Convolution Neural Network Approach for Early Identification of Patchouli Leaf Disease in Indonesia

Rustam [1,*], Rita Noveriza [2], Siti Khotijah [3], Syamsul Rizal [1,4], Melati [2], Nor Kumalasari Caecar Pratiwi [1,5], Muhammad Hablul Barri [6], and Koredianto Usman [1]

[1] Department of Telecommunication Engineering, School of Electrical Engineering, Telkom University, Jawa Barat, Indonesia
[2] Research Center for Horticultural and Estate Crops, National Research and Innovation Agency, Jakarta, Indonesia
[3] Department of Computer Science and Information Engineering, College of Electrical Engineering and Computer Science, National Taiwan University of Science and Technology, Taiwan
[4] Department of IT Convergence Engineering, College of Engineering, Kumoh National Institute of Technology, Gumi, South Korea
[5] Department of Electronic Engineering, College of Engineering, Jeonbuk National University, Jeonju City, South Korea
[6] Department of Biomedical Engineering, School of Electrical Engineering, Telkom University, Jawa Barat, Indonesia
Email: rustamtelu@telkomuniversity.ac.id (R.); rita_noveriza2000@yahoo.com (R.N.); skhotijah0902@gmail.com (S.K.); syamsul@telkomuniversity.ac.id (S.R.); melatinazar@yahoo.co.id (M.); caecarnkcp@jbnu.ac.kr (N.K.C.P.); mhbarri@telkomuniversity.ac.id (M.H.B.); korediantousman@telkomuniversity.ac.id (K.U.)
*Corresponding author

***Abstract*—Indonesia is the largest supplier of patchouli oil in the world market, contributing 80%–90%. Most patchouli oil products are exported in the perfume, cosmetics, pharmaceutical, antiseptic, aromatherapy, and insecticide industries. The emergence of patchouli leaf disease significantly reduced the production of wet, dry, oil, and patchouli alcohol. Therefore, selecting patchouli cuttings (seedlings) that are entirely healthy and disease-free is very important to prevent disease transmission from one area to another. In addition, the selection of disease-free seeds is also essential to prevent the use of diseased patchouli plant propagation. So far, the early identification of patchouli plant health is carried out through visual observations by experts using antiviral serum tested in the laboratory. However, this testing process is expensive. Therefore, in this paper, we proposed a novel Convolutional Neural Network (CNN) architecture for patchouli leaf diseases. We proposed a system for early identification of whether a patchouli leaf is diseased or healthy. Our CNN model uses three convolution layers, a dense layer, and a dropout layer. We compare the proposed model with well-known models, namely EfficientNetB0, AlexNet, InceptionV3, MobileNetV2, and VGG16. The results show that the proposed model outperformed five well-known models as a comparison. It has been confirmed by predicting the new and different testing data. This research contributes to the early identification of patchouli leaf diseases to reduce the expensive costs of identifying patchouli leaf diseases.**

***Keywords*—leaf disease, patcholi, Indonesia, Convolutional Neural Network (CNN)**

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I. INTRODUCTION

Patchouli (*pogostemon cablin benth*) is one of the essential oil-producing plants, contributing to the foreign exchange of more than 50% of Indonesia's total essential oil exports. Indonesia is the largest supplier of patchouli oil in the world market, with a contribution of 80%–90%. Indonesia's exports fluctuate at an increasing rate of about 12% per year, or between 700 and 2,800 tons. Meanwhile, world demand ranges from 1,200 to 1,500 tons with a growth of 5% per year.

Most patchouli oil products are exported for use in the perfume, cosmetic, antiseptic, and insecticide industries [1]. The main benefit of patchouli oil is that it is used as a fixative (binding other essential oils), which until now has no substitute product. In addition, with the development of treatment methods, patchouli oil can be an option for aromatherapy because it is known to help cure physical and mental illnesses.

Some critical diseases of patchouli that are currently spreading in Indonesia are bacterial wilt, budok, diseases caused by nematodes, white root, and leaf spot, and mosaic disease caused by viruses [2, 3]. The spread of the disease caused by the virus is swift now that its presence has been reported in patchouli production centers in Sumatra, Java, and Sulawesi [4, 5]. Infection with Telosma Mosaic Virus (TeMV) in three high-yielding varieties of patchouli (Tapak Tuan, Lhokseumawe, Sidikalang) at six months after planting (first harvest) can reduce the production of wet, dry, oil, and patchouli alcohol production, 35%, 40%, 9%, and 5%, respectively [6]. The percentage decrease in production and oil content is expected to be more significant in the second, third, and so on harvests.

