

A Novel Unsupervised Method for Tomato Image Segmentation Using Hue Clustering

V.V. Waykule^{1*} D.S. Bormane²

^{1,2}All India Shri Sivaji Memorial Society's College of Engineering, Pune, 411001, India
Email: vvwaykule@aissmscoe.com

Abstract: The segmentation of image is a fundamental component in various tasks such as object detection, image recognition, feature extraction, and classification, as their success heavily relies on the accuracy of the segmentation process. This process involves partitioning an image into various homogeneous segments while preserving its original aspect ratio. The efficacy of different segmentation approaches is influenced by factors such as object arrangement, lighting conditions, presence of shadows, and other relevant elements. It is crucial to acknowledge that there is no one-size-fits-all solution for effectively segmenting all types of images, with certain methods demonstrating superior performance compared to others. The primary objective of the present study is to propose a suitable segmentation approach. Our study introduces an unsupervised method for automatically segmenting images by leveraging color information to differentiate between foreground and background regions. Specifically, we present a novel unsupervised technique for segmenting color images within the HSV color space. Our approach incorporates a clustering based algorithm which does not only rely on user-defined parameters but followed by the application of morphological reconstruction through dilation to enhance results of clustering based on the hue (H) values in HSV color space. Comparative analysis is conducted with existing segmentation techniques such as Otsu thresholding, K-means Clustering, Fuzzy-C Clustering, and UNet, using various evaluation metrics to assess performance. The findings derived from the research investigation substantiate the efficacy of the proposed approach.

Keywords: Segmentation, HSV color space, Clustering, UNet, Fuzzy C-Means, Otsu

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1. Introduction

The tomato plays a significant position in agriculture globally, offering farmers sustenance and economic benefits. Conversely, tomato plants are susceptible to various diseases, leading to substantial losses in output and financial repercussions. The accurate identification and classification of these disorders are crucial for the development of efficient management and regulatory strategies.

The use of molecular techniques for the diagnosis and categorization of crop diseases, particularly those that impacting tomato crops, has gained popularity in recent years. These advanced approaches enable swift and accurate diagnosis, empowering farmers to implement necessary measures to reduce agriculture losses and stop the spread of illness.

Our study proposes a segmented methodology that leverages machine-learning algorithms to achieve enhanced results. These results are then assessed against state-of-the-art techniques. This innovative approach possesses to aid farmers in

early detection and treatment of tomato infections, ultimately boosting crop yields and reducing economic losses.

Image segmentation stands as a critical procedure in image processing, involving the division of an image into multiple segments to simplify or transform its representation into more analyzable parts. The primary objective of segmentation is to extract pertinent information from an image by dividing it into regions or objects with similar characteristics such as color, intensity, texture, or boundaries.

The fundamental purpose of segmentation is to streamline the representation of an image, ensuring that it is easily interpretable and conducive to analyzing only the relevant objects during the subsequent object analysis phase. This process simplifies the image representation by partitioning it into coherent or similar regions.

Remainder of the manuscript is organized as follows. In section 2, we present current research pertaining to the application of deep learning and

machine learning techniques in the domain of disease detection and classification Section 3, presents proposed methodology for effective image segmentation to get more accurate results. Section 4 details the dataset employed to test the suggested methodology in an experiment. Section 5 provides the experimental results and discussion followed by conclusion.

2. Related Work

The fields of machine learning and deep learning displayed considerable potential for enhancing agricultural efficiency and productivity. Here is a quick look at some of the significant research article in this field.

Presented here is a brief of significant research article within this domain. Several studies have been carried out in the field of image segmentation using clustering techniques. Most popular method is K-means clustering algorithm, which is unsupervised algorithm and used to segment the interest area from the background on stretched images. Subtractive clustering is employed to establish the preliminary centroid [1].

The most effective algorithm namely the K-means clustering algorithm is implemented to study this fatal disease. The output of k-means clusters relies on the dataset type and calculations utilized [2]. In this manuscript [3], a new modified Otsu function is proposed that hybridizes the concept of Otsu's between class variance and Kapur's entropy. It combines the ability to find an optimal threshold that maximizes the overall entropy from Kapur's and the maximum variance value of the different classes from Otsu.

This research paper [18] proposes a segmentation method using Lab color space and FCM clustering to identify tomato diseases, achieving accuracies of KNN 85.40%, RF 88.87%, SVM 80.73% and NB 74.60%.

