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Research Article

Identification Research of *Trichagalma Glabrosa* Insect Gall Pests Based on YOLOv5s

Tianpeng Zhang [1] and Wei Wang [2]

[1]*School of Electronic Information & Electrical Engineering, Anyang Institute of Technology, Anyang 455000, Henan, China*
[2]*School of Computer Science and Information Engineering, Anyang Institute of Technology, Anyang 455000, Henan, China*

Correspondence should be addressed to Tianpeng Zhang; zhangtp80@163.com

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In order to solve the problem of low image identification accuracy of *Trichagalma glabrosa* insect gall pests in a complex natural environment, an image identification method of *Trichagalma glabrosa* insect gall pests based on YOLOv5s was designed and introduced in this study. The original images were preprocessed with the grayscale maximum method and different gradients of noise, which reduced the color difference interference with complex backgrounds and improved the image identification rate. A total of 6090 images of insect gall pests under opposite light, back light, and complex backgrounds were constructed, which were divided into a training set and a test set with a ratio of 7 : 3. The results showed that the precision, recall, and mean average precision of YOLOv5s were 94.35%, 95.42%, and 95.8%, respectively. YOLOv5s, YOLOv4, and Faster-RCNN were compared and analyzed under the same test conditions. The identification accuracy of YOLOv5s was higher than that of YOLOv4 and Faster-RCNN, and its model size was only 13.8 MB. It was considered that the designed YOLOv5s method could help accurately and quickly identify *Trichagalma glabrosa* insect gall pests with high identification accuracy and a small model capacity, which was more conducive to the migration application of the model, and provide a new method for the rapid identification of *Trichagalma glabrosa* insect gall pests in a complex natural environment.

1. Introduction

Quercus variabilis and *Quercus acutissima* are distributed in most areas of China. They are not only good ornamental tree species for greening but also good tree species for building windbreak forests, water conservation forests, and protection forests. They play a very important role in forestry production [1]. *Trichagalma glabrosa* is the main pest that harms *Quercus variabilis* and *Quercus acutissima*. Its larvae can induce spherical insect galls on the front and back of the leaves and hide in the insect galls to absorb leaf juice for damage [2]. When the insect galls damage the large areas of leaves, it will seriously weaken the photosynthesis of the leaves, cause the color of the leaves to deepen and turn yellow, or even fall off, which seriously affect the normal growth of the *Quercus variabilis* and *Quercus acutissima* [3, 4].

In recent years, scholars have carried out a lot of research studies on *Trichagalma glabrosa*, which mainly related to the biological characteristics, spatial distribution, main natural enemy species and life history, biological characteristics of dominant natural enemies, screening of effective agents, and others [5]. However, there are few relevant research studies on predicting the occurrence dynamics of *Trichagalma glabrosa* by using the intelligent identification of insect galls. Accurately monitoring the occurrence dynamics of pests is the premise of effective control and the basis of integrated pest management [6, 7]. *Trichagalma glabrosa* mainly relies on artificial monitoring in the forest. It is time-consuming and laborious to investigate the insect galls on the leaves at high altitude because the average tree height in the young *Quercus variabilis* forest is more than 7.6 m [8, 9]. Moreover, the data obtained are not accurate enough for meeting the current production of actual monitoring needs.

With the rapid development of some technologies such as computer vision, image identification, deep learning, and others, the application of image identification technology based on deep learning to the field of intelligent identification of pests and the establishment of digital and intelligent identification models and methods of pests received increasing attention. For example, Omrani et al. [10] used artificial neural networks and support vector machines to classify diseases of apple leaves. Kamal et al. [11] proposed an image identification model of plant leaf pests with a deeply separable convolution structure. Yang et al. [12] proposed a color texture characteristics support vector machines (CTX-SVM) method combined with color texture features for identifying tomato leaf pests in complex environment. Yue et al. [13] proposed a detection model for the diseased spots of apple leaves based on improved the YOLOv3 model. Zhang et al. [14] used an improved target detection algorithm to improve the detection accuracy of YOLOv3 model. Sun et al. [15] constructed a forestry pest detection and identification method based on YOLOv5 model. Shi et al. [16, 17] used chaotic back-propagation neural network to identify items, which greatly improved the speed. In addition, the electronic nose system developed greatly improved the item recognition rate. At present, there are few reports on the identification of *Trichagalma glabrosa* insect gall pests.

