Enhancing fruit recognition with robotic automation and salp swarm optimization for random forest classification

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ABSTRACT

In response to the growing demand for automation and labor-saving solutions in agriculture, there has been a noticeable lack of advancements in mechanization and robotics specifically tailored for fruit cultivation. To address this gap, this work introduces a novel method for fruit recognition and automating the harvesting process using robotic arms. This work employs a highly efficient and accurate model utilizing a single shot multibox detector (SSD) for detecting the precise fruit position. Once the fruit's position is identified, the angles of the robot arm's joints are calculated using inverse kinematics (IK). Finally, the optimal path planning is ensured by the salp swarm optimization (SSO) assisted random forest (RF) classification. This approach enables the precise management of robotic arms without any interference with either the fruits themselves or other robotic arms. Through meticulous consideration of these factors, our method ensures seamless operation in agricultural environments. Experimental validation demonstrates the effectiveness of these techniques in detecting apple fruits outdoors and subsequently automating their harvesting using robotic arms. This successful implementation underscores the potential for widespread application of our approach in enhancing efficiency and productivity in fruit cultivation.

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1. INTRODUCTION

In recent times, there has been a noticeable increase in global concerns regarding food. According to data from the census in 2019, the world's population was recorded at 7.8 billion [1]. Predictions indicate that this number is expected to climb to approximately 8.9 billion by the year 2035 and 10.1 billion by the year 2050. As per additional data from the Food and Agriculture Organization (FAO), world starving affects over 801 million individuals, with projections indicating a worsening trend due to population growth [2]. Consequently, nations are poised to face significant repercussions from impending food scarcity.

The agriculture sector faces significant challenges, such as a declining workforce and rising costs associated with fruit harvesting. Addressing these issues requires a shift towards labor-saving methods and the adoption of massive scale agricultural practices [3]. Recently, automated technologies have made strides in the agricultural sector, yet much of the fruit harvesting process remains reliant on manual labor [4]. To overcome these challenges, the emergence of an automatic fruit harvest robot presents a promising solution. This work tackles two primary processes: identification and localization of fruits on trees using computer vision technology integrated with sensors. Precise robotic arm motion to reach the identified fruit position and harvest it using end effectors, all while ensuring minimal damage to both the target fruit and its host tree [5].

For detecting fruits outdoors in, our methodology relies on an optimization-based machine learning (ML) object identification system fine-tuned for red, green, and blue (RGB) images. This approach equips us to accurately identify fruits even amidst challenging scenarios such as obscured by shadows from leaves and the environmental conditions characterized by varying light levels [6]. Recognizing the inherent limitations of pinpointing fruit locations solely through RGB imagery, we complement our methodology by integrating depth images to bolster precision [7]. In the domain of fruit harvesting via robotic arms, potential collisions with either the robot or surrounding fruits pose significant challenges. To mitigate these risks, we employ inverse kinematics (IK) an optimization-based ML [8]. Due to the intricate nature of the working environment for fruit recognition robotic arms, achieving precise inverse accuracy poses a challenge. This complexity not only hampers the optimum of joint angles but also leads to inadvertent damage to fruits during picking, adversely affecting the economic interests of farmers [9]. To address this, selecting an optimal path and posture for the robot necessitates employing optimization models. These models are characterized by their better robustness, promising to enhance the movement accuracy of the fruits recognition robotic arm and ensure the quality of harvested fruits. The objectives are: i) to introduce a novel method for fruit recognition and automating the harvesting process using robotic arms, ii) to present a single shot multibox detector (SSD) for detecting the precise fruit position and IK for the robotic arm's calculation, and iii) to present salp swarm optimization (SSO) with random forest (RF) for optimal path planning.

The remaining sections are: related works are presented in section 2. Section 3 defines the proposed fruit recognition model using robotic arms. Section 4 analyzes the outcomes and section 5 is the conclusion.

