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Early Identification of Skin Cancer Lesions with CNN Model

Levina Tracy Jurem[1], Ida Laila bin Ahmad[1]*

[1] *Faculty of Electrical and Electronic Engineering,*
Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, MALAYSIA

*Corresponding Author: ida@uthm.edu.my
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Abstract

Skin cancer is considered to be the most common and dangerous type of cancer. Information technology techniques are required to identify the possibility of skin cancer. Therefore, there is a need for an early and accurate skin cancer detection by employing an efficient deep learning technique. This research work proposes automatic diagnosis of skin cancer by employing Convolution Neural Network (CNN) model. The purposed model is able to classify the image as benign and malignant skin lesions and obtained an accuracy of 86.74%. Moreover, a notable characteristic of this research lies in its utilization of the CNN model integrated within a Graphical User Interface (GUI) application developed using the Tkinter toolkit. The GUI application are designed to be user-friendly, allowed user to experience enhanced and simplified interaction. The work implemented is expected to be helpful model in the early detection of skin cancer in the field of medicine and healthcare.

1. Introduction

The depletion of the ozone layer leads to a yearly rise in skin cancer cases as it enables the penetration of ultraviolet (UV) sunlight through the atmosphere [1]. Skin cancer that develops in the skin can lead to abnormal growth in the outermost layers of the skin called the epithelium, resulting in a condition commonly identified as a skin lesion. Mutations are induced by it and it also disseminates throughout various regions of the body. It frequently manifests on painless elevated portions of the skin, resembling smooth, pearly bumps caused by sun-related damage to the skin's tiny blood vessels [2]. The American Cancer Society reports an estimated 100,350 cases of melanoma in American adults (60,190 men and 40,160 women). In the year 2020, it is projected that approximately 6,850 adults will succumb to melanoma, comprising 4,610 men and 2,240 women [3]. Thankfully, if skin cancer is detected and treated promptly during its initial stages, the chances of survival are significantly high [4].

Deep learning algorithms have recently boosted the accuracy of identifying skin cancer lesions. In recent years, deep learning algorithms have been used to develop early identification of skin cancer lesions system with high accuracy. As deep learning algorithms engage with training data, they are progressively enhancing their precision and accuracy, leading to fresh understandings regarding diagnostics, treatment possibilities, and patient results [5]. Deep learning is known for its high accuracy and excellent performance because it can automatically learn features from inputs [6]. Convolutional Neural Networks (CNNs) based models have proven to be effective in solving complex tasks like classification, segmentation, and object detection in computer vision and pattern recognition [7]. Despite this, improvements in user-friendliness and dataset size are needed. The M. S. Junayed, and et al., model is accurate but not user-friendly [8]. Moreover, The MobileNet V2 model by Nurul Fatihah shows promise but can be improved by using a larger dataset and segmentation techniques [9]. Researchers should create accessible applications for both healthcare professionals and individuals concerned about skin health. Nonetheless, a larger dataset will enhance the model's ability to distinguish between various skin abnormalities, while segmentation techniques will improve lesion boundary identification for more precise predictions. Thus, the utilization of a CNN model in this work aligns with findings from existing literature reviews that have demonstrated similar approaches. These reviews have highlighted the superior accuracy of CNN, which utilizes convolution as a mathematical operation involving matrix multiplication, typically in at least one layer [10,11]. This research employed deep learning and CNN algorithms to diagnose, classify, and segment images of melanoma skin cancer.

This study's goals are to develop an automated system for skin cancer detection utilizing CNN techniques, design a graphical user interface (GUI) for the system that has been created, simulate the algorithm using Jupyter Notebook and Tkinter, and run accuracy tests to assess the system's performance. The goal is to develop a reliable tool that will allow patient to receive further diagnosis and treatment by medical professionals after this early skin cancer detection and provide a seamless user experience using the system.

2. Methodology

2.1 System Overview

The workflow for Early Identification of Skin Cancer Lesions with CNN Model, as in Fig. 1 consists of two parts of development which are model development and GUI development. The system starts with collection of images of skin lesion from device gallery. Then, the image data was preprocessed to develop in the deep learning process. It will go through resizing, augmentation, data splitting and normalization. For feature extraction technique, the preprocessed images were used to develop the deep learning by train and evaluating the images with CNN model. To build the GUI application, the Tkinter tool was used to deploy the model.

