Developing Artificial Intelligence Prototype for Classifying Crude Stingless Bee Propolis towards Innovation in Dentistry

Danica Sawa Samuel[1], Alexander Jusmin[1], Nur'Azira Zulkifli[1], Zaidah Ibrahim[2], Norizan Mat Diah[2], Nurul Ain Ramlan[3] and Ikmal Hisham Ismail[3,*]

[1]*Student, Faculty of Dentistry, Universiti Teknologi MARA, Jalan Hospital, 47000 Sungai Buloh, Selangor, Malaysia.*

[2]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.*

[3]*Centre of Comprehensive Care Studies, Faculty of Dentistry, Universiti Teknologi MARA, Jalan Hospital, 47000 Sungai Buloh, Selangor Malaysia*

Abstract: *Introduction:* Stingless bee propolis demonstrates excellent therapeutic properties and its innovation in dentistry. Due to species-specific variations in chemical composition, the nutraceutical potential of each propolis type may be differ.

Purpose: To create an Artificial Intelligence (AI) prototype to classify three different propolis namely *Geniotrigona thoracica*, *Heterotrigona itama*, and *Tetrigona apicalis*, using crude macerated, SEM images.

Methods and Materials; An AI prototype was developed with AI model to perform propolis classification using crude macerated SEM images, for each species. Fine-tuning on the number of images and the number of epochs of the AI model is performed to achieve high performance, which will then use to develop a prototype.

Results: Initial experiment with a small dataset achieved accuracy of 0.67. After augmenting the dataset with 50 additional images per species, accuracy improved to 0.86 after 80 epochs. Other metric evaluations such as precision, recall and F1 score have also been applied to measure the AI model's performance. The results demonstrate that as the size of the training images and epoch increase, the classification performance is improved. This model has been utilized to develop a prototype with graphical user interface that allows user to insert a new macerated SEM images and the prototype will reveal the propolis species. Expert verification of this prototype has been performed, for use to classify the propolis.

Conclusion: The accuracy of propolis image classification can be further enhanced by using a larger dataset and a higher epoch value. The finding of this study can be used as quality control procedures to profile stingless bee propolis by improving the selection and enriching sustainable sources, as nutraceuticals, employed in dentistry. Future work include the utilization of colour images of crude macerated propolis.

Keywords: Artificial Intelligence, Nutraceutical, Propolis, Prototype.

1. INTRODUCTION

Meliponines, also known as stingless bees (SLB), are the largest group of eusocial bees in the world with more than 600 species have been described. They are found in South and Central America, the southern regions of North America, Africa, Northern Oceania, and Southeast Asia including Malaysia [1]. SLBs produce honey, bee bread, and propolis where, three species that are commonly found in Malaysia are *Heterotrigona itama* (HI), *Geniotrigona thoracica* (GT) and *Tetrigona apicalis* (TA) [2]. Al-Masoodi *et al* (2022), also described the method to lyophilize the ethanolic extract of propolis. The composition of propolis depends on the type of plants accessible to the bees [3]. It is a mixture of salivary secretions and plant resins collected by bees and is produced to seal the hive and prevent the entry of air and invading insects, besides diseases [4]. Different propolis have different properties and component based on its geographical origin, different species, and seasons [5] and are known to contain numerous beneficial chemical compounds and biological activities that can be utilized in sectors such as pharmaceutical and health for their antimicrobial, antifungal, antiviral, anticancer, antidiabetic, antioxidant activities, and several more [6].

Clinical trials have proved the effectiveness of various natural compounds in the treatment of dental caries, among which catechol, emetine, quinine, and flavone are the most reported [7]. Numerous studies have indicated that propolis has no toxicity and no side effects in animal models or humans [8]. Thus, propolis have attracted a great deal of interest for the treatment of a few human infections and also has been used in the development of new drugs of biotechnological products [9].