Numerous image segmentation algorithms have been developed in the literature, from the earliest methods, such as thresholding, histogram-based bundling, region growing [4], k-means clustering, watershed methods, to more advanced algorithms such as active contours, graph cuts, conditional and Markov random fields and sparsity-based methods. In recent years, however, deep learning (DL) frameworks [5] have produced a novel paradigm of image segmentation models that exhibit significant enhancement in performance, often offering the highest accuracy rates on widely recognized benchmarks. Zang et al., [6] applied Segment Anything Model across different

modalities, anatomies and body regions. Its performance on multi-modal and multi-target medical datasets is not demonstrated to be good. MFSNe uses differently scaled feature maps for computing the final segmentation mask using raw input RGB images of skin lesions to get more accurate results [7].

The contemporary literature on deep-learning-based image segmentation encompasses more than 100 such segmentation methodologies proposed to date. It provides insights into various aspects of these methods, including the training data utilized, the selection of network architectures, loss functions, training strategies, and their principal contributions. S. Zhang et al., [8, 9] modified U-Net by introducing Resblock and Respath. It increases the network depth and improve the network's expression ability.

The segmentation method was studied by refining the textural features and then fed into the SVM classifiers [20]. It has minimized the false positive rate for different multi-class approaches. Finally, the combination of PSO and SVM are detected for grapefruit diseases [19]. Nevertheless, certain climate-oriented image characteristics are overlooked in this investigation. Color-based segmentation was enhanced to identify diseases in pomegranate leaves [15] by extracting information related to color, morphology, and textures to classify the affected portions of the pomegranate foliage. The majority of research has focused on improving classification outcomes through various machine learning classifiers. Neural network classifiers further augmented this endeavor during the climatic parametric monitoring of plant species. The investigation of plant leaf diseases utilizing textural attributes has been conducted. The GLCM matrix was formulated from the extracted textural features [16]. This advancement has contributed to a reduction in the duration required for training classifiers [17]. In the referenced study, the author has introduced SVM classifiers to detect the affected regions of tomato plant leaves. The consistent weight estimation across diverse kernels has revealed the highest rates of RMSE errors.

3. Proposed Methodology

Image resizing is the process of changing the dimensions of a digital image, making it larger or smaller while preserving its aspect ratio. Image Resizing allows for standardizing the dimensions of images, which simplifies feature extraction and pattern recognition tasks. It can enhance the speed

and accuracy of algorithms by reducing computational complexity. Here we resize the image into [227x227(rows and columns)].

In this context, we introduce an innovative hybrid segmentation methodology referred to as the 'IKCHSV' segmentation method, which integrates Improved K-means Clustering with HSV color transformation employed for the purpose of image segmentation. Mathematically explained as below:

1. Let the input RGB image is represented as

$$I = \{I(x, y)\} \text{ where } I(x, y) \in R^3$$

Each pixel consists of red, green, and blue components:

$$I(x, y) = [R(x, y), G(x, y), B(x, y)]$$

2. Pre-processing contains noise removal and normalization operations:

$$I_p = \mathcal{X}(I)$$

Where \mathcal{X} denotes median filter and CLAHE enhancement operations.

3. **K-means clustering operation:**

Processed image is clustered into K clusters:

$$\min \sum_{i=1}^K \sum_{x \in C_i} \|x - \mu_i\|^2$$

Where C_i = cluster i

μ_i = centroid of cluster i

Output:

$$S_i = \{C_1, C_2, \dots, C_k\}$$

4. **Colour Space Conversion:**

RGB image is converted into HSV colour space:

$$I_{HSV} = T_{RGB} \rightarrow HSV(I_p)$$

Where each pixel is presented as:

$$I_{HSV}(x, y) = [H(x, y), S(x, y), V(x, y)]$$

5. **Refined K-means Segmentation:**

K-means is reapplied in HSV space for better separation:

$$S_s = K - \text{means}(I_{HSV})$$

It improves segmentation accuracy under varying illumination.

