Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777678

BEST HYPERPARAMETER COMBINATION ANALYSIS ON CNN FOR HUMAN SKIN DISEASE DETECTION

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Abstract
Convolutional Neural Networks (CNN) have been widely used for image classification tasks, including human skin disease detection. In recent years, various improvements have been made to CNN architectures, with the aim of increasing the accuracy and efficiency of these networks. However, to achieve optimal performance on a specific task, it is essential to select the best combination of hyperparameters that can significantly impact the performance of the CNN. In this study, we investigate the effects of different hyperparameter combinations on the accuracy of CNN-based human skin disease detection models. Our research employs popular CNN architectures, such as VGG16, InceptionV3, and ResNet50, and explores various hyperparameter tuning approaches, including grid search, random search, and Bayesian optimization. We also assess the benefits of data augmentation and transfer learning in enhancing the performance of the CNN models. Through our experiments, we aim to identify the best hyperparameter configurations for human skin disease detection and provide insights into the performance of different tuning approaches.
Keywords: Convolutional Neural Networks (CNN), Hyperparameter Tuning, Human Skin Disease Detection.

1. Introduction

Human skin diseases are among the most common health problems worldwide, affecting millions of people each year [1]. Early and accurate detection of skin diseases is essential for effective treatment and prevention, skin diseases that occur in humans have a significant impact on the quality of life [2]. In modern era, utilizing a digital image processing-based system for diagnosing skin diseases is an innovative solution that healthcare professionals can utilize. This method of assistance enables patients to receive timely and appropriate treatment, thereby reducing the transmission of diseases to others and expediting the overall diagnostic process

[3]. Image processing has become an established technology that has been used in various fields, including the medical field, because of the ability of computers to process visual information. This includes the application of image processing techniques to identify skin diseases [4]. In recent years, the application of deep learning techniques, particularly Convolutional Neural Networks (CNN), has demonstrated promising results in various computer vision tasks, including the detection of human skin diseases [5], [6].The high number of layers in convolutional neural network (CNN) structures allows them to independently grasp the characteristics, resulting in enhanced image classification performance[7].

2. Related Works

Image processing is a familiar concept in the world of technology because images are a form of information that can be analyzed and manipulated by computers. Likewise, in the medical field, image processing techniques are used to assist in the identification and diagnosis of various diseases, including the detection of skin diseases in humans [8].

The prevalence of skin diseases in recent years has prompted the significant role of automated recognition systems. The disease detection process needs to be sufficiently mature in accurately identifying a skin condition. In the study conducted in the journal [9], the CNN algorithm was employed, achieving a high accuracy of 98% with a dataset consisting of seven types of skin diseases, namely Acne and rosacea, Actinic keratosis basal cell carcinoma, Eczema, Nail Fungus, Psoriasis, Seborrheic, Light Diseases and Disorders of Pigmentation.

In another study, CNN was employed for the detection of malignant and non-malignant skin diseases. The aim of the research was to develop a CNN architecture for skin identification. The results showed that CNN achieved an accuracy of 93% for malignant skin diseases and 74% for non-malignant skin diseases [10].

CNN with the NASNet architecture was employed for skin disease identification. The use of CNN with the NASNet architecture allowed for more accurate recognition without segmentation. In the study, the developed model achieved a relatively high accuracy ranging from 75% to 84%. The best performance based on training accuracy was obtained from Xception with 85% [11].

In a study on melanoma, an efficient and accurate method for melanoma identification was proposed. The researchers implemented the Mixed Skin Lesion Picture Generate method based on Mask R-CNN to address data imbalance and designed a melanoma detection framework called Mask-DenseNet+. Experimental results on the ISIC dataset showed improved accuracy (90.61%), sensitivity (78.00%), specificity (93.43%), and AUC (0.9502) compared to previous methods. The proposed method proved to be feasible and effective, achieving the initial goal of melanoma detection[12].

This study employs the Convolutional Neural Network (CNN) method for image classification. CNN is a learning technique that addresses limitations of previous methods. It can handle variations in image positions, such as rotation, scaling, and translation, while reducing the number of independent parameters. Compared to other approaches, this method achieves high levels of accuracy in image processing [13].