In this study, based on the image database of *Trichagalma glabrosa* insect gall pests obtained from field investigation, the identification method of *Trichagalma glabrosa* insect gall pests based on the YOLOv5s model was proposed, which can effectively improve the image identification accuracy of *Trichagalma glabrosa* insect gall pests in complex natural environment and provide accurate data for the prevention and control of the *Trichagalma glabrosa* insect gall pests.

2. Materials and Methods

2.1. Materials

2.1.1. Data Collection. In this study, the images of *Trichagalma glabrosa* insect gall were collected in Baiyun Temple National Forest Park, Huixian County, Henan Province, China. The geographical location was at this latitude of 35°26′ north and longitude of 113°31′ east. The *Quercus variabilis* leaves with insect gall pests were collected from May to July 2022. The collected images are all the leaves of the *Quercus variabilis* under natural light, including leaves with different distances, different insect gall densities, and different insect gall locations to ensure the stability and accuracy of image identification. A total of 1015 original images were collected in this experiment. The format of the images was JPG with the horizontal resolution of 96 dpi, the vertical resolution of 96 dpi, and the bit depth of 24. The sample images are shown in Figure 1.

2.1.2. Test Platform. The test process was carried out under the Win10 operating system with the processor model of Intel(R) Core(TM) i7-10700K CPU @ 3.80 GHz 3.79 GHz and the graphics card of Nvidia GeForce RTX 2080Ti. The deep learning framework is PyTorch1.6. The programming platform is PyCharm, and the programming language is Python.

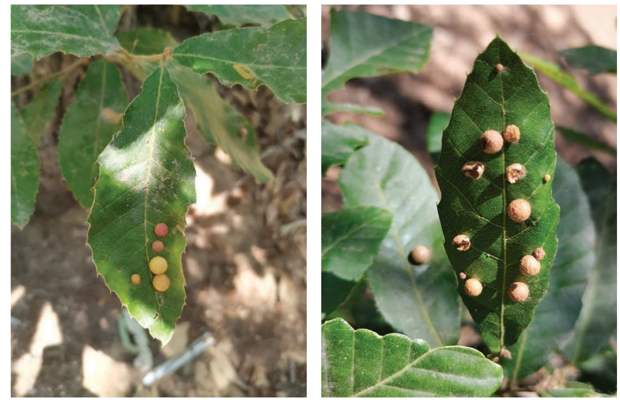


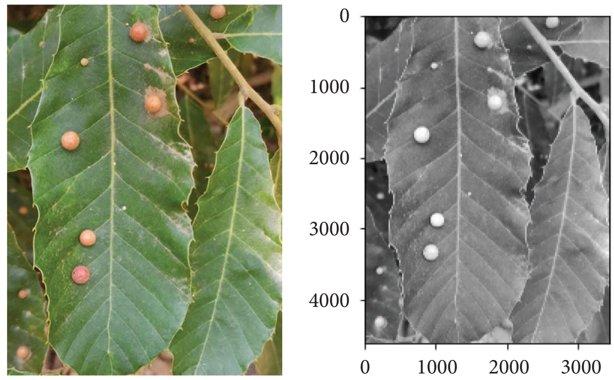
Figure 1: The sample image example.

2.2. Test Methods

2.2.1. Image Preprocessing. First of all, the all images were classified into three datasets: opposite light, back light, and complex scene. Since the background of the images will cause large errors in the target identification process, the scope of the insect gall on the leaf images should be preserved and other background ranges should be reduced in the early image preprocessing. In this study, the original image data were preprocessed by using grayscale maximum method to reduce the interference of background data, and then, the generated grayscale image data were used to expand the training sample, as shown in Figure 2.

A total of 1015 original images were collected, and 2030 copies were stored in the image database after image preprocessing. Then, the images were normalized, and the offline data were enhanced by adding 5% noise and 10% noise, respectively. Thus, the processed data were taken as the sample of image data, and our sample data reached 6090 copies. Subsequently, LabelImg was used to label the images, generate XML label data, and mark the target area. At the end, the labeled dataset was divided into a training set and a test set with a ratio of 7 : 3.