2. RELATED WORKS

Hemming *et al.* [10] presented multi path-convolutional neural network (MP-CNN), integrated by the selection of color elements and support vector machine (SVM) for the identification of cucumbers using robots. In this existing work, 15 color elements were extracted and redundant features were eliminated by the I-RELEIF. OTSU model was used for the segmentation process and the recognition accuracy attained was 90%. Mao *et al.* [11] developed a semantic action model to harvest avocado on the basis of SSD. Initially, the avocado fruits were harvested, inspected and transported. The deep learning (DL) model MobileNet was utilized for extracting features and trained for detecting 9 objects. Accuracy and F1 score values achieved were 86% and 83% respectively.

Vasconez *et al.* [12] presented an orange fruit harvest model in the unstructured environment for a robotic model. Initially, the input images were obtained by the RGBD cameras and provided to the convolutional neural network (CNN) model for detecting oranges. Then, the rapidly exploring random trees (RRT) was used for finding the path planning. Here, the accuracy and recall values achieved were 94% and 95%. Zeeshan *et al.* [13] presented a model that comprises three classifiers for the classification of date fruit images with respect to type, maturity and harvest. These models leverage CNN, incorporating fine-tuned and transfer learning techniques using pre-trained approaches. To develop a resilient vision model, an extensive image dataset of date fruit bunches was created. F score values achieved were 98.9 (type), 96.7 (maturity), and 98% (harvest).

Altaheri *et al.* [14] introduced a strawberry harvest robot model using low cast dual arm and optimized harvest process. This enhanced the efficiency and minimized the collision. Enhancements were implemented on the conventional gripper to make the robot to directly pick strawberries and eliminated the necessity for repacking. Here, the success rate varied from 50% to 97.1%. Xiong *et al.* [15] introduced an integrated approach for designing mechatronics and controlling motion for a prototype aimed at harvesting apples. The DL model was utilized for detecting and localization of fruits captured by an RGBD camera. This existing work incorporated a three-degree freedom manipulation featuring a unique hybrid actuation model. This hybrid system enables precise and dexterous motions essential for efficient harvesting tasks.

Based on where they originate, swarm intelligence algorithms can be broadly classified into three categories: i) it comes from the basic foraging instinct of animals. For instance, the shuffled frog leaping algorithm (SFLA) is proposed in 2003 [16]; and the whale optimization algorithm (WOA) proposed in 2016 [17]; ii) it originates from the pure social behavior of biological populations, such as the artificial bee colony algorithm (ABC) is proposed in 2005 [18]; the firefly algorithm (FA) is proposed in 2008 [19]; the cuckoo search (CS) method is proposed in 2009 [20]; the mayfly algorithm (MA) is proposed in 2020 [21]; iii) social behavior and foraging behavior derived from biological populations, like the bacterial foraging optimization (BFO) is proposed in 2002 [22]; the bat algorithm (BA) is proposed in 2010 [23], the sparrow search algorithm

(SSA) is proposed in 2020 [24]. The study of ant colonies, migrating bird flocks, and other cooperative social group activities gave rise to swarm intelligence [25]. Large-scale individual group behavior studies are used to model group behaviors, develop rules, and suggest algorithms that are then applied to real-world issues. There are two categories of swarm intelligence algorithms: ant colony optimization algorithms describe the collective intelligence that arises from a collection of basic agents. The other is to think of group members as particles rather than agents that are represented by PSO algorithms. In light of this conclusion, the ant colony method and particle swarm algorithm are chosen for introduction in this paper.
From the detailed literature review, the following research gaps are identified:

a. Algorithmic optimization and efficiency
- Computational complexity: investigate the computational efficiency of the salp swarm algorithm (SSA) when combined with RF for real-time fruit recognition, especially in resource-constrained robotic systems.
- Parameter tuning: explore automated and dynamic parameter tuning methods for SSA and RF to enhance accuracy and efficiency without manual intervention.

b. Dataset limitations
- Diverse fruit datasets: address the need for more extensive and diverse datasets that cover a wide variety of fruits under different conditions, such as lighting, occlusion, and fruit maturity stages.
- Data augmentation: investigate advanced data augmentation techniques tailored for fruit recognition to improve the robustness of the classification model.

c. Real-world application challenges
- Environmental variability: study the performance of the sparrow search algorithm and random forest (SSA-RF) model in varying environmental conditions, such as different lighting, weather, and background scenarios commonly encountered in orchards.
- Robustness to noise: examine the robustness of the SSA-RF model to noise and artifacts introduced by the robotic system's sensors and actuators.