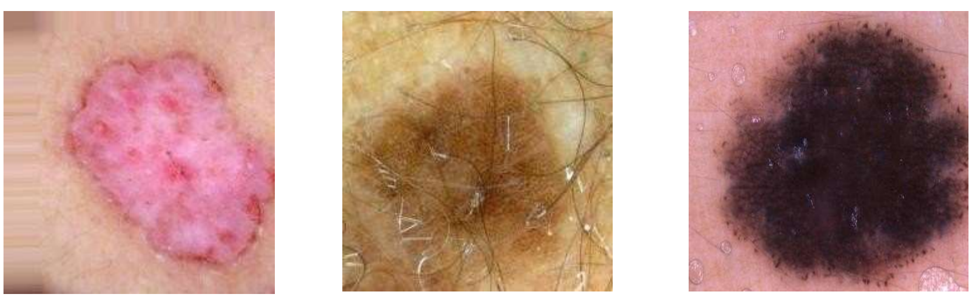
3. Methodology

Our study was conducted in a structured and sequential manner, starting with dataset acquisition and followed by preprocessing and the design of a model architecture using Convolutional Neural Network (CNN) as the method for skin disease detection. The dataset used was obtained from a secondary source on Kaggle, and the research employed a qualitative experimental approach. The research methodology began with dataset collection, followed by preprocessing, the application of hyperparameter tuning, testing the model without hyperparameter tuning, and finally testing the model with hyperparameter tuning.

3.1. Dataset

For the human skin disease detection task, we use the kaggle dataset, which is a public dataset containing 1,605 images of dermatoscopic lesions from different patients, categorized into three classes, including Eczema, Keratosis, dan Melanocytic Nevi. The dataset is split into 80% for training and 20% for testing.

The data we collected originates from two sources, namely Face Skin Diseases created by Amellia Mega in May 2022, and Skin Diseases Dataset created by Ammar Abasi in May 2022. From these two sources, we carefully curated the dataset, categorizing it into three distinct disease types, and subsequently uploaded it on Kaggle under the title "Dataset Skin Diseases."



(a) (b) (c)

Fig. 1. Human Skin Diseases (a) Eczema. (b) Seboroik Keratosis. (c) Melanocytic Nevi.

3.2. Preprocessing

The preprocessing stage is a crucial step in preparing the data before it is used in subsequent stages. The preprocessing stage involves normalization, data labeling, and augmentation. This stage takes as input a dataset that will be used in the hyperparameter tuning and model testing stages. The following are the steps involved in the preprocessing stage,

3.2.1. Data augmentation

Data augmentation is a process of modifying the existing data to increase its quantity while ensuring that the program recognizes the augmented data as distinct instances. This technique aims to prevent overfitting, particularly in cases where the available dataset is limited, and it can enhance the performance of the model [14]. By implementing data augmentation techniques, such as image rotation, flipping, or scaling, the dataset is artificially expanded with variations of the original images. This helps the model learn from diverse examples and enhances its ability to generalize and make accurate predictions[15].

In this study, data augmentation was performed by rotating the images by 30 degrees, applying a 10% zoom or magnification, shifting the images by 10% in both width and height dimensions, and horizontally flipping the images.

3.2.2. Gethering data

The purpose of data gathering is to merge the data obtained from Kaggle. The data is stored in a variable that contains the directories of the training, validation, and testing data, which will be used in the subsequent stages. The following is the total number of data after merging the datasets.

3.2.3. Splitting data

Data splitting involves dividing the data into training data, which is used for model training, validation data, which is used for hyperparameter tuning, and testing data, which is used for model evaluation. The data is split with a ratio of 8:1:1 for training, validation, and testing, respectively. The data used for data splitting is the augmented data, resulting in a total of 6,905 image datasets. Thus, the initial count of 1,605 datasets has increased to 6,905 image datasets.

3.2.4. Resize image

The resize image process is applied to improve the quality of the images, making them appear smoother, by mapping the source images to resized images. In this step, all the images of human skin diseases are resized to 128x128 pixels.

3.2.5. Normalization

Normalization is applied to accelerate convergence during the training phase by equalizing the pixel size of the images. In this study, we implemented a normalization technique called rescale, aiming to improve accuracy and reduce loss during the training process [1]. Data normalization is performed by transforming the range of each pixel from 0-255 to 0-1.