2.2.2. YOLOv5s Network Model. YOLOv5 is a classic one-stage target detection algorithm, which has the advantages of fast running speed and good identification performance, and it is usually applied to real-time target detection systems in the industry. Currently, YOLOv5 has four versions: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. Among them, the YOLOv5s model has small depth and fewer parameters, and its reasoning speed is faster than that of the other three versions, which is more suitable for the identification and the detection of *Trichagalma glabrosa* insect gall pests. The network structure of YOLOv5s mainly consists of four parts: Input, Backbonc, Neck, and Output, which is shown in Figure 3. In the Input section, the original images were normalized and adjusted to the size of 640 $*$ 640. Then, Mosaic data enhancement and adaptive image



(a) (b)

Figure 2: (a) Original image; (b) image preprocessed by the gray maximum method.

scaling were adopted to scale and splice the images and adaptively fill the images into the network.

The Backonc section was used to complete the feature extraction of the images, which used a 6 ∗ 6 convolution to replace the original Focus module in the first layer, so that the images could be better processed in parallel. In addition, several Maxpool layers were added to the SPP module to form the SPPF module, which can compress the model to a greater extent. In order to integrate multilayer features, the Neck layer used the FPN + PAN structure. The FPN mainly transmitted semantic features from top to bottom, and the PAN mainly strengthened positioning information from bottom to top. The output section was mainly used to compare losses and evaluate the number of iteration regression, and the CIOU_Loss was used as the loss evaluation of the boundary frame.

2.2.3. Evaluation Criterion. In this study, four indexes such as precision (P), recall (R), mean average precision (mAP), and model size were used to evaluate the identification model of *Trichagalma glabrosa* insect gall pests. When IoU (Intersection over Union) ≥ 0.5, it is a true positive example. When IoU < 0.5, it is a false positive example. When IoU = 0, it is a false negative example. The calculation of precision, recall, and mean average precision are shown in the following formulae.

$$mAP = \frac{\sum_{C=1}^{C} \mathrm{AP}(C)}{C}, \tag{1}$$

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \times 100\%, \tag{2}$$

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\%, \tag{3}$$

where TP is the number of the true positive, FP is the number of the false positive, and FN is the number of the false negative. The true positive represents the actual positive case, which is classified as positive by the classifier; the false positive represents the actual negative case, which is classified as positive by the classifier; the false negative represents the actual positive case, which is classified as negative by the classifier. C is the number of detection categories. In this study, only identification is required, and hence, $C = 1$. AP is the average precision, which represents the enclosed area of the precision-recall curve.

3. Results

3.1. Model Training. The frame diagram of the overall model is shown in Figure 4, which was divided into two parts. One was the training stage, and the other was the test stage. During the training process, the images were firstly processed with gray scale and noise to improve the robustness of the model. Then, the dataset was expanded, and the target was calibrated by LabelImg. Finally, the calibrated data were sent to the network for model training. In the test phase, target identification was performed on the input images.

In this study, a total of 500 rounds of training were conducted. The results from the network training are shown in Figure 5. At the beginning of the model training, the learning efficiency was high, and the loss curve converged fast. When the number of iterations reaches about 289 times, the model learning efficiency gradually reaches saturation, and the loss value fluctuated around 0.02. The precision value of the final training model was 94.35%, the recall value was 0.92, and the mean average precision value (IoU = 0.5) was 95.42%.

3.2. Identification Results. In order to test the generality of the model, it is necessary to study the identification of *Trichagalma glabrosa* insect gall images in different environments because of the variety of scenes under real natural conditions. In order to verify the identification effect of YOLOv5s in different environments, three identification environments of opposite light, back light, and complex background were constructed according to the real scene in the natural environment. The images for the identification effect are shown in Figures 6–8.