d. Integration with robotic systems
- Sensor fusion: explore methods for integrating multiple sensors (e.g., RGB cameras, hyperspectral cameras, and LiDAR) to enhance fruit recognition accuracy and reliability.
- Real-time processing: investigate techniques for real-time fruit recognition and classification, ensuring that the SSA-RF model can process and respond to data swiftly within the robotic system's operational constraints.

e. Adaptability and scalability
- Adaptive learning: develop adaptive learning algorithms that enable the SSA-RF model to continuously learn and improve from new data collected by the robotic system over time.
- Scalability to different crops: research the scalability of the SSA-RF model to different types of fruits and other crops, ensuring that the methodology can be generalized and applied across various agricultural applications.

f. Comparative studies
- Benchmarking with other models: conduct comparative studies with other state-of-the-art fruit recognition algorithms to establish the relative strengths and weaknesses of the SSA-RF approach.
- Hybrid models: investigate the potential of hybrid models that combine SSA-RF with other machine learning or deep learning techniques to achieve better performance.

g. Human-robot interaction
- User-friendly interfaces: develop intuitive interfaces and feedback mechanisms for human operators to interact with and monitor the fruit recognition system.
- Error handling and recovery: study strategies for handling recognition errors and enabling the robotic system to recover gracefully from misclassifications or operational failures.

h. Economic and social impact
- Cost-benefit analysis: perform cost-benefit analyses to evaluate the economic viability and return on investment of deploying SSA-RF-based fruit recognition systems in commercial farming.
- Social acceptance: investigate the social acceptance and impact of robotic fruit recognition systems on labor markets and farming communities.

3. METHOD

In this study, the IK problem of robot arms for fruit recognition is introduced. Initially, this work employs SSO to compute the robotic arms of joint angles for apple fruit recognition. Subsequently, we utilize the evaluation results of the RF model to refine the accuracy of recognition, thereby improving overall performance. Figure 1 shows the pipeline of the automated harvest model by robot which involves the stages like fruit identification, localization, IK, path planning, and classification.

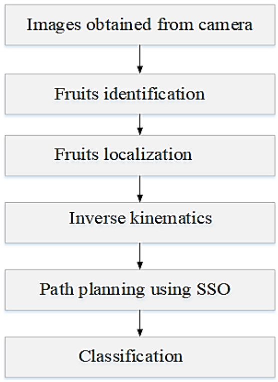


Figure 1. Pipeline of the automated harvest model by robot

3.1. Apple fruit identification

Initially, the RGB images are captured from RGBD cameras integrated into the robotic arm. These images undergo fruit identification, where it's imperative to integrate various features like texture and color for enhanced performance. To achieve this, the study adopts the SSD, a renowned object detection algorithm, for fruit identification within the images. SSD is chosen due to its emphasis on both speed and accuracy, aligning with the requirements of the study. The details about the identified bounding box B is extracted from the outcomes of SSD's fruit identification process. The term B is defined as:

$$B = [\alpha_1, \alpha_2, \ldots\ldots, \alpha_n] \tag{1}$$

The term α is bounding data and it has coordinates of pixel values of $(amin_{min})$ and $(amax_{max})$

$$\alpha = [aminmax^T max_{min}] \tag{2}$$

3.2. Fruits localization

In the subsequent stage, the fruit is treated as a sphere, and its coordinates along with the radius are defined based on the B information (α) obtained in the prior section, as well as the RGB images. With the understanding that the spherical form of the fruit projects to the 2D image, we aim to identify the circular shape of the fruit within the B identified by single SSD. To achieve this, the Hough transformation technique is employed for detecting circles, enabling the identification of fruit circling within the RGB images.