6. **Binary mask creation:**

Binary mask M_b is generated:

$$M_b(x, y) = \begin{cases} 1, & \text{if } (x, y) \in \text{target region} \\ 0, & \text{Otherwise} \end{cases}$$

7. **Binary Image Processing:**

Morphological operations are applied:

$$M_r = (M_b \oplus B) \ominus B$$

Where,

\oplus = dilation

\ominus = erosion

B = structuring element

8. **Channel Separation:**

HSV channels are separated:

$$H = I_{HSV}(:, :, 1) \quad S = I_{HSV}(:, :, 2) \quad V_{HSV} = I(:, :, 3)$$

9. **Thresholding on HSV Channels:**

$$M_H = \begin{cases} 1, & H_{\min} \leq H \leq H_{\max} \\ 0, & \text{otherwise} \end{cases}$$

$$M_S = \begin{cases} 1, & S_{\min} \leq S \leq S_{\max} \\ 0, & \text{otherwise} \end{cases}$$

$$M_V = \begin{cases} 1, & V_{\min} \leq V \leq V_{\max} \\ 0, & \text{otherwise} \end{cases}$$

10. **Mask Application on Channels:**

Each channel mask is applied

$$M_{HSV} = M_H \cap M_S \cap M_V$$

11. **Mask Inversion:**

The inverted mask is computed as:

$$M_{inv} = 1 - M_{HSV}$$

12. **Mask Combination:**

Final mask is obtained by combining binary and HSV masks:

$$M_f = M_c \cup M_{inv}$$

13. **Mask Overlay on original image:**

Segmented output image:

$$I_{seg}(x, y) = I(x, y) * M_f(x, y)$$

14. **Segmented Output:**

$$I_{seg} = \{I_{seg}(x, y)\}$$

The result generated by aforementioned methodology is shown in Fig 1.

In this study, an ensemble methodology is presented to segment region of affected leaves. An ensemble of K-means Clustering with morphological operations employed as the segmentation approach. In coordination with the preprocessing step and LAB space conversion, a channel and b are separated from the input leaf image, which have most important information about the leaf region. Once after splitting the channels, the K-means clustering algorithm is applied followed by morphological operations. To derive the ensemble mask, the RGB image undergoes conversion into the HSV color space.

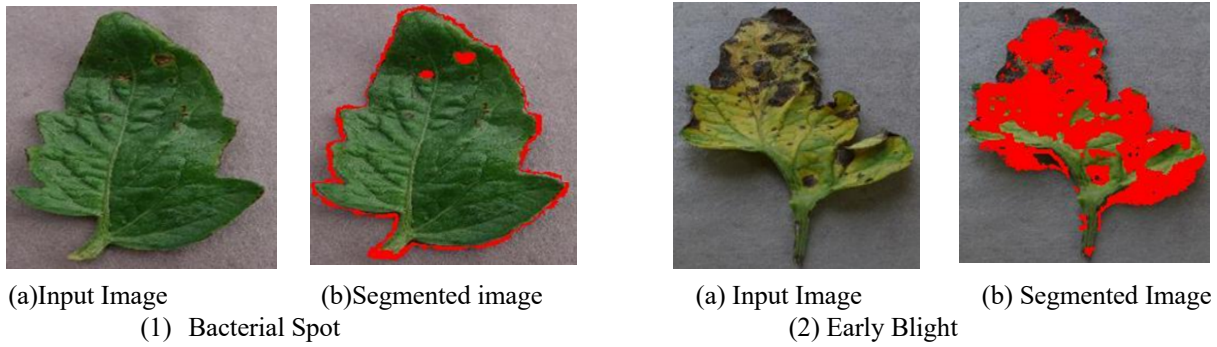


Figure 1. Improved K-means Clustering and HSV colour transformation segmentation

After performing logical operation on H channel and inverting the resultant mask, final mask has been created. Final mask is overlaid on original image to get segmented region. The proposed methodology is further elucidated Fig 2.