3.2.6. Labeling Data

Labeling is the process of assigning identities to images, which helps the model classify the images and improve classification accuracy. In this study, labeling was performed to categorize the images into three different categories: Eczeme, Seboroik Keratosis, and Melanocytic Nevi.

3.3. CNN Architectures

The design of the CNN model in this study consists of an input layer, convolutional layers, pooling layers, dropout layers, batch normalization, and fully connected layers. The convolutional layers use filters with values of (32, 64, 128), a kernel size of (3,3), a stride of 1, and padding set to "same", with the activation function being softmax. The dropout layer is divided into two parts, one before the pooling layer and another after the pooling layer.

We experiment with three popular CNN architectures: VGG16, InceptionV3, and ResNet50. These architectures have been proven to achieve state-of-the-art results in various image classification tasks. We employ transfer learning by initializing the models with pre-trained weights from the ImageNet dataset and fine-tuning the last few layers to adapt the models to the skin disease classification task.

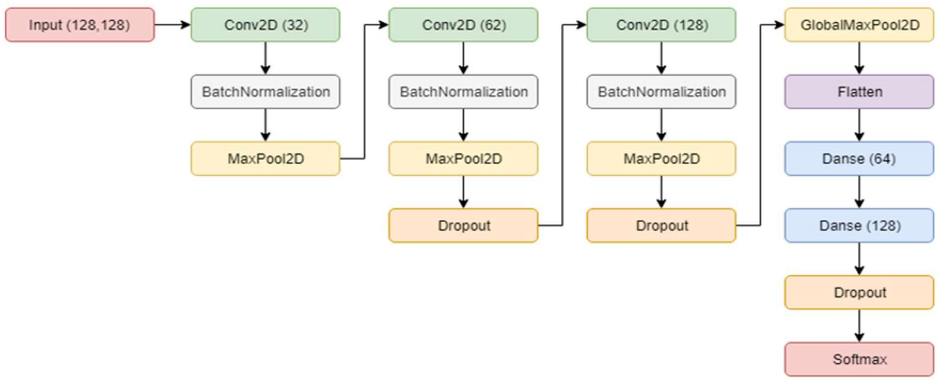


Fig. 2. CNN Architectures

3.4. Hyperparameter Tuning Approaches

The purpose of the hyperparameter tuning phase is to identify which parameters have the most significant impact on the created model architecture.

Parameters in deep learning algorithms have a significant impact on CNN models, thus hyperparameter tuning plays an important role in machine learning for deep learning algorithms. During hyperparameter tuning, the parameters are tested one by one using the attributes listed in the

Table 1. The parameters to be tested for comparison.

No.	Hyperparameter	Parameter
1.	Optimizer	Adam, Adamax, SGD, RMSProp
2.	Convolutional Layer	3
3.	Dropout setelah pooling layer (APL Dropout)	0.05, 0,1
4.	Dropout fully connected layer (Dropout)	0.25, 0,1
5.	Dense layer	64, 128

To search for the best hyperparameter combination, we explore three popular tuning approaches:

1. **Grid search**: A systematic search through a predefined set of hyperparameter values, where all possible combinations are evaluated. This method is exhaustive but computationally expensive.
2. **Random search**: A search that samples hyperparameter values from a predefined distribution. This method is less computationally expensive than grid search but may not cover all possible combinations.

3. **Bayesian optimization**: A probabilistic approach that models the objective function as a Gaussian process and iteratively selects the next hyperparameter values based on the acquisition function. This method balances exploration and exploitation and can be more efficient than grid search and random search.

The hyperparameters under consideration include learning rate, batch size, optimizer (SGD, Adam, or RMSprop), and the number of fine-tuned layers in the CNN architecture.

3.5. Evaluation Metrics

The performance of the CNN models is evaluated based on the accuracy, precision, recall, and F1-score on the test set. We also analyze the confusion matrix to gain insights into the model's performance on individual classes.

4. Results and Discussion

Our experiments reveal that the choice of hyperparameters significantly affects the performance of the CNN models for human skin disease detection. The best hyperparameter combination varies across different CNN architectures, emphasizing the importance of hyperparameter tuning for each specific model.