Artificial intelligence is a combination of conventional science disciplines, scientific theories, and practices using mathematical logic, statistics, and

*Address correspondence to this author at the Centre of Comprehensive Care Studies, Faculty of Dentistry, Universiti Teknologi MARA, Jalan Hospital, 47000 Sungai Buloh, Selangor Malaysia;
E-mail: ikmal_hisham@uitm.edu.my

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probabilities, through computers to imitate the cognitive abilities of humans [10]. Convolutional Neural Network (CNN) is a popular AI method for image classification, including classifying pollen-bearing honeybees [11] and stingless bees [12]. While some researchers have explored the application of AI with stingless bees, there is a lack of study on identifying stingless bee species based on propolis classification. Thus, this study aimed to develop an Artificial Intelligence (AI) prototype to classify three different propolis namely *Geniotrigona thoracica*, *Heterotrigona itama*, and *Tetrigona apicalis*, using crude macerated images.

2. METHODS AND MATERIALS

The systematic procedures employed in this research are data acquisition, which describes the collection of the propolis images, proposed model architecture design, which briefly explains the MobileNet architecture, and experimental approach that discusses the approaches on improving the classification performance of the proposed model.

2.1. Crude Macerated Propolis Preparation

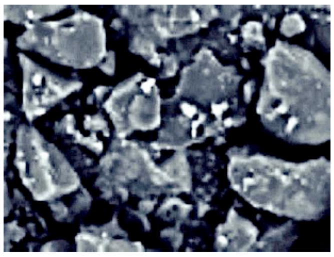
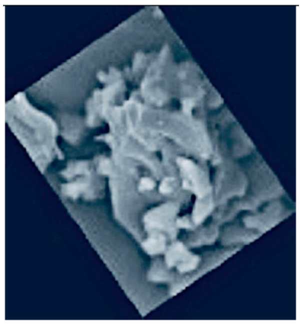
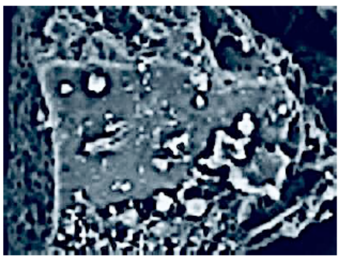
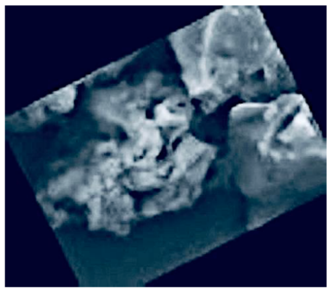
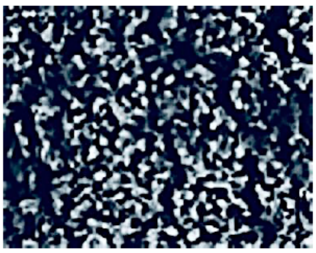
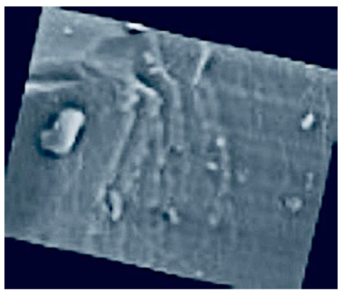
The propolis from three species were weighed (5g each) and macerated using a blender. These samples were further processed for Scanning Electron Microscope (SEM), as outlined below.

2.2. Data Acquisition

To date, no dataset for stingless bee propolis classification exists in the literature. Therefore, the acquisition of stingless bee propolis images from three species available in Raub, Pahang, Malaysia was carried out to establish a new dataset. The acquisition of images were obtained through collection of SEM images of crude macerated propolis.

This study collected six images per type of propolis, totalling 18 macerated images. These images were all in .jpg format, saved as the dataset. Table **1** illustrates some sample images from the dataset. The accuracy of the image classification of an AI model relies heavily on the volume of the dataset, which can lead to poor model generalizability [18]. A dataset with just 18

Table 1: Some samples of crude macerated SEM images acquired.