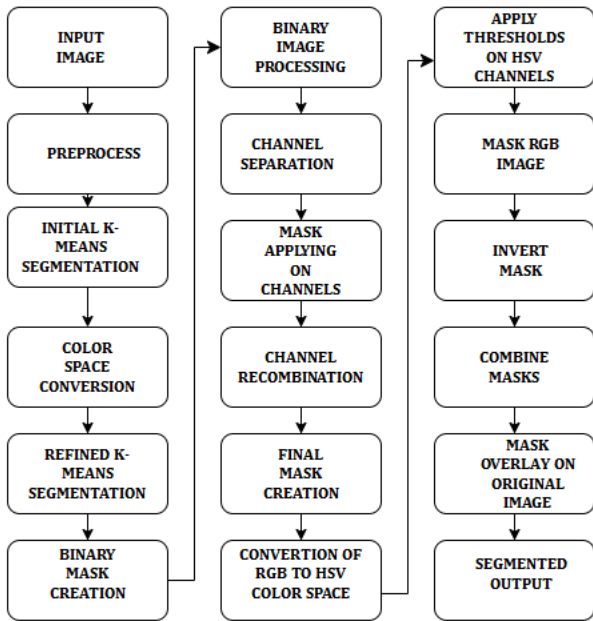


Figure 2. Block Diagram of Proposed approach

4. Experimental verification and Result Analysis

4.1 Dataset and Experimental Setting:

The data collected during the research was gathered through the utilization of a Samsung Galaxy A50 smartphone equipped with an Android Version 11 camera, generating 522 photographs along with 1531 images were sourced from the tomato-leaf-multiple-sources dataset available on Kaggle. The dataset contains in all s 2053 images, each with a dimension of 227×227 .

To tackle the challenges posed by limited training samples and the susceptibility to over fitting resulting from various modifications applied to the acquired imagery, multiple methodologies were systematically employed. These methodologies included mirror and left-right flipping, the application of CLAHE (Contrast Limited Adaptive Histogram Equalization) for image enhancement, image sharpening, and employment of Median Filter to reduce noise, affine transformations, image scaling, rotation, shear transformation, and image completion.

1.1 Result Analysis:

In the field disease image analysis, the predominant focus is frequently directed towards delineating the infected regions or areas of significance from the background. The precision of image segmentation constitutes a vital criterion in assessing the efficacy of segmentation algorithms within the realm of computer vision. This metric evaluates the capability of a model to accurately categorize each pixel in an image according to its respective class or object.

Comparative analysis was conducted on the outcomes derived from the proposed approach and other segmentation Methodologies like K-means Clustering, Otsu thresholding, Fuzzy C Means Clustering, Unet that is visually depicted in Table 1. Advantages and limitations of diverse methodologies for image segmentation utilized for the examination of tomato leaf images. The proposed algorithm provides a balanced approach, combining efficiency and robustness, making it suitable for practical applications in agricultural disease detection.

Upon examination of the Fig 3. It becomes apparent that the enhanced K-Means algorithm, which employs HSV color segmentation, excels in preserving the intricate details of the tomato leaf, thereby facilitating a clearer and more exact identification. In contrast, alternative segmentation

methodologies tend to obscure the complex features of the tomato leaf images, subsequently resulting in inaccuracies in the process of segmentation.

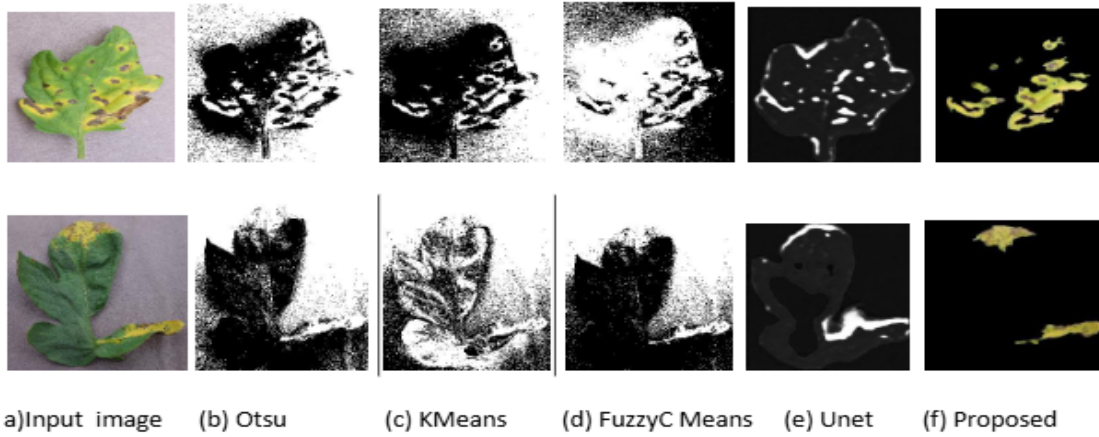


Figure 3. Result of various segmentation methods

The metrics utilized for assessing segmentation models comprise the Accuracy, Precision, Dice Similarity coefficient, and Jacquard index. Normal signifies the absence of diseases, while Abnormal indicates the presence of diseases.