Under the opposite light, back light, and complex background, the identification effect of precision values with the YOLOv5s model were 96.1%, 91.5%, and 86.5%, respectively; recall values were 95.7%, 90.1%, and 84.7%, respectively; and mean average precision values were 96.4%,

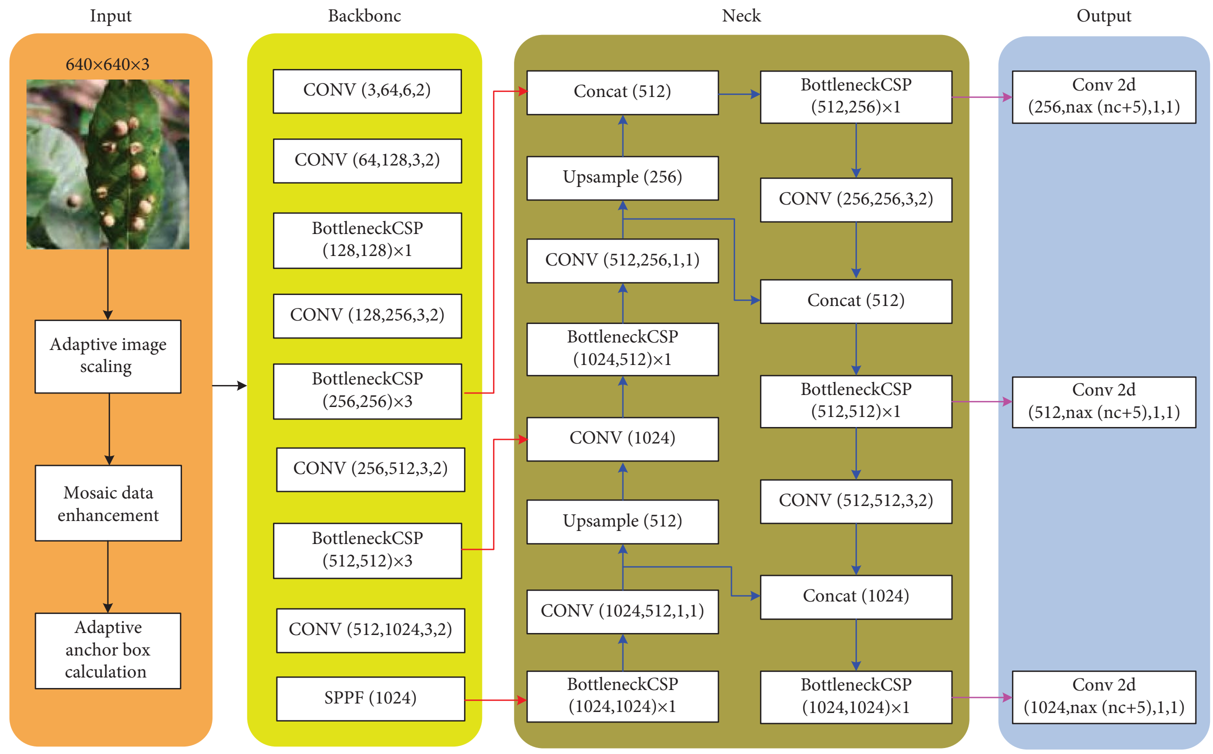


Figure 3: The network model of YOLOv5s.

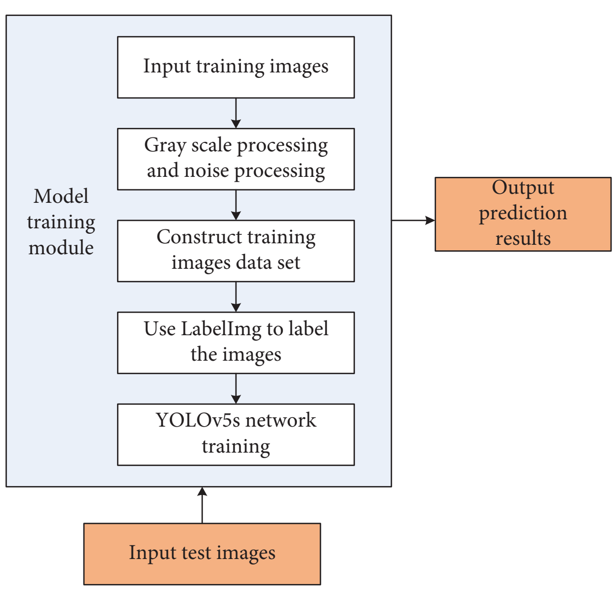


Figure 4: The flowchart of the YOLOv5s model training test.

92.7%, and 86.9%, respectively. YOLOv5s showed excellent identification performance and better reliability in three different environments.