In terms of tuning approaches, Bayesian optimization outperforms grid search and random search in terms of both accuracy and computational efficiency. This finding highlights the effectiveness of Bayesian optimization in finding the optimal hyperparameter combination in a more efficient manner.
Data augmentation and transfer learning are found to substantially improve the performance of the CNN models, demonstrating their usefulness in enhancing the generalization capabilities of the models.

Among the three CNN architectures, ResNet50 achieves the best performance on the skin disease classification task, followed by InceptionV3 and VGG16. This result suggests that deeper and more complex architectures can be more effective in capturing the intricate patterns present in dermatoscopic images.

The research findings were obtained through several stages, including hyperparameter tuning tests on the CNN model and evaluating the impact of hyperparameter tuning on the classification results of the CNN model using two scenarios. The details of the scenarios to be conducted in this study can be seen in **Table** 2.

Table 2. Testing scenarios

No.	Skenario
1	CNN Model without hyperparameter tuning
2.	CNN Model with hyperparameter tuning

4.1. Results of CNN Model Testing without Hyperparameter Tuning

The results of the first scenario testing of the CNN model, as shown in **Figure 3**, were obtained without hyperparameter tuning. The testing was performed using Adamax optimizer, APL Dropout 0.05, dropout 0.25, and a dense layer of 128. The training process was conducted with 100 epochs and a batch size of 40. The results of the first scenario can be seen in **Figure 3**.

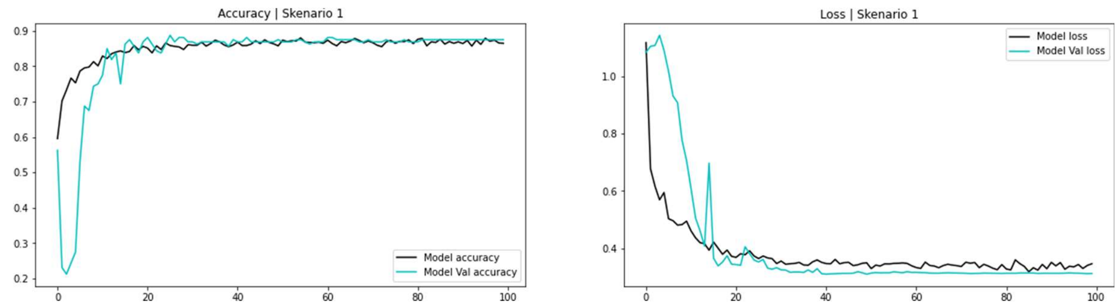


Fig. 3. Accuracy and Loss Results Without Hyperparameter Tuning

4.2. Result of Hyperparameter Tuning

The hyperparameter tuning process on the proposed CNN model resulted in 32 parameter combinations being tested, leading to the highest accuracy of 81.25%. The top 5 hyperparameter tuning results are presented in **Table 3.**

Table 3. The best parameters from hyperparameter tuning

No.	Optimizer	Convolutional Layer	APL Dropout layer	Dense Layer	Dropout layer	Akurasi
1.	RMSprop	3 Layer	0,05	64	0,5	81,25%
2.	RMSprop	3 Layer	0,1	128	0.5	79,37%
3.	RMSprop	3 Layer	0,05	64	0,25	73,75 %
4.	SGD	3 Layer	0,1	64	0,25	70,00%
5.	Adam	3 Layer	0,05	64	0,25	68,75 %

4.3. Results of CNN Model Testing with Hyperparameter Tuning

The results of the testing on the second scenario of the CNN model, as shown in **Figure 4**, were obtained with hyperparameter tuning. The testing was performed using RMSProp optimizer, APL Dropout of 0.05, dropout of 0.5, and a dense layer of 64. The training process was conducted for 100 epochs with a batch size of 40. The results of the second scenario can be seen in **Figure 4**.