True positive (TP) denotes the number of samples accurately recognized as abnormal.

False positive (FP) represents the number of samples inaccurately classified as abnormal.

True Negative (TN) indicates the number of samples correctly identified as normal.

False Negative (FN) refers to the number of samples incorrectly recognized as normal.

The subsequent parameters are investigated.

Precision: It pertains to the ratio of correctly acquired values, as expressed by the formula:

$$\text{precision} = \frac{TN}{TN + FP} \quad (1)$$

Detection Accuracy: This metric quantifies the number of precisely predicted values.

$$\text{accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

Dice Similarity coefficient: This metric measures the correspondence at the pixel level between a projected segmentation and its authentic counterpart.

$$\text{Dice Similarity Coefficient} = \frac{2 * TP}{(2 * TP + FP + FN)} \quad (3)$$

Jaccard Index (IOU): It gauges the level of

intersection between the actual truth and the predicted segmentation.

$$\text{Jaccard Index} = \frac{TP}{(TP + FP + FN)} \quad (4)$$

In order to verify the superiority of the proposed methodology, an evaluative comparison was conducted assessing the efficacy of various segmentation models utilizing identical datasets. A review of Table 1 reveals that Accuracy and Dice Similarity coefficient values of the four models are significantly elevated. However, it is imperative to acknowledge that the proposed model exhibits a considerable increase in complexity. Compared result of above method and other state-of-the-art segmentation methods like Otsu, K-means, C-Fuzzy Means and UNet. Refer Figure 4.

The proposed methodology exhibits enhanced precision and superior Dice Similarity coefficient values when compared with alternative segmentation techniques. The segmentation methodology enhances both detection speed and accuracy as compared to alternative strategies.

Furthermore, the proposed method evidences a relatively reduced processing duration in contrast to the U-Net model. This is illustrated in Figure 5. This finding highlights the efficacy of the proposed methodology concerning the temporal resources expended during execution.

5. Conclusion and Future Scope

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The HSV color space is well-aligned with human color perception, rendering it effective for differentiating between various regions based on color attributes. This method can handle variations in lighting and color intensity better than RGB. When combined with K-means clustering; it provides good

balance between segmentation accuracy and computational efficiency. It is particularly effective in scenarios where color differentiation is crucial.