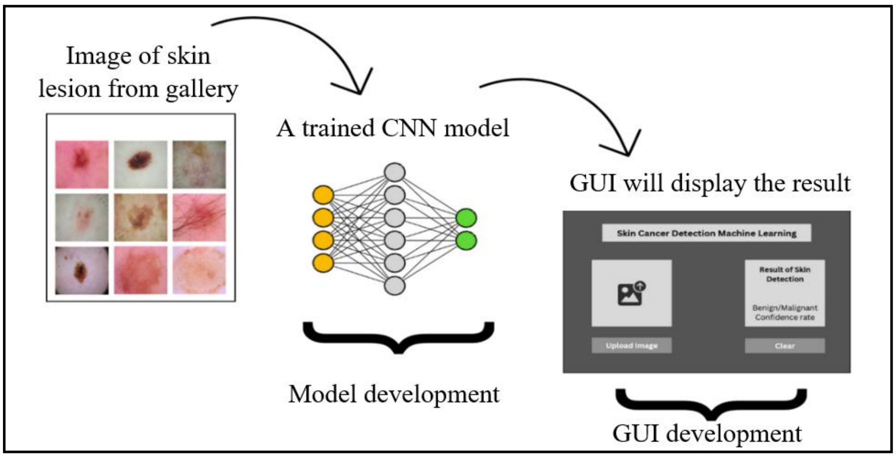

Fig. 1 *System overview*

2.2 Data Collection

These include benign and malignant skin lesion datasets that can be found the International Skin Imaging Collaboration (ISIC) archive [10] which contains a total of 1800 images depicting benign moles and 1497 images featuring classified malignant moles. All of the pictures have been resized to a lower resolution of 224x224x3 in RGB format. Fig. 1 shows the sample dataset used in this work.

2.3 Data Preparation

Selecting, constructing (data attributes), reformatting and integrating (merge the data) of the data are involved in the data preparation phase. Additionally, the dataset was split randomly into two sections, where for training there were 1197 pictures of malignant skin and 1440 pictures of benign skin. Meanwhile for testing, 300 pictures of malignant skins and 360 pictures of benign skin were put separately.

2.4 Convolution Neural Network (CNN)

The Convolutional Neural Network (CNN) architecture is optimized and consists of multiple layers of interconnected nodes, including convolutional layers, pooling layers, and fully connected layers where it extracts meaningful features from the input data and accurately classify it into different categories. A CNN model can be used to distinguish skin cancer lesions where it is trained using labelled sets for both training and validation. The CNN model is made to recognise trends and traits linked to skin lesions that are malignant or benign. After training, the CNN model can be deployed to new picture analysis for actual skin cancer lesion recognition. This technique enhances the efficacy and reliability of the diagnostic procedure by making it easier to precisely and automatically identify skin cancer lesions. The CNN architecture for skin cancer lesion detection can vary based on factors like dataset size and computational resources. The development of the CNN model to detect skin cancer is shown in Fig. 2 while the flowchart of model development is shown in Fig. 3.