Selecting patchouli cuttings (seeds) that are completely healthy and virus-free is very important to prevent virus transmission from one area to another. Virus infection is systemic, and patchouli plants are propagated vegetatively (cuttings). Therefore, it is essential to know whether the patchouli plant material used as the parent for propagation is free from viral infection.

So far, the early identification of patchouli plant health is carried out through visual observations by experts using antiviral serum tested in the laboratory. However, this testing process is expensive. An inexpensive and fast detection technique in the field, such as artificial intelligence methods, is necessary.

As a part of artificial intelligence, the Convolutional Neural Network (CNN) approach has been widely used to detect plant leaf disease infections early [7–10]. CNN has been applied, including image segmentation [11–14] and medical diagnosis [15–21]. As for the identification of leaf diseases, CNN has been applied for tomato [22–26], rice [27–31], banana [32–35], cotton [36–38], as well as bean and potato [39]. In previous research, we also identified the origin of Indonesian cloves based on their metabolite composition [40–43]. Based on this literature study, specific studies on the implementation of CNN for identifying patchouli leaf diseases still need to be completed. Therefore, we proposed a novel CNN architecture for patchouli leaf diseases. We proposed a CNN model using three convolution layers, a dense layer, and a dropout layer. We compare the proposed model with well-known models, namely EfficientNetB0, AlexNet, InceptionV3, MobileNetV2, and VGG16, for more comprehensive results. The proposed model is more straightforward than the aforementioned, as described in the method section. Our proposed model outperforms several well-known models. Therefore, we confirm that our model is suitable for the patchouli dataset because it is small. Meanwhile, the other models used for comparison are more complex. Hence, the results for the patchouli dataset as a small dataset are less suitable than the simple model we proposed. Therefore, based on this result, we propose using our simple and non-complex model for the small dataset category.

The rest of this paper is described as follows. Section II describes the materials and methods used in this study. Section III presents the identification results of each model and its discussion. Finally, in Section IV, we concluded the findings of this study.

II. Materials and Methods

A. Dataset

The dataset used in this study was obtained from Balai Penelitian Tanaman Rempah dan Obat (Indonesian Spices and Medicinal Crops Research Institute). The image dataset consists of JPG images with a 3,096×4,128 pixels resolution. This study used a dataset consisting of two classes, namely the healthy and diseased patchouli leaves. The patchouli leaf visualization used can be seen in Fig. 1. The number for healthy conditions was 200 images and the number for diseased conditions was 200 images. Then the dataset is splited, 80% for the training data and 20% for the validation data. To get better results, we using new and different testing data, 20 images each for healthy and diseased classes. These images have never been involved in the training and validation process.

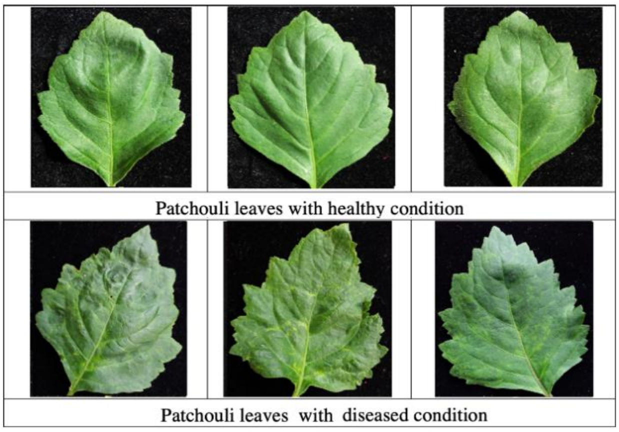

Fig. 1. Photos of healthy and diseased patchouli leaves.

B. Convolution Layer

The CNN technique employs the convolutional layer to extract characteristics from the image by utilizing local information. The kernel is positioned at the top-left corner of the image. The pixel values within the kernel are multiplied by the appropriate kernel values, resulting in a set of products. These products are then summed together, and finally, the bias is added to the sum. The kernel is shifted by one pixel, and this operation is iterated until all potential positions in the image are filtered.