Propolis Type	Original Macerated Images	Augmented Macerated Images
Geniotrigona thoracica		
Heterotrigona itama		
Tetrigona apicalis		

annotated samples were considered as an exceedingly small dataset that is due to the labour-extensive process. Data augmentation is one of the commonly used approaches to increase the generalisability and robustness of the model by increasing the size of the dataset. In this approach, the dataset was artificially expanded by creating new samples through various transformations such as flipping, scaling and rotation [19]. Table **2** shows several samples of new images achieved after the augmentation process.

2.3. Proposed Model

Developing a mobile AI application seems to be practical and beneficial for researchers and users since everybody owns a mobile phone. An efficient and widely used CNN architecture for mobile devices is Mobile Net [13]. MobileNet model is substantially smaller, but it performs similarly to top recognition models in terms of accuracy [14]. CNNs require significant computing resources and power, but mobile phones have limited resources like processing power and power source. MobileNet uses depthwise and pointwise convolutions to overcome hardware resources limitations. Figure **1** shows where the propolis images will go through data augmentation (to increase the size of the dataset), fine-tuning process (to improve the classification performance), and lastly classification process. Figure **2** shows the MobileNet architecture applied in this research [15]. Generally, a CNN consists of convolution layer that extracts features from the input image, pooling layer that downsizes the feature map while full connection layer performs the classification. In a MobileNet, depthwise convolution performs a single convolution on each input channel while the pointwise convolution combines the output of depthwise convolution linearly with 1*1 convolution. Global average pooling computes the average of all pixels in each feature map and returns a single element. The full connection layer applies Softmax, an activation function that classifies the flattened feature map as either *Geniotrigona thoracica*, *Heterotrigona itama*, or *Tetrigona apicalis.*

2.4. Experimental Approach

Several experiments have been conducted to achieve a reliable MobileNet model for propolis classification based on macerated images. Two approaches have been performed which are increasing the number of training images and fine-tuning the number of epochs, related to the training process.

The first dataset consists of 18 original images of the macerated images. The ratio of 90:10 has been applied for training and testing images, resulting in four images for training and two images for testing for each propolis type being used in the experiment. Four different values of epoch have been fine-tuned for both datasets. An epoch is the number of passes a training dataset makes through an algorithm [16]. One pass is counted when the dataset has completed both the forward and backward passes. The epoch values of 20, 40, 60 and 80 have been assessed. The classification performance is being evaluated based on four metrics, namely accuracy, precision, recall and F1 Score. Accuracy measures the number of correctly classified images, which includes both true positive and true negative. Precision evaluates the positive classes that have been correctly classified. Recall evaluates the proportion of actual positives that were correctly

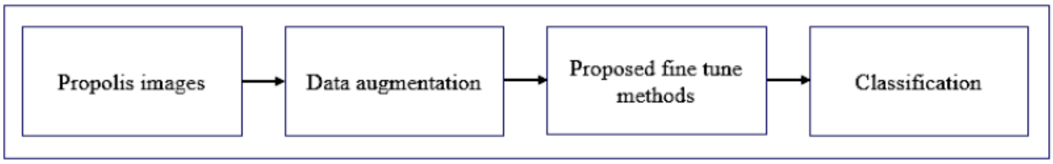


Figure 1: Block diagram of proposed approach.