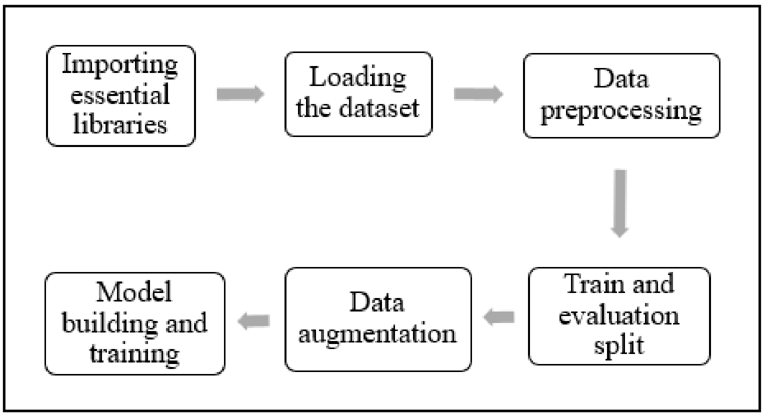

Fig. 2 *Block diagram of CNN model development*

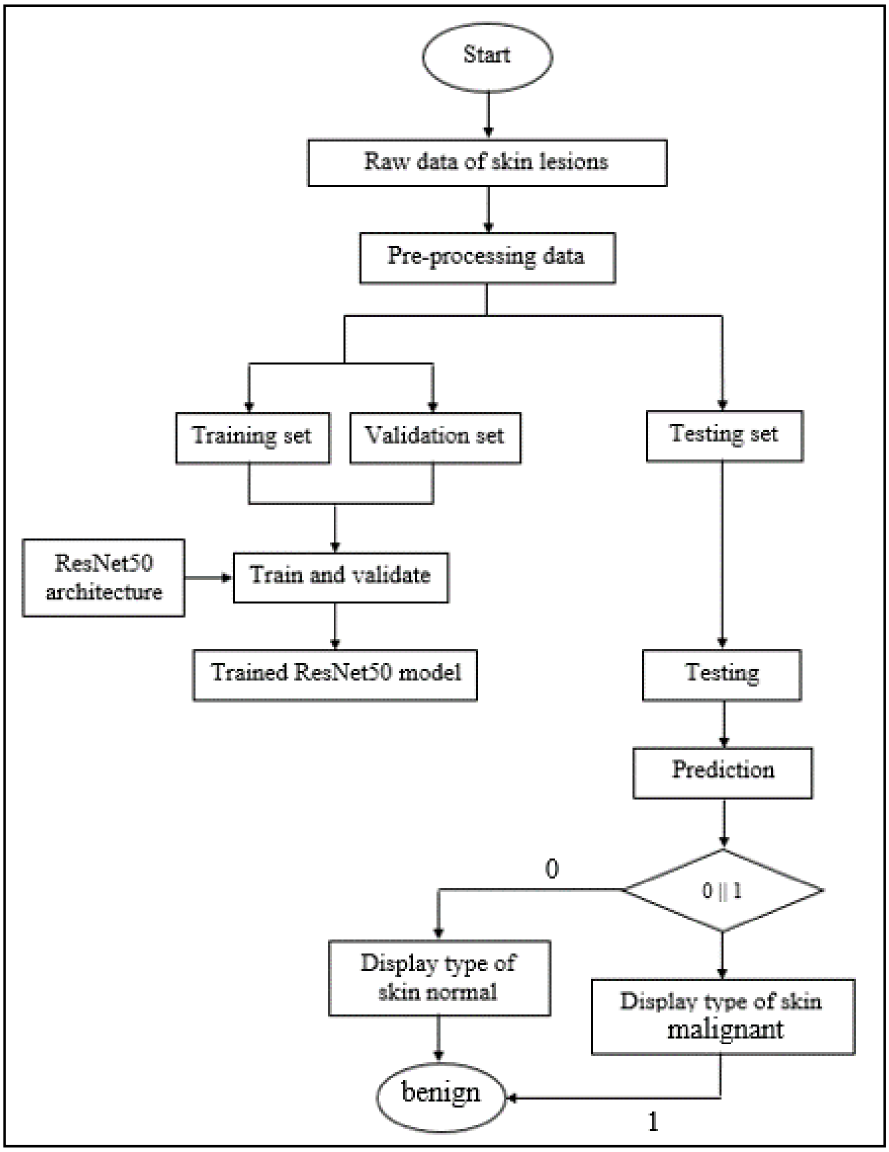

Fig. 3 *Flowchart of model development*

2.5 GUI Application Development using Tkinter

A graphical user interface (GUI) is deliberately made to be simple and user-friendly where anyone may use them without any prior experience with programming [10]. To create the GUI for the skin cancer detection application the pre-trained CNN model for skin cancer detection needs to be loaded and then saved in the HDF5 format. Furthermore, various frames were designed. The GUI consists of a main window and separate frames for different purposes. These frames include input parameters frame that allows users to upload an image of a skin lesion for analysis then, the output parameters frame shows the results of the skin cancer detection process, including a graphical representation of accuracy and loss. The workflow of the developed user-friendly GUI is shown in Fig. 4.