C. Pooling Layer

The pooling layer is implemented after the convolution layer. The dimensions of the resultant matrix formed from the convolution layer are decreased in the pooling layer. While it is possible to utilize filters of various sizes in the pooling layer, a commonly employed choice is a filter with dimensions of 2×2. This layer can utilize many functions, including max pooling, average pooling, and L2-norm pooling [44]. The study employed a max-pooling filter with a stride of two. Max pooling involves finding the highest value inside rectangular sections and transferring it to a new matrix. Maximum pooling partitions the input image into many rectangular sections according to the size of the filter, and the resulting output is the highest value inside each rectangular zone.

D. Activation Layer

1) Rectified Linear Unit (ReLU)

The activation function exhibits a nonlinear relationship between the input and output layers. Nonlinear network learning takes place through the activation function. The often employed activation functions encompass linear, sigmoid, hyperbolic tangent, and Rectified Linear Unit (ReLU). Nonlinear ReLU is commonly employed in Convolutional Neural Networks (CNN). The ReLU activation function sets values below zero to zero, while values above zero remain unchanged. The ReLU function is mathematically defined as follows:

$$ReLU(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{otherwise} \end{cases} \tag{1}$$

2) Softmax

The softmax activation function is utilized in the last layer to compute the expected probability for each class. The output is determined by selecting the class with the highest probability. The mathematical expression for the softmax function is provided in the reference [45].

$$S(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{K} e^{y_j}} \tag{2}$$

where e^{y_i} and e^{y_i} state the probability belonging to the i and j categories respectively. K denotes the number of categories. The softmax function calculates the prediction of each category, $S(y_i)$.

E. Loss Function

In this study, we use binary cross-entropy as a loss function. Binary cross-entropy is given as follows.

$$J_{bce} = -\frac{1}{M}\sum_{m=1}^{M}\left[y_m \times \log\left(h_\theta(x_m)\right) + (1 - y_m) \times \log\left(1 - h_\theta(x_m)\right)\right] \tag{3}$$

where M denotes member of training examples, y_m states target label for training example m, x_m denotes input for training example m, and h_θ states model with neural network weights θ.

The first term in Eq. (3) discourages the occurrence of probabilistic false negatives throughout the training process. For example, let us say we have a training sample with a goal value of 1, but the output of the machine learning model is 0.8. It is established that there is a 20% probalistic of a false negative occurring. From a Bayesian perspective, the model exhibits a confidence level of 20% in an incorrect outcome. The loss function penalizes this 20% by returning the −log(0.8) = 0.09 result. When the binary classifier produces a one as output, it correctly predicts the training example, resulting in a −log(1) = 0 loss. This also holds for the second term and probabilistic occurrences of false positives [46].

The stages carried out in this study are described in Fig. 2. The first stage is image input from the dataset that has been prepared, namely the image of healthy and diseased patchouli leaves. The next stage is the CNN model training using EfficientNetB0, AlexNet, InceptionV3, MobileNetV2, VGG16, and our proposed model. In the final stage, the training result database was used to identify healthy or diseased patchouli leaves in the new and different testing data.

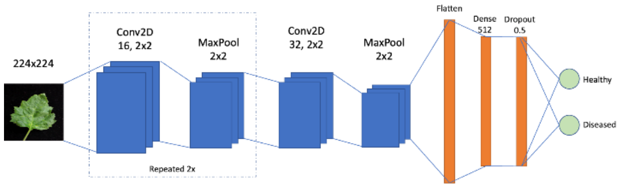

Fig. 2. The proposed model for Patchouli leaf disease identification.

F. EfficientNetB0

The EfficientNet model was introduced by Tan and Le [47]. The findings of this research were showcased at the prestigious International Conference on Machine Learning in 2019. The researchers studied model scaling and discovered that achieving a careful equilibrium between the network's depth, width, and resolution can enhance performance. Upon analyzing this discovery, they proposed a novel scaling technique that consistently scales all aspects of a network's depth, width, and resolution. A neural architecture search was employed to build a novel baseline network. They increased the models' size to create a group of deep learning models known as EfficientNets. These models produce significantly higher accuracy and efficiency than earlier Convolutional Neural Networks.