4. Performance Comparison of Different Identification Algorithms

In order to verify the effect of YOLOv5s on the image identification of *Trichagalma glabrosa* insect gall pests, YOLOv5s was compared with YOLOv4 and Faster-RCNN under the same conditions, and the number of training iterations was set to 500. Then, the models were evaluated using the same test dataset. Four evaluation indexes of YOLOv5s, YOLOv4, and Faster-RCNN are listed in Table 1, which were precision, recall, mean average precision, and model size, respectively.

It can be seen from Table 1 that the precision values of YOLOv5s, YOLOv4, and Faster-RCNN were 94.35%, 89%, and 71.28%, respectively; the recall values were 95.42%, 87%, and 87%, respectively; the mean average precision values were 95.8%, 89%, and 87.52%, respectively; and the model sizes were 13.8 MB, 243 MB, and 108.2 MB, respectively. It could be concluded that the precision value of YOLOv5s was 5.35 and 23.07 percentage points higher than that of YOLOv4 and Faster-RCNN, respectively; the recall value was 8.42 percentage points higher than that of YOLOv4 and Faster-RCNN, respectively; the mean average precision was 6.8 and 8.28 percentage points higher than that of YOLOv4 and Faster-RCNN, respectively; and the model size was 229.2 MB and 94.4 MB smaller than that of YOLOv4 and Faster-RCNN, respectively.

In this study, the identification effects of YOLOv5s, YOLOv4, and Faster-RCNN were compared and analyzed for *Trichagalma glabrosa* insect gall pest images under opposite light, back light, and complex background. According to the comparison results shown in Table 2, the identification effect of YOLOv5s was better than that of YOLOv4 and Faster-RCNN in different backgrounds. Therefore, YOLOv5s was more suitable for the image identification of *Trichagalma glabrosa* insect gall pests.