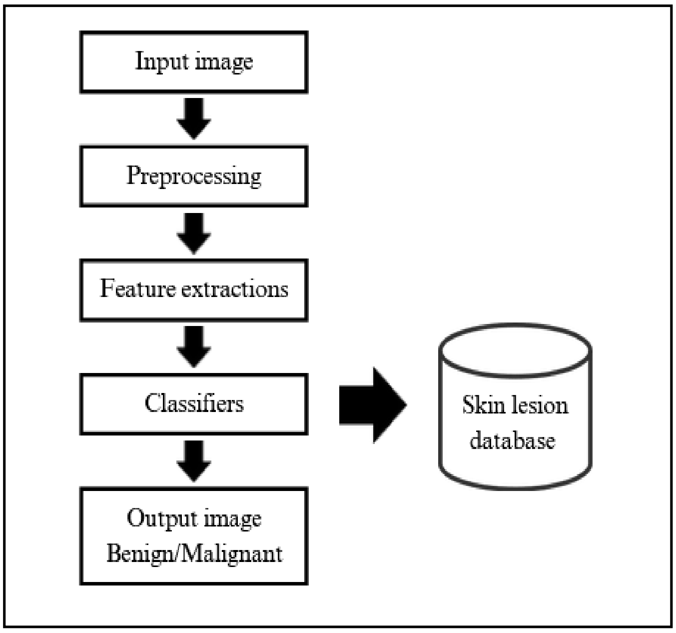

Fig. 4 *Workflow of the GUI application*

3. Result and Discussion

Results analysis will assist in understanding the performance in each area of the work. The results contain the learning curve of the model, confusion matrix and classification report. Besides, the model system result, receiver operating characteristic (ROC) curve and area under the ROC curve (AUC) curve as well as raw prediction using test datasets. Then, the second part of this work is the GUI development for the system deployment.

3.1 Learning Curve of The Model

In Fig. 5, the accuracy of using CNN model to detect skin lesion images is 86.74% of correct predictions on the test data. Further improvement can be made on the model using more complex layers get a better performance. The accuracy and loss curve graphs are shown Fig. 6. These plots help visualize the CNN model's performance and assess if overfitting or underfitting is occurring. In the accuracy curve graph the training accuracy and the validation accuracy are both rising. This determined that the model is learning and improving its predictions. Meanwhile, in loss curve graph, the training accuracy and the validation accuracy are both decreasing. This indicates that the model is minimizing the difference between predicted and actual values.

```
accuracy_score(np.argmax(y_test, axis=1), np.argmax(Y_pred, axis=1))

0.8674242424242424
```

Fig. 5 *Accuracy score using CNN model*

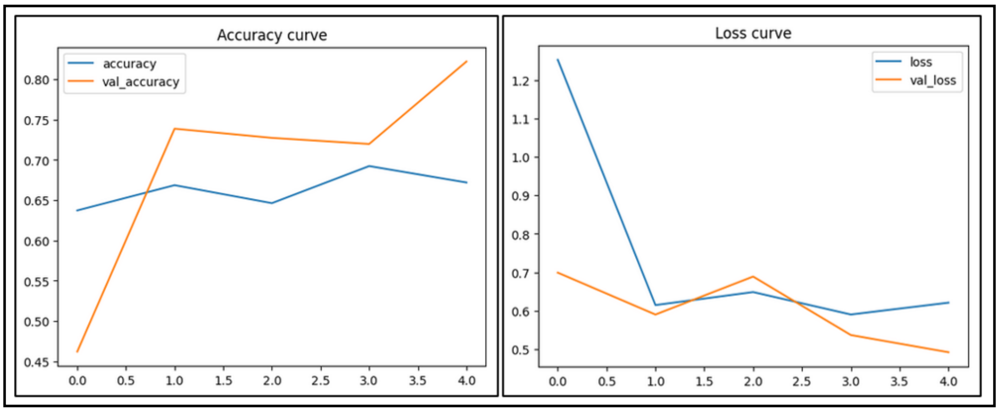

Fig. 6 *Accuracy and loss curve graphs*

3.2 Confusion Matrix

The Fig. 7 describes the confusion matrix by using CNN model with the actual and predicted labels shown in 2x2 as there are two classification of skin detection which are benign and malignant. From the confusion matrix, the TN is where 129 predictions were made correctly classified a benign. Then, the FP is where 20 predictions were made incorrectly a benign as a malignant. Next, 15 predictions were categorized as FN because it incorrectly classified a malignant as benign. Lastly, 100 predictions were categorized as TP where the model made correct classification of a malignant.