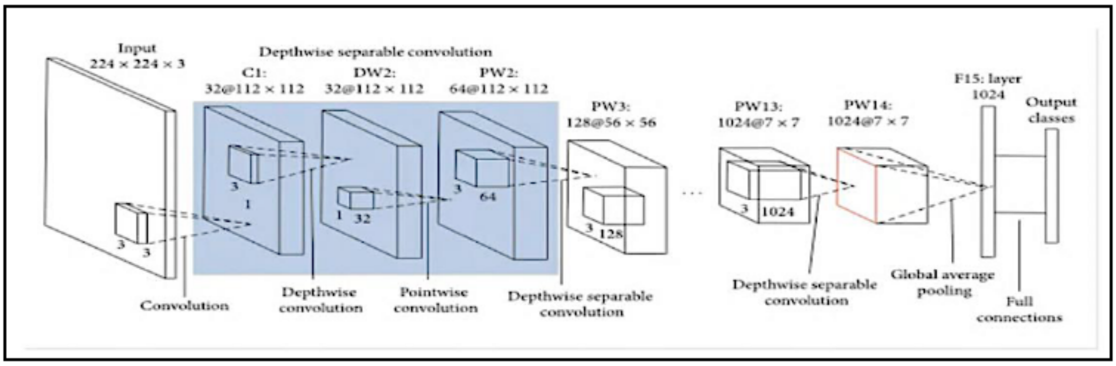


Figure 2: Stingless bee propolis MobileNet classification model [13].

classified. F1 Score evaluates the harmonic mean of precision and recall. The formulas for Accuracy, Precision, Recall and F1 Score are listed as Equations (1), (2), (3) and (4), respectively.

Accuracy = (True Positive + True Negative)/(True Positive + True Negative + False Positive + False Negative) (1)

Precision = True Positive/(True Positive + False Positive) (2)

Recall = True Positive/(True Positive + False Negative) (3)

F1 Score = 2 * ((Precision * Recall)/(Precision + Recall)) (4)

where

True Positive = correctly classified as positive.

True Negative = correctly classified as negative.

False Positive = incorrectly classified as positive.

False Negative = incorrectly classified as negative.

3. RESULTS

Table **2** presents the comparative classification results of the original datasets of SEM macerated images with the augmented image dataset, highlighting the accuracy, precision, recall and F1 score achieved across different training epochs. Furthermore, Figure **3** illustrates the graphical representation of the comparative analysis between the small original image dataset with the slightly larger augmented image dataset, displaying the results of accuracy, precision, recall and F1 Score. By examining Table 2 and Figure 3, it is evident that the results of all metric evaluations increase as the number of epochs increases.

Figure **4** illustrates the sample interface of the stingless bee propolis classification application. Figure **4a**) shows the main page that consists of three command buttons, namely “General info about Stingless Bee”, “General info about Stingless Bee Propolis” and “Stingless Bee Propolis Classification”. If user clicks the top command button, Figure **4b**) will be displayed and if user clicks the second command button, Figure **4c**) will be displayed. If user clicks the third command button, Figure **4d**) will be displayed where user selects “Macerated Propolis Image

Table 2: Comparative Results Based on Accuracy, Precision, Recall and F1 Score of the Original Datasets and the Addition of Augmented Images for SEM Macerated Images

Epoch	Original Images				Original + Augmented Images			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
20	0.33	0.17	0.33	0.22	0.73	0.81	0.73	0.67
40	0.5	0.47	0.5	0.41	0.73	0.82	0.73	0.67
60	0.67	0.5	0.67	0.56	0.8	0.88	0.8	0.78
80	0.67	0.5	0.67	0.56	0.87	0.91	0.87	0.86