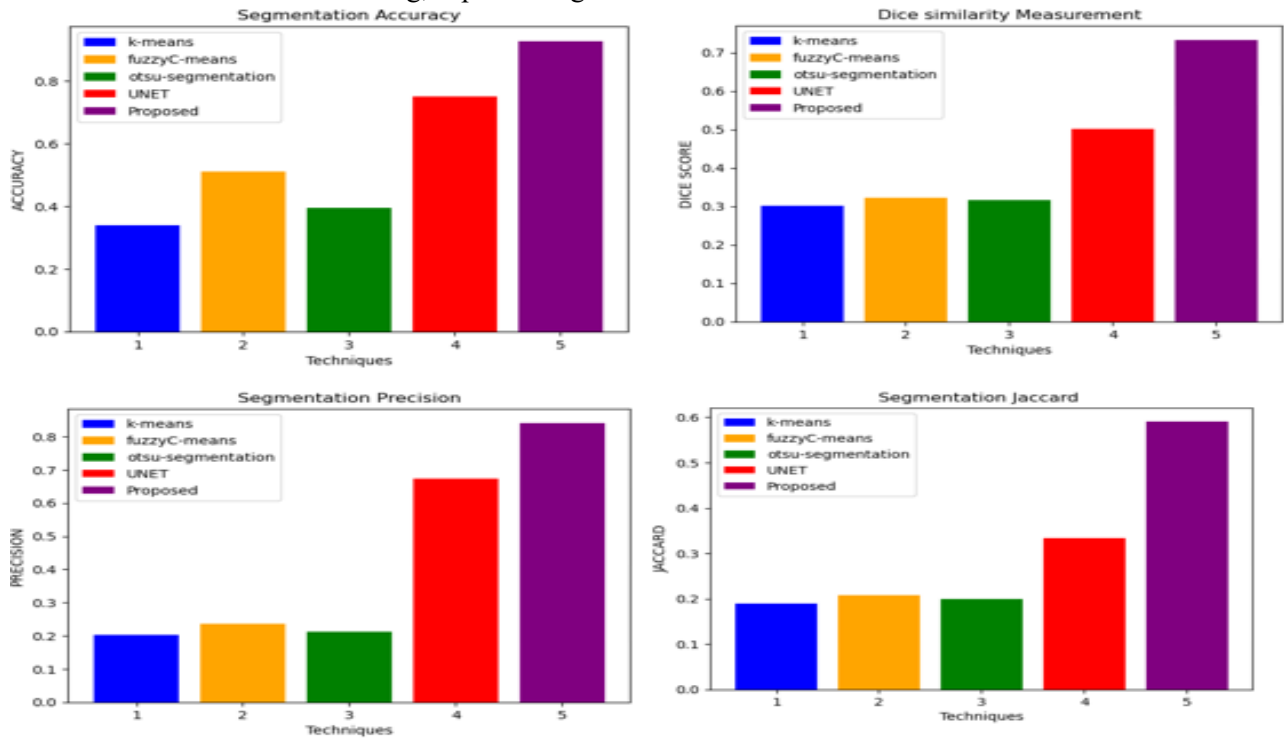


Fig 4. Fig 4. Accuracy, Dice Similarity, Precision, Jaccard of segmentation techniques

Table 1. Comparison using Different Measures of segmentation

<i>Techniques Used</i>	<i>Accuracy (%)</i>	<i>Precision (%)</i>	<i>Jacquard (%)</i>	<i>Dice Similarity (%)</i>
K-Means	38	20	19	30
Fuzzy C-means	52	24	22	32
Otsu	39	21	20	31
UNet	78	69	33	60
Proposed	97	86	86	73

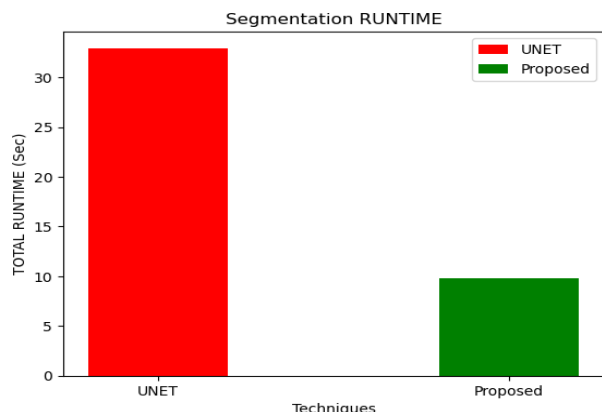


Fig 5. Segmentation Runtime

Proposed method outperformed Otsu, K-means, C-Fuzzy Means, and UNet. Otsu's method is simple and effective for threshold-based segmentation, particularly in images with bimodal histograms. Nonetheless, it encounters difficulties when analyzing images characterized by more complex color distributions. Standard K-means effectiveness can be limited by the choice of color space and the initial selection of cluster centroid. The C Fuzzy Means algorithm enables soft clustering, allowing pixels to be allocated to multiple clusters with differing degrees of membership, thereby offering advantages in addressing uncertainty throughout the segmentation procedure. It generally provides better segmentation results than standard K-means but at the cost of increased computational complexity. UNet is a deep learning-based method that excels in segmenting complex images with intricate details. It possesses the capability to learn from annotated data to enhance segmentation accuracy. Typically, it outperforms all traditional methods; however, it necessitates a substantial amount of labeled data and considerable computational resources. While C-Fuzzy Means and Otsu's method possess distinct merits, they may not exhibit the same level of versatility as K-means in conjunction with HSV or UNet for this specific application.

In forthcoming research endeavors, the examination of hybrid segmentation methodologies may yield significant advancements in precision and operational efficacy. Sophisticated deep learning methodologies for the optimization of image segmentation processes can be examined.

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Conflict of Interest

The authors declare no conflict of interest.

Author contributions

A. Waykule V. V.

B. Bormane D. S.

A.- Writing-Original Draft, Data curation, prepared Figures and Tables

B.-Writing-Review and Editing, validations, supervision, Project administration

A.B.- Conceptualization, Methodology, reviewed manuscript

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