

# Android-Based Herpes Disease Detection Application Using Image Processing

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**Abstract:** Herpes is a viral infection that causes a skin disease that is widespread throughout the world. Herpes virus is a DNA virus transmitted via infected skin, saliva, and other body fluids. Herpes is characterized by chickenpox-like nodules in one area of the skin, swollen tissue surrounding the nodule, and blister formation on the nodule. Digital image processing that can detect herpes disease is anticipated to reduce physical contact between physicians and patients during skin disease diagnosis. This study's methodology includes collecting data on herpes disease, developing machine-learning models using the CNN algorithm, and deploying the model as an Android application. This study makes use of actual data collected via smartphones, Pocket Cameras, and internet-sourced photographs. The data include 12,645 images of skin affected by herpes and normal skin. Using 100 epochs and the Adadelata optimizer, the accuracy of this study is 85 percent.

**Keywords:** Adadelata Optimizer, Android, CNN Algorithm, Herpes, Image Processing

## INTRODUCTION

The skin is the largest organ in the human body, covering all other organs and tissues (Hanin, Patmasari, and Nur 2021). The significance of the skin's function in the human body is magnified by the fact that even minute changes in function can affect other organs (Mailiza and Setiadhi 2018). The skin is in direct contact with the external environment, making it susceptible to infection and disease (Dyah, Murika, and Larasakti 2021). Herpes is one of the skin diseases that can be spread through direct contact (Nurkhasanah and Murinto 2022). The herpes virus is a DNA virus that spreads via infected skin, saliva, and other body fluids (Gautama, Hendrik, and Hendaya 2016). Herpes is characterized by chickenpox-like nodules on one region of the skin, inflamed tissue surrounding the nodule, and the nodule growing into a blister (Bonita and Dwi 2017)(Bonita and Murtiastutik 2017).

In general, it is more difficult for a skilled dermatologist to detect skin abnormalities early on (Dewi and Anggraini 2020). Using digital image processing to diagnose skin diseases permits a diagnosis to be established without touching the skin directly. Consequently, the development of Computer Aided Diagnosis Systems (CADs) has become a crucial area of medical research. Machine learning plays a vital role in the automation of several medical processes (Roihan, Sunarya, and Rafika 2020). Texture analysis must be performed in order to detect the determinants of skin disease during the automatic classification procedure (Haryadi et al. 2022). In machine learning, Convolution Neural Network (CNN) is a technique often used for image processing (Salawazo et al. 2019). CNN employs convolution by introducing a convolution kernel (filter) of a given size into an image (Nugroho, Fenriana, and Arijanto 2020)(Kasim and Satya Nugraha n.d.). By multiplying a piece of an image with the applied filter, the computer acquires new information that is representative (Stephen, Raymond, and Santoso 2019).

Implementation of CNN (Convolutional Neural Network) can be utilized to detect human emotions (A. et al. 2017). In this research on emotion/expression detection, numerous emotions can be classified according to their class, including angry emotions, happy emotions, frightening emotions, nasty feelings, surprising emotions, neutral emotions, and sad emotions. According to the results, the calculation of 40 epochs provided an accuracy of 81.92 percent for training and 81.62 percent for testing (Amaanullah et al. 2022)(Khoiruddin, Junaidi, and Saputra 2022).

In this study, therefore, we will use image processing to identify herpes disease using the Convolution Neural Network (CNN) technique (Ramprakash et al. 2020), followed by the implementation of the resulting model in an Android application to demonstrate its high accuracy.

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**METHOD**

This research methodology is executed methodically in order to get a good workflow that can be used as a guide for researchers undertaking this research, so that the results acquired do not diverge and the desired goals may be achieved correctly and in accordance with the predetermined aims.