G. Alexnet

This model, Alexnet [48], emerged as the winner of Imagenet's large-scale visual recognition contest. AlexNet consists of eight layers with adjustable parameters. The model comprises five layers, incorporating a sequence of max pooling followed by three fully connected layers. ReLU activation is used in each layer except for the output layer. The researchers discovered that employing the Rectified Linear Unit (ReLU) as an activation function significantly enhanced the training process, resulting in a nearly six-fold increase in speed. In addition, dropout layers were employed to mitigate overfitting in the model. The model underwent training using the ImageNet dataset. The ImageNet dataset has over 14 million photos across a thousand distinct categories.

H. InceptionV3

Szegedy *et al.* [49] suggested InceptionV3, which exhibits superior generalization capabilities, as described in their publication. This architectural design emerged as the victor in the 2014 ImageNet Competition. In 2015, Google introduced InceptionV3, a neural network architecture comprising many stacked and enhanced Inception Modules. The Inception Module consists of four main components: 1×1 convolution, 3×3 convolution, 5×5 convolution, and 3×3 max pooling. The outcomes of the four component actions are merged on the channel.

I. MobileNetV2

Sandler *et al.* [50] proposed MobileNetV2 in 2018. Every block in MobileNetV2 consists of a 1×1 expansion layer, along with depthwise and pointwise convolutional layers. The pointwise convolutional layer in V2 is defined as a tensor with many channels. The limiting factor is the leftover bottleneck block. Before delving into depth-wise convolution, a 1×1 expansion convolutional layer will augment the number of channels in the data based on the expansion factor. The remaining connection was the MobileNetV2 block. A residual connection is present to facilitate the flow of gradients through the network. MobileNetV2 offers the option to use batch normalization and ReLU6 as activation functions in every layer. Nevertheless, the paper layer's output lacked an activation function [51]. The MobileNetV2 design comprises 17 consecutive bottleneck residual blocks, followed by a traditional 1×1 convolution [52], a global average pooling layer, and a classification layer.

J. VGG16

In 2014, Simonyan and Zisserman [53] proposed the VGG16 model. This model has several distinctions from prior high-performance models. The first model employs a small 3×3 receptive field with a stride of 1 pixel, while the AlexNet model utilizes an 11×11 receptive field with a stride of 4 pixels. The 3×3 filters were merged to create an expanded receptive field. Using numerous smaller layers instead of a single large layer has the advantage of including more nonlinear activation layers with the convolution layers. It leads to enhanced decision functions and enables the network to converge rapidly. Furthermore, VGG employs a diminutive convolutional filter, mitigating the network's inclination to overfit during training sessions. The best size for a filter is 3×3, as a smaller size is insufficient to collect both horizontal and vertical information.

K. The Proposed Model

In this study, the proposed model is using three convolution layers, dense layer, and dropout layer. The first and second layers are using 16 filters and third layer is using 32 filters. All layers using 2×2 of filter size. Then Flatten layer is used to create one dimensional set of data. Dense layer with 512 neurons is used in this model. To avoid the overfitting, the dropout layer with 0.5 is used. The proposed model can be seen in Fig. 2.

L. Evaluation Metrices

The model's performance is evaluated based on several parameters, including accuracy, precision, recall, F1 score, and AUC-ROC. Before these parameters are introduced, the concept of a confusion matrix is introduced first. The confusion matrix displays the accurate or inaccurate prediction outcomes in binary classification. The concept comprises four components: True Positive (TP, predicted positive and was positive), False Positive (FP, predicted positive but was negative), True Negative (TN, predicted negative and was negative), and False Negative (FN, predicted negative but was positive). Next, the accuracy is computed utilizing the subsequent formula.

$$Accucary = \frac{TP+TN}{TP+FP+TN+FN} \tag{4}$$

Furthermore, precision predicts the proportion of correct predictions.

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

Recall predicts the correct proportion of positives.

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

The F1-Score considers precision and recall rates.

$$Recall = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{7}$$

III. RESULTS AND DISCUSSIONS

In the Results section, we present the performance of each model, including our proposed model. We evaluated the performance of each model based on several parameters, including the accuracy, precision, recall, F1-Score, and AUCROC.