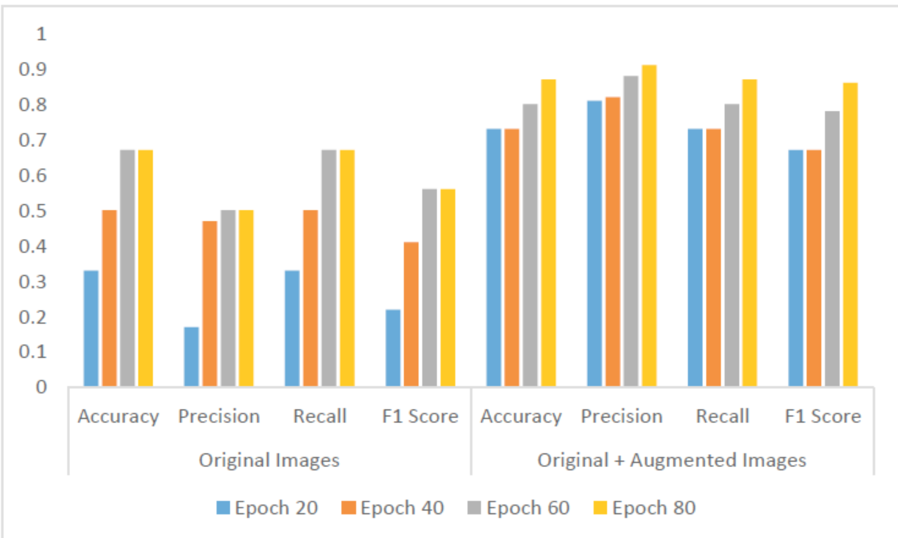


Figure 3: Graphical representation of the comparative analysis of the classification performance between original image dataset and the augmented image dataset.