3.3. Inverse kinematics

In the IK solution for the robot arm, the process involves selecting the spatial coordinates of a desired target position and determining the corresponding values for each degree of freedom that achieve the desired posture. It is important to note that a single spatial coordinate with respect to the multi-values for the robotic arm's degrees of freedom. The designated coordinates for the endpoint of the robotic arm, intended for apple fruit, are established as: $Q = [Q_x, Q_y, Q_z, 1]^T$, following the inversion process, the resultant combination of the robot arm's joint angles or degrees of freedom is determined as $\delta = [\theta_1, \theta_2, \theta_3, \theta_4, \ldots\ldots, \theta_j]^T$ and the respective endpoint is $Q = [Q'_x, Q'_y, Q'_z, 1]^T$. Hence, the robotic arm error is determined as:

$$\beta = \sqrt{(Q_x - Q'_x)^2 + (Q_y - Q'_y)^2 + (Q_z - Q'_z)^2} \tag{3}$$

$$\begin{cases} min\sqrt{(Q_x - Q'_x)^2 + (Q_y - Q'_y)^2 + (Q_z - Q'_z)^2\beta} \\ Q[Q'_x, Q'_y, Q'_z, 1] = \prod_{l=1}^{j} T_{l-1,l}(\theta_1, \theta_2, \theta_3, \theta_4, \ldots\ldots, \theta_j)Y \\ -170\, degree < \theta_1 < -170\, degree \\ -150\, degree < \theta_2 < -150\, degree \\ 75\, degree < \theta_3 < 170\, degree \\ -190\, degree < \theta_4 < -190\, degree \\ -125\, degree < \theta_5 < -125\, degree \\ -190\, degree < \theta_1 < -190\, degree \\ -170\, degree < \theta_1 < -170\, degree \\ Y = [0,0,0,1]^T \end{cases} \tag{4}$$

3.4. Path planning using swarm optimization

After selecting the spatial coordinates by the IK, the metaheuristic algorithm SSO is presented for optimal path planning. SSO influences the characteristics of salps and they are barrel shaped planktonic tunicates. For depict the salp chain the population is partitioned into two distinct entities: the commander and the followers. Positioned at the apex of the chain, the commander salp assumes the pivotal role of dictating the overall direction of movement. Meanwhile, the remaining salps form the cohort of followers, trailing behind the commander in a coordinated manner. This hierarchical structure ensures cohesive movement of the entire salp chain, with the leader setting the course for navigation. Let the matrix Y is the salp's position with n (number of solution) and d (dimensional space). Food is the aim of the salps in $n \times d$.

$$Y = \begin{bmatrix} y_1^1 & y_2^1 & \dots & y_d^1 \\ y_1^2 & y_2^2 & \dots & y_d^2 \\ \dots & \dots & \dots & \\ \dots & \dots & \dots & \\ y_1^n & y_2^n & \dots & y_d^n \end{bmatrix} \quad (5)$$

The commander's position at k^{th} dimension of Y_k^1 is computed as:

$$Y_k^1 = \begin{cases} F_k + c1\big((ub_k - lb_k)c2 + lb_k\big) & c3 \geq 0 \\ F_k - c1\big((ub_k - lb_k)c2 + lb_k\big) & c3 < 0 \end{cases} \quad (6)$$

where F_k, ub_k, and lb_k are the source of food, upper and lower bounds at k^{th} dimension; $c1, c2$, and $c3$ are randomized numbers. The parameter $c1$ is essential in maintaining the exploitation and exploration stage and it is computed as:

$$c1 = 2 \times exp - \left(\frac{4t}{t_m}\right)^2 \quad (7)$$

where t and t_m are the present and maximum iterations. Once the commander position is updates, the SSO begins to update the position of followers,

$$Y_k^l = \frac{1}{2}\left(Y_k^l + Y_k^{l-1}\right) \quad (8)$$

where Y_k^l is the l^{th} position of follower in the k^{th} dimension. The process of optimal path using SSO is given in Algorithm 1.