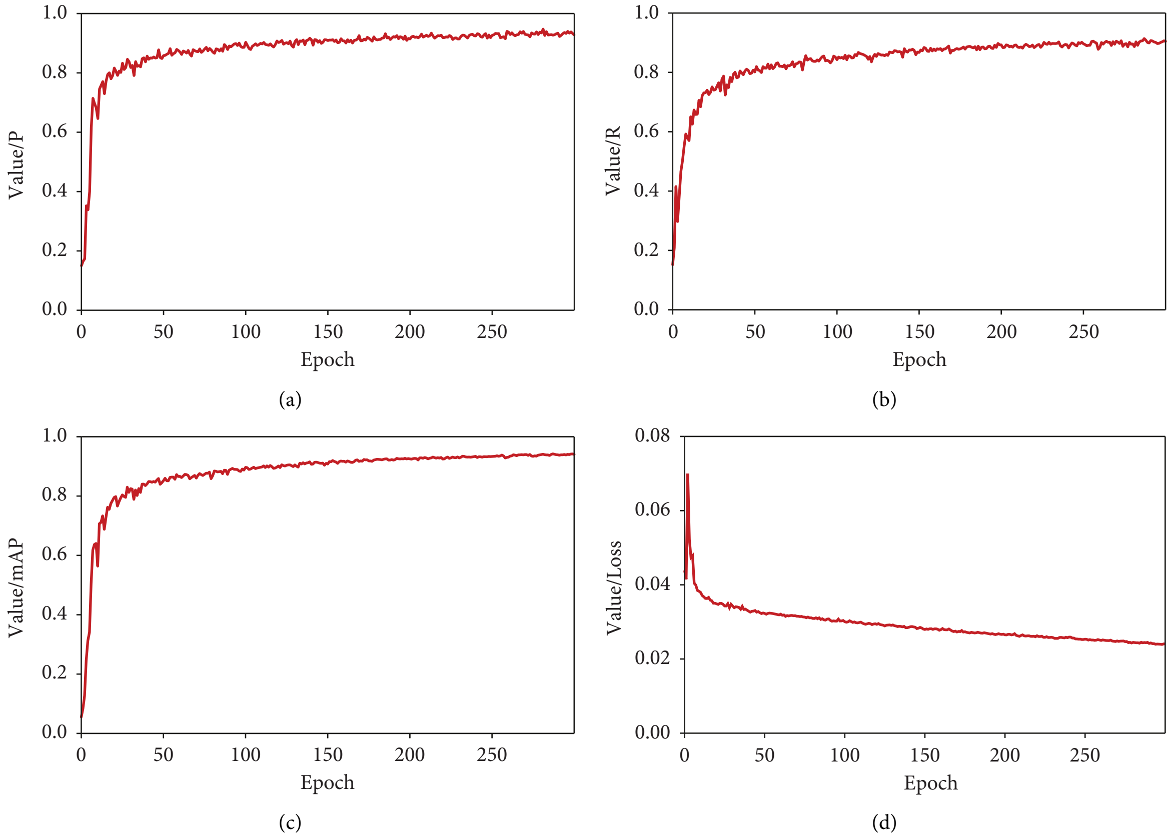


Figure 5: (a) Change diagram of precision values; (b) change diagram of recall values; (c) change diagram of mean average precision values; (d) change diagram of loss value values.

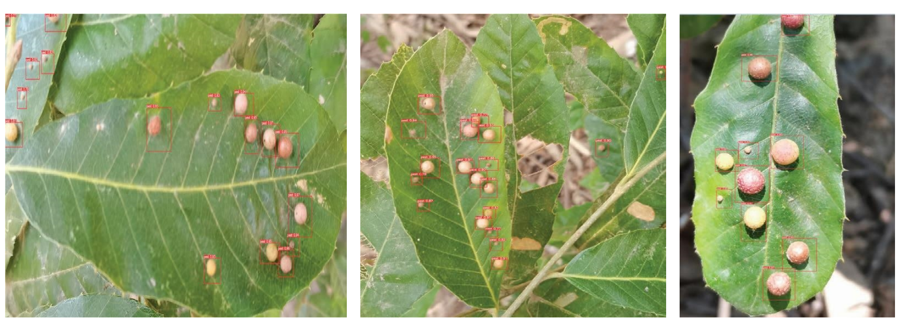


Figure 6: The identification effect under opposite light.

Figure 7: The identification effect under back light.

Figure 8: The identification effect under complex background.

Table 1: Performance evaluation of the three target identification algorithms.

Network	Precision (%)	Recall (%)	Mean average precision (%)	Model size (MB)
YOLOv5s	94.35	95.42	95.8	13.8
YOLOv4	89	87	89	243
Faster-RCNN	71.28	87	87.52	108.2

Table 2: Performance comparison of the three target identification algorithms under different backgrounds.

Network	Background	Precision (%)	Recall (%)	Mean average precision (%)
YOLOv5s	Opposite light	96.1	95.7	96.4
	Back light	91.5	90.1	92.7
	Complex background	86.5	84.7	86.9
YOLOv4	Opposite light	90.1	92.4	91.8
	Back light	84.6	84.5	82.6
	Complex background	78.9	76.8	80.1
Faster-RCNN	Opposite light	78.4	75.4	76.7
	Back light	68.1	67.5	61.9
	Complex background	67.2	66.4	64.7

5. Conclusion

In order to quickly and efficiently identify *Trichagalma glabrosa* insect gall pests, one method of using YOLOv5s to perform the image identification of *Trichagalma glabrosa* insect gall pests was constructed in this study. The main findings were as follows:

(1) For several target identification algorithms, a large number of studies were conducted, and YOLOv5s was selected for the image identification of *Trichagalma glabrosa* insect gall pests. Through experiments, it has been verified that the precision, recall, mean average precision, and model size of YOLOv5s were better than those of YOLOv4 and Faster-RCNN.

(2) The different scenes were constructed according to the natural environment, that is, the images of *Trichagalma glabrosa* insect galls under opposite light, back light, and complex background were constructed. Experiments were conducted to verify the high efficiency of YOLOv5s under different scenes.

(3) During the test of some scenes, there were some problems; for example, the insect galls of some small pixel and the back of leaves were missed or falsely identified. In the future, further research on the fusion of these specific scene constructions and the feature of *Trichagalma glabrosa* insect gall will be conducted to reduce the probability of missing identification or false identification so as to improve the identification effect of the *Trichagalma glabrosa* insect gall images in complex scenes.

Data Availability

The (DATA TYPE) data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

All the authors have accepted responsibility for the entire content of this submitted manuscript and approved the submission.

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