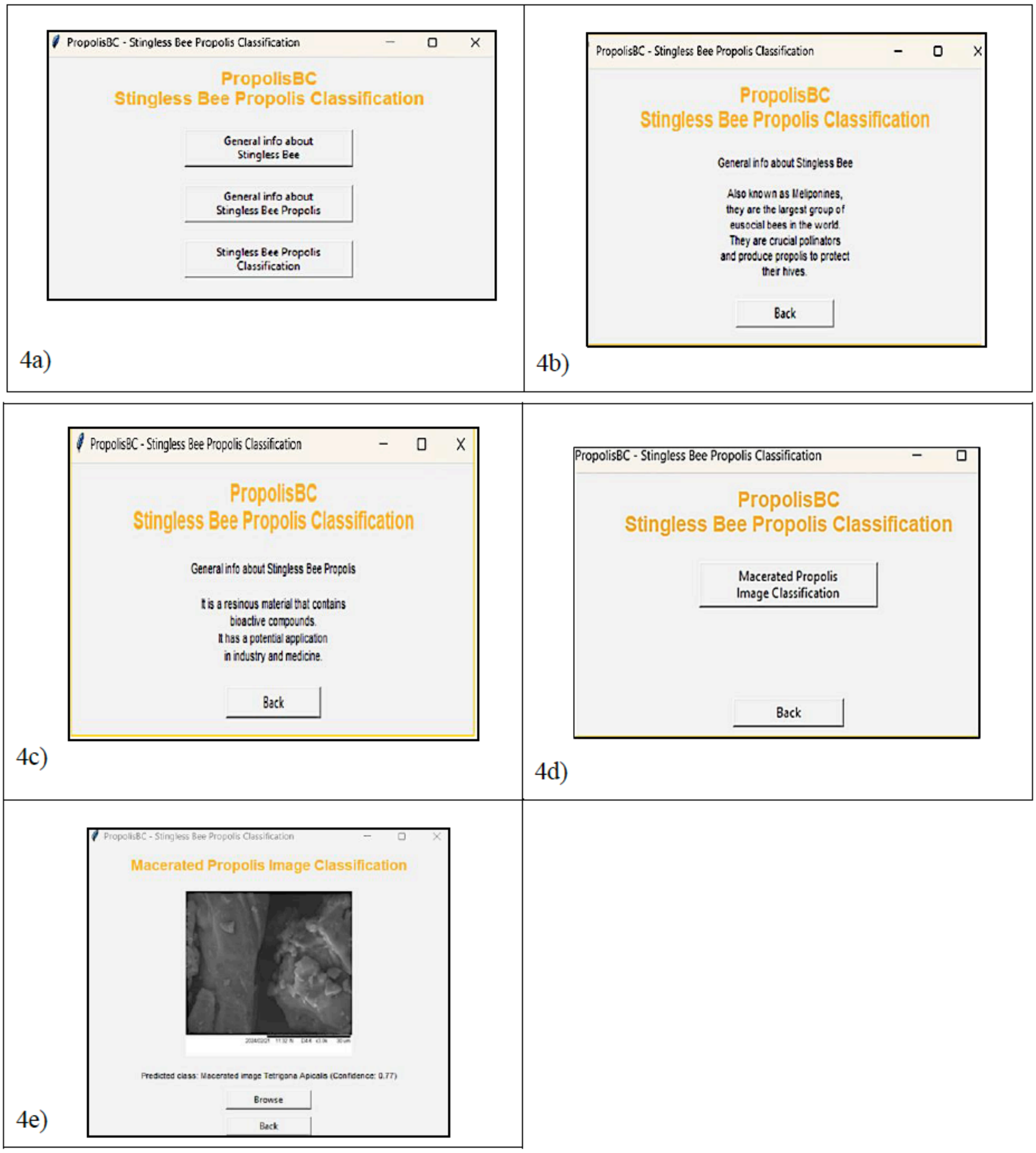


Figure 4: Sample interface of the mobile application. **a**) main page **b**) sub-page that displays a general info about stingless bee **c**) sub-page that displays a general info about stingless bee propolis **d**) sub-page that lists the type of images to be classified **e**) sub-page that displays the name of the propolis when user loads a macerated image.

Classification", user can browse and load a macerated image and Figure **4e**) will be displayed where the MobileNet model classified the image with percentage of confidence on the accurateness of the classified name of the propolis.

4. DISCUSSION

In this study, a propolis macerated image classification model was implemented using MobileNet, and its performance was measured using four standard classification metrics, namely accuracy, precision, recall and F1 score. Due to constraints in acquiring new propolis images, data augmentation was used to expand the dataset. This technique artificially increases the training set by creating modified copies of existing data such as by rotating or flipping the images [18]. The best achieved accuracy of the MobileNet model was 0.87, indicating that the model correctly classified a significant proportion of the test images. Further examination showed that the highest precision achieved was 0.91, and recall was 0.87. Precision reflects the proportion of true positive predictions among all positive classifications made by the model. A high precision indicates that the model is effective at minimizing false. On the other hand, recall evaluates the ability of the model to correctly identify all relevant instances, and a high recall suggests fewer false negatives. The results implies that the model performs well in both classifying relevant instances and avoiding incorrect positive classification, suggesting good classification performance. The F1 Score was 0.86, which is relatively high, indicates the model's balanced ability in handling both types and errors. In general, the MobileNet model demonstrated strong classification performance.

The developed mobile application features a simple, user-friendly interface that enables users to load crude macerated images for immediate propolis classification. It has potential applications in various fields, including dentistry, agricultural biodiversity, and academic research. This application supports the development of targeted dental formulations, such as antimicrobial agents or restorative materials. In clinical settings, AI can optimize the selection of propolis variants based on efficacy leading to innovative products that improves patient outcomes. Overall, AI-driven analysis of propolis paves the way for more effective and tailored interventions in dentistry.

5. CONCLUSION

This research proposed two datasets comprising three commonly available stingless bee propolis, represented as macerated images. Automatic propolis classification was performed using MobileNet, an AI model. The results demonstrated that the MobileNet model has achieved highly promising performance despite the small dataset. The model obtained strong performance across all the four key evaluation metrics, including accuracy, precision, recall and F1 score. These results highlight not only the model's capability to correctly classify the propolis macerated images overall, but also its effectiveness in minimizing both false positives and false negatives. The findings from this study can improve quality control procedures for profiling stingless bee propolis, thereby enhancing selection and enriching sustainable sources for use in dentistry. Future work includes experimenting with other AI methods to classify trees located near stingless bee habitats, in order to explore associations between tree species and propolis. Furthermore, nutraceutical derived from propolis could be developed by planting trees of suitable polyphenol sources near hives, regardless of the bee species or hive location.

6. FUTURE RESEARCH

6.1. Standardizing Picture Setting for Crude Macerated Propolis Samples

The crude macerated propolis SEM images shown in Tables **1** and **2** were in black and white, generated by the SEM software. Future color images will be captured and later use for deep learning (DL) training with the Studio Light Box shown in Figures **5** and **6**. The improved setup outlined in the guidelines in Table **3**. A sample of the colored photograph of the crude macerated was captured and is shown in Figure **7**.