Algorithm 1. Process of optimal path using SSO
Initializing Y
Set the fitness of all solution as Y_l
Updating salp's best solution
The value of $c1$ is computed by the (7)
for $k = 1{:}N$**do**
  if $k == 1$ **then**
  Salp's position is updated by the (6)
    else
    Salp's position is updated by the (8)
  end if
end for
when $t < t_m$
Return best solution

3.5. Classification

RF is a powerful classification model renowned for its combining learning capabilities. In this study, the RF is examined through a multi-step process. Initially, a recursive analysis model is applied to the chosen targeted train data, resulting in the creation of a stochastic classification. Subsequently, thorough examination and analysis of the classifier yield a sequence of discernible patterns. At last, by exploiting these identified principles, new data is summarized and optimized. Essentially, the aim is to infer the quality of unknown data by applying the established rules derived from known data. In the train set Y, after the completion of l^{th} training times, the series of classifications is given as $\{h_1(Y), h_2(Y), \ldots\ldots, h_l(Y)\}$. The outcome of the classification is given as:

$$H(y) = argmax \sum_{j=1}^{l} I(h_j(y) = Z) \quad (9)$$

where h_j is the decision term, Z and I are the output and exponential term.

4. RESULTS ANALYSIS

The following section defines the outcomes of the fruit recognition model. The images are obtained from the Sendai City Agriculture and Horticulture Center. Figure 2 defines the sample images captured by the RGBD camera. Images were conducted to observe the fruit from a bottom-up perspective, minimizing any occlusion caused by surrounding leaves, other fruits and branches.

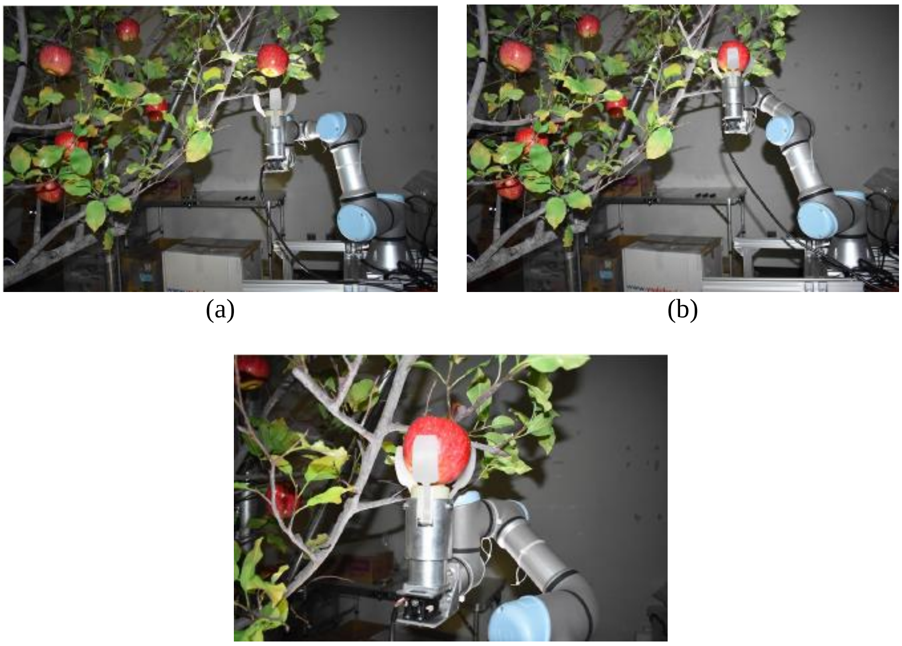
Figure 2. Samples of images captured by the RGBD camera

Performing the experimental analysis on the fruit harvesting season poses significant challenges. The tree samples are shown in Figure 3. Therefore, the experiments are conducted using a tree model instead as shown in Figure 3(a). The proposed approach is capable of identifying apples even when they are partially obscured by leaves and other apples. But, this approach is complex to identify apples located at the periphery of the image and those situated far from the RGBD. Apples at the image's edge are often truncated, leading to detection challenges, while those distant from the camera appear smaller and are consequently harder to detect. Nevertheless, these detection limitations are inconsequential for this study since these fruits are beyond the operational range of the robotic arm as shown in Figure 3(b).

(a) (b)

Figure 3. Tree samples; (a) model of fruit tree and (b) identified fruits

The harvesting process of the harvest robot involved several steps as shown in Figure 4. Initially, the robot positioned its hand beneath the targeting apple by descending 9.8 cm as shown in Figure 4(a), followed by the robot hand capturing the apple and initiating the harvest process as shown in Figures 4(b) and (c). The average time required for harvesting apple is 15 seconds, the harvesting rate is 92% and the Picking time is 5.2 seconds. Table 1 presents the analysis of the proposed apple identification model.