A. Accuracy

Fig. 3 shows that the proposed model outperformed five well-known models used for comparison. None of the five methods exceeds 0.9 for validation data and new and different testing data. Meanwhile, our proposed model has an accuracy of 0.96 on validation data and 0.95 on new and different testing data. These accuracy values demonstrate the superiority of our proposed model over the other models.

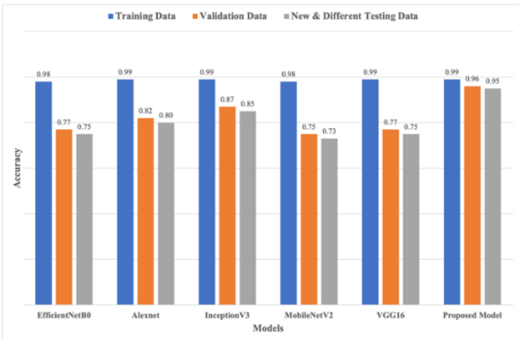

Fig. 3. Accuracy of each model.

B. Precision

Fig. 4 shows the five well-known models used to compare validation data and new and different testing data. All of them exceed 0.8, but none exceed 0.9. The results in Fig. 4 also show that there are no symptoms of overfitting. Meanwhile, our proposed model has precision values of 0.89 and 0.94 for validation data and new and different testing data, respectively. This result shows that our proposed model outperforms other benchmark models.

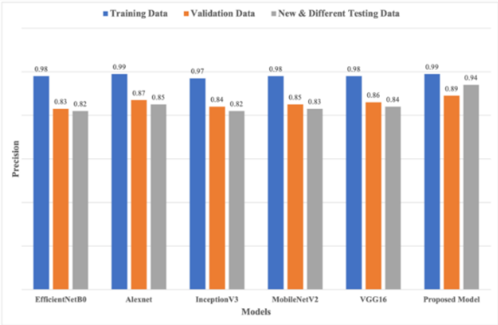

Fig. 4. Precision of each model.

C. Recall

The recall values in Fig. 5 show that all models have excellent recall values in the validation data. Meanwhile, in the new and different testing data, only the AlexNet model reached 0.9, and our proposed model reached a value of 0.95. These results demonstrate the superiority of our model over other models. Fig. 5 also shows no overfitting in the recall values obtained.

Fig. 5. Recall of each model.

D. F1-Score

The F1-Score in Fig. 6 shows that the values of the five well-known models used are 0.75 to 0.81 for validation data and new and different testing data. However, all well-known models have an accuracy above 0.97 for training data. These results show that the F1-Score is below the training and validation data values. Meanwhile, our proposed model shows almost the same F1-Score as five well-known models on the training data. Our proposed model outperforms well-known benchmark models on validation data and new and different testing data.

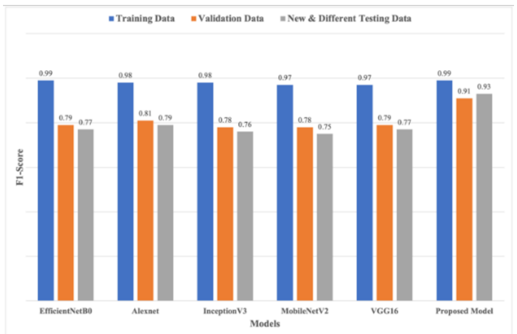

Fig. 6. F1-Score of each model.