Table 3: Guidelines: Setting-up "Mini Studio Light Box"

1	**Device:**	Android (Samsung S23+)
2	**Camera Setup:**	Zoom X8 magnification, No flash, White balance – default setting, 1:1 frame ratio, motion photo off
3	**Camera-to-Sample Distance:**	25 cm
4	**Sample Container:**	White colour crucible
6	**Light Source:**	White light (warm, blue and **white** setting options), maximum brightness setting
7	**Mini Studio Lightbox Dimension**	25 cm (Height) × 25 cm (Width) × 25 cm (Length)

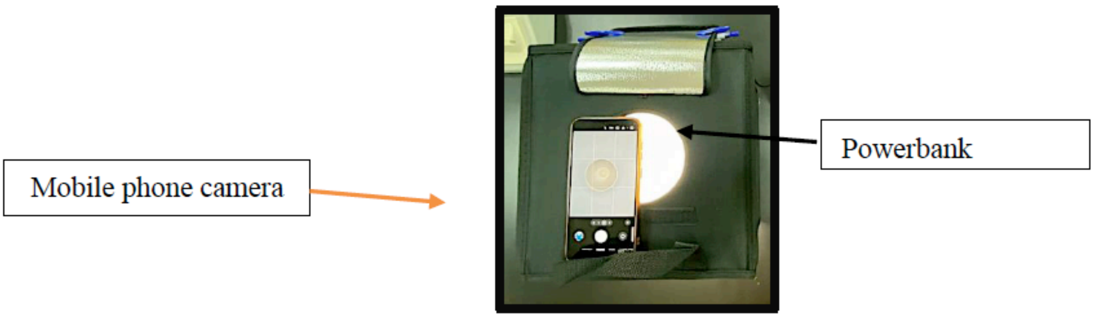


Figure 5: Top view. Innovation of Mini Studio Light Box.

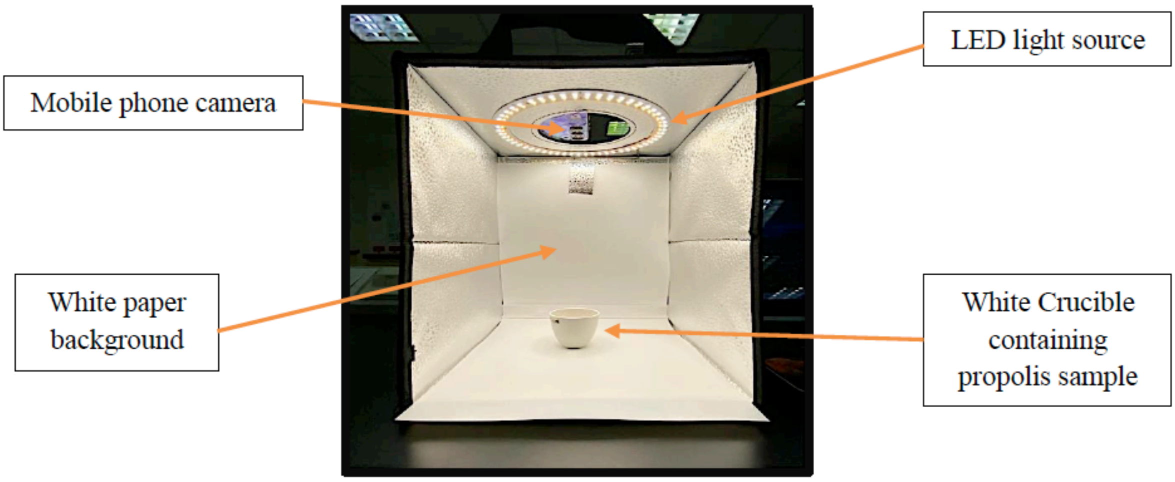


Figure 6: Front view. Innovation of Mini Studio Light Box.

Figure 7: Front view. Sample photograph of crude macerated TA propolis at X8 magnification.

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CONFLICT OF INTEREST

None declared.

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