(a) (b) (c)

Figure 4. Images of; (a) targeted apple, (b) harvesting, and (c) acquisitive apple

Table 1. Analysis of the proposed apple identification model

Parameter	Value
Total apples	170
Identified apples	158
Unidentified apples	12
Incorrectly identified apples	0
Accuracy	97.20%
F-score	97.70%

Table 2 defines the comparative analysis of different fruits [4] and it is observed that the proposed harvesting model takes the high rate of harvesting and less picking time.

Table 2. Comparative analysis

Fruits	Rate of harvesting (%)	Picking time (seconds)
Tomato	60	23
Apple	84	6
Cherries	72	14
Sweet pepper	61	24
Kiwi	80.6	5.8
Proposed (apple)	92	5.2

The proposed model can have significant impacts across various dimensions of agriculture, technology, and society. The key potential impacts are:

a. Agricultural productivity and efficiency
- Increased yield: improved accuracy in fruit recognition and classification can lead to better yield estimates and optimized harvesting schedules, reducing waste and maximizing crop output.

– Reduced labor costs: automation of fruit recognition and picking processes can significantly reduce the reliance on manual labor, lowering operational costs for farmers.
– 24/7 operation: robotic systems can operate continuously without fatigue, ensuring timely, and efficient harvesting even in large-scale farms.

b. Quality control and food safety
– Consistent quality: automated fruit recognition can ensure consistent quality by accurately identifying and sorting fruits based on size, ripeness, and defects.
– Early detection of diseases: enhanced recognition capabilities can help in the early detection of diseases or pests, enabling timely intervention and reducing crop loss.

c. Environmental sustainability
– Resource optimization: precision agriculture facilitated by accurate fruit recognition can optimize the use of water, fertilizers, and pesticides, promoting sustainable farming practices.
– Reduced waste: by minimizing human error and ensuring precise harvesting, robotic systems can reduce the amount of unharvested or wasted produce.

d. Economic impacts
– Market competitiveness: farms that adopt advanced robotic systems can become more competitive by reducing costs and improving productivity, potentially leading to better market positioning.
– Investment in technology: successful implementation of SSA-RF-based fruit recognition can attract investments in agricultural technology, spurring innovation and development in the sector.

e. Technological advancements
– Innovation in robotics and AI: the development and refinement of SSA-RF models for fruit recognition can drive advancements in robotics, ML, and sensor technology.
– Cross-industry applications: techniques and technologies developed for fruit recognition can be adapted and applied to other industries, such as manufacturing, logistics, and healthcare.

f. Social implications
– Job displacement and creation: while automation may reduce the need for manual labor in fruit picking, it can create new jobs in technology development, system maintenance, and data analysis.
– Skill development: the agricultural workforce may need to acquire new skills related to operating and managing advanced robotic systems, leading to changes in educational and training programs.

g. Research and development
– Academic and industrial collaboration: the challenges and opportunities in implementing SSA-RF models can foster collaboration between academic researchers and industry practitioners, driving further research and innovation.
– Continuous improvement: ongoing research into SSA-RF and related technologies can lead to continuous improvement in algorithms, hardware, and applications, maintaining the momentum of technological progress in agriculture.

5. CONCLUSION

In this investigation, we executed automatic fruit harvesting by employing a technique that entails apple fruit identification and subsequent harvesting utilizing a robotic arm equipped with a specialized harvesting hand designed to preserve both the fruit and its tree. However, the existing inverse kinematics solution for apple harvesting has exhibited several shortcomings, including less precise, low speed and an unpredictable apple production. To address these challenges, this work presented a SSO algorithm for optimal path planning. Additionally, we leveraged the RF to optimize the selection of the optimal picking path and posture, thereby minimizing unwanted defects to the apples during harvesting. The proposed apple fruit identification model is anticipated to remain applicable even when targeting closely related species. Furthermore, by retraining the algorithm with the specific characteristics of the targeting apple, successful harvesting outcomes can be achieved.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SCM], upon reasonable request.

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