TABLE I. PERFORMANCE OF ALL MODELS

Models		**Training Data**	**Validation Data**	**New and Different Testing Data**
EfficientNetB0	Accuracy	0.98	0.77	0.75
	Precision	0.98	0.83	0.82
	Recall	0.97	0.96	0.83
	F1-score	0.99	0.79	0.77
	AUC-ROC	0.98	0.73	0.70
Alexnet	Accuracy	0.99	0.82	0.80
	Precision	0.99	0.87	0.85
	Recall	0.98	0.97	0.90
	F1-score	0.98	0.81	0.79
	AUC-ROC	0.99	0.75	0.72
InceptionV3	Accuracy	0.99	0.87	0.85
	Precision	0.97	0.84	0.82
	Recall	0.97	0.96	0.80
	F1-score	0.98	0.78	0.76
	AUC-ROC	0.98	0.74	0.71
MobileNetV2	Accuracy	0.98	0.75	0.73
	Precision	0.98	0.85	0.83
	Recall	0.97	0.96	0.82
	F1-score	0.97	0.78	0.75
	AUC-ROC	0.99	0.76	0.72
VGG16	Accuracy	0.99	0.77	0.75
	Precision	0.98	0.86	0.84
	Recall	0.98	0.97	0.83
	F1-score	0.97	0.79	0.77
	AUC-ROC	0.99	0.76	0.73
Proposed Model	Accuracy	0.99	0.96	0.95
	Precision	0.99	0.89	0.94
	Recall	0.99	0.98	0.95
	F1-score	0.99	0.91	0.93
	AUC-ROC	0.99	0.84	0.94

E. AUC-ROC

Fig. 7 shows that the well-known model has an AUC-ROC value on validation data and new and different testing data lower than the training data. The AUC-ROC values in Fig. 7 shows the superiority of our proposed model compared to the well-known model used as a comparison.

Fig. 7. AUC-ROC of each model.

Table I shows the overall results of the experiments carried out in this study. Table I presents the Accuracy, Precision, Recall, F1-Score, and AUC-ROC values for each model used.

Based on the Accuracy, Precision, Recall, F1-Score, and AUC-ROC values presented in Table I, we can analyze that our proposed model consistently outperforms the five well-known models used as comparisons. The model we proposed has only three layers of convolutional layers. The number of layers is smaller than the five well-known models used for comparison. The proposed model on new and different data testing consistently outperforms the five well-known models.

Based on these findings, we can confidently assert that our proposed model is appropriate for distinguishing between healthy and diseased patchouli leaves. Meanwhile, the five well-known models used as performance comparisons were not optimal because patchouli leaf disease was a small dataset. Meanwhile, the well-known models used for comparison are more complex. Hence, the results for the patchouli dataset as a small dataset are less suitable than the simple model we proposed. Thus, these models do not perform optimistically for the patchouli leaf dataset.

We recommend the proposed model as an early detection system for patchouli leaf disease based on these results. The model can act as an early identification system for patchouli leaf disease that will assist farmers in selecting patchouli seeds or parents for patchouli cultivation. This system will help identify healthy patchouli seedlings by identifying the presence or absence of disease in patchouli leaves. Ensuring that the patchouli used as seeds/parents are free from disease (healthy) will prevent the spread of patchouli disease from one area to another. It is based on the fact that Patchouli seeds are often brought from an area providing patchouli seeds to another area, which will be used as a place or area for patchouli cultivation.

IV. Conclusions

This study focuses on the early diagnosis of patchouli leaf disease in Indonesia using a Convolutional Neural Network (CNN) technique. Currently, specialists rely on laboratory testing of antiviral serum to promptly detect the health status of patchouli plants. Nevertheless, this testing procedure incurs high costs. Thus, this paper introduced a novel Convolutional Neural Network (CNN) structure for detecting patchouli leaf disease. We have devised a technique that aims to detect the health status of a patchouli leaf at an early stage, distinguishing between damaged and healthy leaves. The architecture of our CNN model consists of three convolutional layers, followed by a dense layer and a dropout layer. We compare the proposed and established models, including EfficientNetB0, AlexNet, InceptionV3, MobileNetV2, and VGG16. The results demonstrate that the proposed model surpassed five renowned models in comparison. The confirmation was obtained through the prediction of novel and distinct testing results. This research aims to facilitate the early detection of patchouli leaf disease, mitigating the financial burden of diagnosing such diseases.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

R initiated the research topic, provided guidance in the research, assisted in refining the research findings, conceived and designed the experiments, analyzed and interpreted the data, analysis tools or data and wrote the paper. RN contributed reagents, materials, and wrote the paper. SK assisted in refining the research findings, conceived and designed the experiments, analyzed and interpreted the data. SR provided guidance in the research and assisted in refining the research findings. M contributed reagents, materials, and wrote the paper. NKCP provided guidance in the research and assisted in refining the research findings. MHB provided guidance in the research and assisted in refining the research findings. KU provided guidance in the research and assisted in refining the research findings. All authors had approved the final version.

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