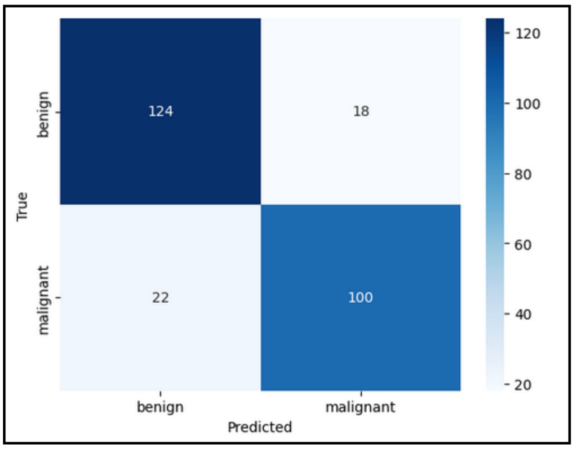

Fig. 7 *Confusion matrix for CNN model*

3.3 Classification Report

From Fig. 8 indicates the performance evaluation based on the classification report of the CNN model. According to the classification report, the CNN predicted 89% of the classes accurately. The classification of benign skin is 90% and malignant skin have precision of 83%. Meanwhile, for recall, classification of benign skin and malignant skin shared the same percentage which is 87%. Moreover, benign skin classification has better F1-score of 88% than malignant skin which only achieved 85%.

```
print(classification_report( np.argmax(y_test, axis=1), np.argmax(Y_pred, axis=1),
                            target_names=['benign', 'malignant']))

              precision    recall  f1-score   support

      benign       0.90      0.87      0.88       149
   malignant       0.83      0.87      0.85       115

    accuracy                           0.87       264
   macro avg       0.86      0.87      0.87       264
weighted avg       0.87      0.87      0.87       264
```

Fig. 8 *Classification report of CNN model*

3.4 ROC and AUC Curve

The ROC curve and AUC curve are tools used to evaluate the performance of classification model in this research and provide insights into the model's classification performance, particularly in binary classification tasks. The ROC curve displays the relationship between the true positive rate (correctly predicted benign or malignant skin lesion) and the false positive rate (incorrectly predicted benign or malignant skin lesion) across different classification thresholds. A higher AUC indicates that the model has better discrimination ability, meaning it is more capable of correctly identifying positives and negatives rate. The graphical representation of the ROC of this research is shown in Fig. 9 and the AUC of CNN model is 87%.

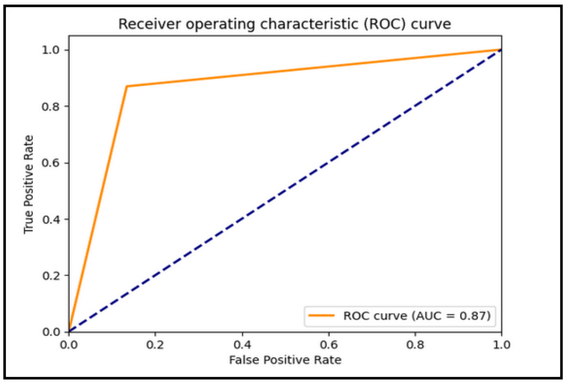

Fig. 9 *ROC and AUC curve of CNN model*

3.5 Raw Prediction Using Test Data

In Fig. 10 and Fig. 11 displayed the results of raw prediction using test dataset in the Jupyter Notebook. The predicted class name is assigned based on the class index (0 for "Benign" and 1 for "Malignant"). Both percentage of class probability were 99.99% for testing malignant image and 78.35% for testing benign skin.