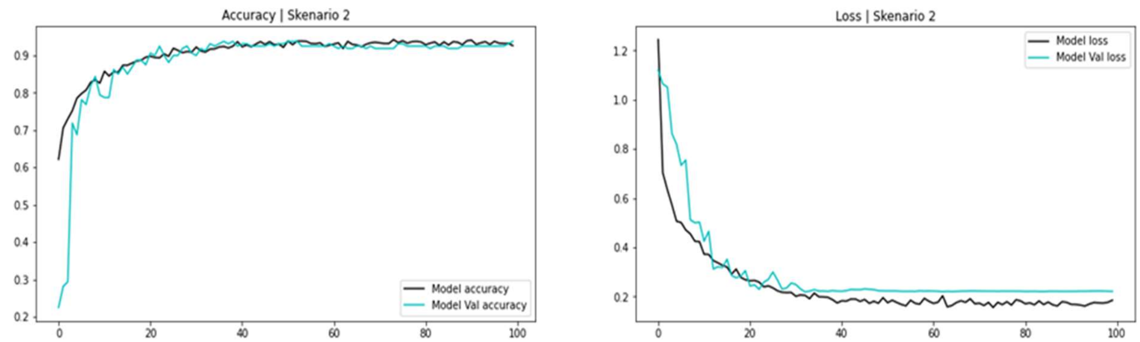


Fig. 4. Accuracy and Loss Results with Hyperparameter Tuning

Based on the training results using hyperparameter tuning, an accuracy of 97.81% was achieved. As shown in **Figure 4**, the visualization indicates that this combination produces a more stable model in terms of accuracy and loss. The training results also demonstrate the good performance of the model with hyperparameter tuning. Furthermore, the research results from each scenario reveal some differences in the confusion matrix, which can be observed in **Table** 4.

Table 4. Confusion matrix

Model	**Confusion Matrix (Average Macro)**		
	Accuracy	**Precission**	**Recall**
Scenario 1	91,63	0,93	0,90
Scenario 2	97,81	0,97	0,96

Based on the research results in **Table 4**, it is shown that there is an increase in accuracy by 6.18%, and there is also an increase in precision and recall percentages. The percentage increase in the confusion matrix between Scenario 1 and Scenario 2 indicates that the model with hyperparameter tuning demonstrates better performance.

5. Conclusion

This study provides a comprehensive analysis of the effects of different hyperparameter combinations on the accuracy of CNN-based human skin disease detection models. We demonstrate the importance of hyperparameter tuning in achieving optimal performance and highlight the benefits of data augmentation and transfer learning. Our findings can serve as a guide for practitioners and researchers in selecting the best hyperparameter configurations for human skin disease detection using CNN models.

In this study, we evaluated the performance of CNN models based on accuracy, precision, recall, and F1-score on the test set. Additionally, we analyzed the confusion matrix to gain insights into the model's performance across individual classes.

Our findings indicate that the choice of hyperparameter combinations significantly impacts the performance of CNN models for human skin disease detection. We emphasize the importance of hyperparameter tuning to achieve optimal performance.

Furthermore, we also discovered that data augmentation and transfer learning substantially enhance the performance of CNN models. This highlights the benefits of both techniques in improving the model's generalization capabilities.

Our findings can serve as a guide for practitioners and researchers in selecting the optimal hyperparameter configurations and utilizing data augmentation and transfer learning techniques for human skin disease detection using CNN models.

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Based on the research on human skin disease image detection, the best combination of hyperparameters was found to be 3 convolutional layers, 0.05 APL dropout, 0.5 dropout layer, 64 dense layers, and RMSProp optimizer. The accuracy percentage of scenario 1 without hyperparameter tuning resulted in 91.63%, while scenario 2 with hyperparameter tuning achieved an accuracy of 97.81%. The appropriate use of hyperparameters can significantly improve the classification quality of the CNN model. The testing results indicated that the proper selection of hyperparameters affects the CNN model's quality, thus requiring prior analysis of the employed hyperparameter combinations. Additionally, the accurate selection of data augmentation can also influence the accuracy of a classification model.

For future research, it is recommended to explore different combinations of hyperparameters, such as learning rate, learning rule, and batch size. Due to the difficulty in acquiring a diverse dataset of skin diseases, it is advisable to broaden the scope of the study by including various other common skin conditions like herpes, eczema, psoriasis, and ringworm, which are frequently experienced by the general public.

In testing the system regarding the images to be evaluated, it is expected to explore other improved data augmentation techniques for better classification results. Additionally, high-quality images are needed for both training the model and conducting the system testing.

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