward Feed Perceptron Neural Network (SFFPN) is used to reach a high precision accuracy of 96%. 67%, outperforming previous methods. The approach that was used was based on light-weighted processing of images and mathematical implementations to extract sepal and petal dimensions which then were used to define the inputs to the neural network. The system not only does the job of manual feature extraction but also provides an automatic and robust solution for iris flower classification. The results show that Deep Learning models are highly effective for botanical applications, ultimately leading the way for more developments in image-based plant identification systems. Furthermore, future research can look into more sophisticated image processing methods, employ transfer learning from pre-trained models, and cope with unbalanced datasets. In addition to this, implementing 3-dimensional modeling for correct dimension extraction turns out to be a massive opportunity for improving the efficacy and precision of plant sorting systems.

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