Fig. 10 *Classification of test dataset is correctly predicted as malignant*

Fig. 11 *Classification of test dataset is correctly predicted as benign*

3.6 GUI Application Result

The results of testing the GUI application of CNN Model System for Automated Detection of Skin Cancer are shown in Fig. 12 and Fig. 13. The test datasets of benign and malignant skin lesions obtained from ISIC archive were used to test this GUI application. To make sure it is function effectively, the confidence percentage were also displayed below the result of the skin tested. Fig. 14 shown were correctly identified in all three rotations, with consistent confidence percentages of 0.86% and 0.80% for no rotation, left rotation, and right rotation respectively. The result depicted at Fig. 14 projects the effectiveness of this approach by rotating the image of skin lesions to left and right, as a means of enhancing skin lesion detection.

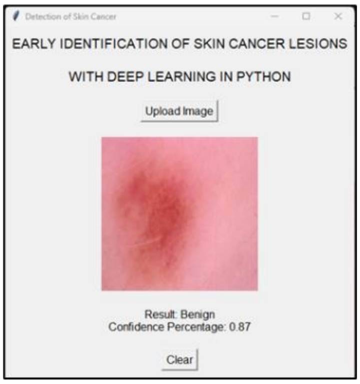

Fig. 12 *Classification of test dataset is correctly predicted as benign*

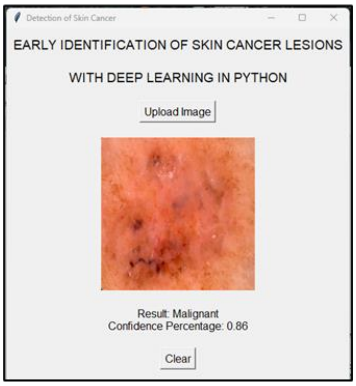

Fig. 13 *Classification of test dataset is correctly predicted as benign*

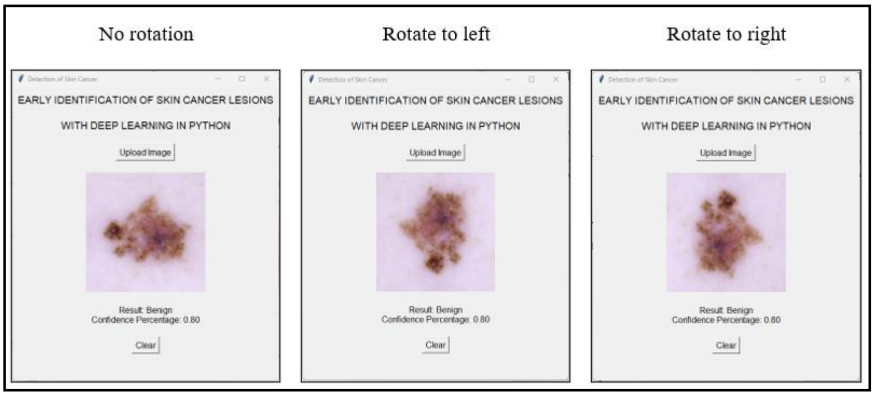

Fig. 14 *Result of skin lesion with different angle rotations*

3.7 Discussion

This work discovered that the GUI application of the CNN model system can identify seven (7) out of eight (8) test datasets correctly and also almost have the same confidence rate whenever the image of dataset was manipulated in term of rotations. The CNN model's inaccurate predictions may result from both presence of noise or artifacts in the test dataset such as unusual lighting conditions, or image artifacts, could contribute to misclassifications and a susceptibility to overfitting, hindering its performance on unseen data with variations not present in the training set. Furthermore, identifying the early stages of lesion formation often pose challenges for accurate diagnosis. Although the sample images selected for this work comprise a diverse range of clear malignant and benign lesions, these images predominantly depict lesions that were relatively straightforward for diagnosis, lacking the complexity often associated with early-stage lesions.

4. Conclusion

In conclusion, all objectives of this work have been achieved successfully by demonstrating the efficacy of an automated skin cancer detection system using a CNN model. The CNN method had gone through several performance evaluations such as the accuracy, sensitivity, F1 score, confusion matrix and AUC score. Nevertheless, the accuracy score of the CNN to recognize skin cancer lesions is good since it is more than 86.74%. Moreover, the GUI application of the CNN system was done and can be use easily to identify the skin lesion type. Thanks to Tkinter and TensorFlow, the trained CNN model can be deployed in the GUI. Last but not least, there are several improvements that can be made to this application in the future such as noise reduction, early stopping to decrease overfitting and patient communication feature.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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