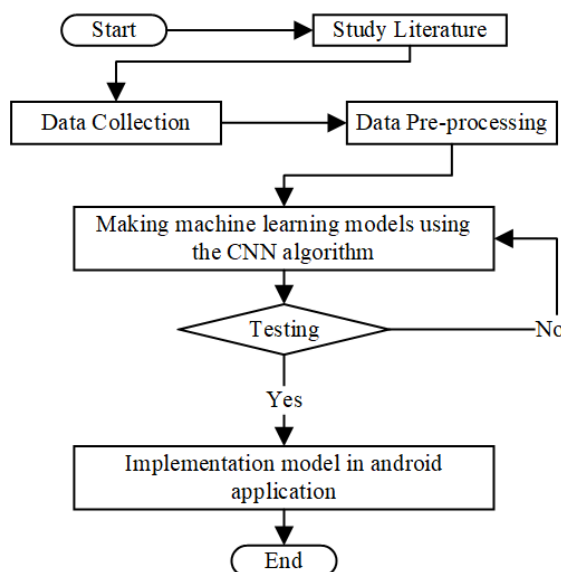


Figure 1 . Framework

To achieve the intended objectives, it is necessary to evaluate the pertinent literature. A review of the relevant literature was conducted to collect the fundamental knowledge and theories applied in this work.

Collecting data on herpes disease is the next step in the process of doing this research (Shen et al. 1992); data collecting is undertaken to gather the essential information to achieve the research objectives. The dataset for this study is comprised of actual data gathered by smartphone camera, pocket camera, and online photos. The data include 12,645 photos of skin infected by herpes and normal skin.

Following the collection of the dataset and pertinent literature is data preprocessing. The preprocessing phase is the phase of data selection that seeks to obtain clean, research-ready data. The methods include changing various types of data within the dataset in an effort to enhance data comprehension, as well as picking selections with a focus on data consistency, missing values, and redundancy.

After collecting and preparing adequate data, the CNN algorithm is applied to testing and training data (Sharma, Pal, and Jaiswal 2022). Adadelta will be utilized as the optimizer in this investigation. After identifying the most acceptable or suitable model for the herpes disease prediction example, the performance of the model is evaluated using up to 20% of the total data.

The culmination of this research is to build an android application that can detect herpes based on skin images using the CNN method. This application uses blackbox testing to measure the functionality of the application.

**RESULT**

**CNN Architecture**

CNN network design consists of Image for detection, Input Neuron, Convolution + Activation (ReLU) + Pooling layer, Fully connected layer, classification, and Detection output (Kumar et al. 2021)(Khemphila and Boonjing 2011). The following figure depicts the network architecture of the Convolutional Neural Network:

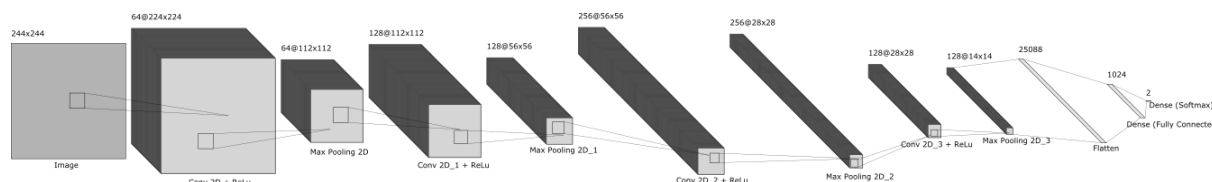


Figure 2. CNN Architecture

Several areas of the image above are identifiable as detection images (Shrestha et al. 2020), which will be recognized. In the figure, the training size is 224x224 pixels with RGB (Red, Green, and Blue) colors, which have three channels; hence, the 150,528 neurons that enter the first layer or Input neuron section are the result of

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224x224x3 calculations. Each neuron has a parameter value ranging from 0 to 255, and network parameters range from 0 to 255.

### Training and Examining Procedures for Accuracy

Instruction and Evaluation on Accuracy Steps are the training and testing procedure's stages, which indicate the training and testing's outcomes. The following are the outcomes of the training and testing phases for the dataset.

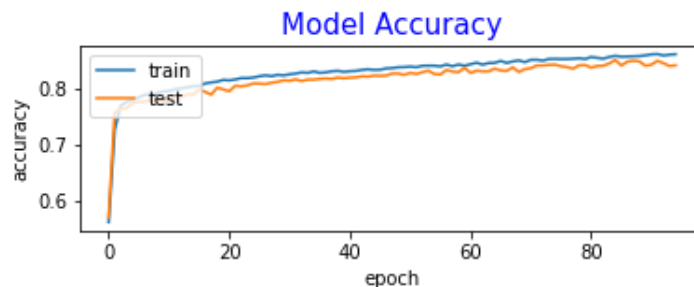


Figure 3. Graphic Display of Training and Testing

Figure 3 displays the results of training and testing, which reveal that the accuracy of the picture dataset used for training and initial testing is poor. From the 20<sup>th</sup> to the 100<sup>th</sup> epoch, the precision level begins to increase.

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Herpes Identification-Model1.ipynb
File Edit View Insert Runtime Tools Help Changes will not be saved

+ Code + Text Copy to Drive

Epoch 90/100
317/317 [=====] - ETA: 0s - loss: 0.3272 - accuracy: 0.8578
Epoch 00090: val_loss did not improve from 0.34044
317/317 [=====] - 1013s 3s/step - loss: 0.3272 - accuracy: 0.8578 - val_loss: 0.3420 - val_accuracy: 0.8395
Epoch 91/100
317/317 [=====] - ETA: 0s - loss: 0.3265 - accuracy: 0.8596
Epoch 00091: val_loss did not improve from 0.34044
317/317 [=====] - 1013s 3s/step - loss: 0.3265 - accuracy: 0.8596 - val_loss: 0.3453 - val_accuracy: 0.8414
Epoch 92/100
317/317 [=====] - ETA: 0s - loss: 0.3258 - accuracy: 0.8601
Epoch 00092: val_loss did not improve from 0.34044
317/317 [=====] - 1012s 3s/step - loss: 0.3258 - accuracy: 0.8601 - val_loss: 0.3548 - val_accuracy: 0.8482
Epoch 93/100
317/317 [=====] - ETA: 0s - loss: 0.3258 - accuracy: 0.8577
Epoch 00093: val_loss improved from 0.34044 to 0.33835, saving model to model\model1.h5
317/317 [=====] - 1005s 3s/step - loss: 0.3258 - accuracy: 0.8577 - val_loss: 0.3384 - val_accuracy: 0.8438
Epoch 94/100
317/317 [=====] - ETA: 0s - loss: 0.3238 - accuracy: 0.8591
Epoch 00094: val_loss did not improve from 0.33835
317/317 [=====] - 1015s 3s/step - loss: 0.3238 - accuracy: 0.8591 - val_loss: 0.3707 - val_accuracy: 0.8391
Epoch 95/100
317/317 [=====] - ETA: 0s - loss: 0.3236 - accuracy: 0.8598
Epoch 00095: val_loss did not improve from 0.33835
317/317 [=====] - 1005s 3s/step - loss: 0.3236 - accuracy: 0.8598 - val_loss: 0.3427 - val_accuracy: 0.8403
Epoch 96/100
317/317 [=====] - ETA: 0s - loss: 0.3221 - accuracy: 0.8578
Epoch 00096: val_loss improved from 0.33835 to 0.33544, saving model to model\model1.h5
317/317 [=====] - 1023s 3s/step - loss: 0.3221 - accuracy: 0.8578 - val_loss: 0.3354 - val_accuracy: 0.8505
Epoch 97/100
317/317 [=====] - ETA: 0s - loss: 0.3213 - accuracy: 0.8604
Epoch 00097: val_loss did not improve from 0.33544
317/317 [=====] - 1003s 3s/step - loss: 0.3213 - accuracy: 0.8604 - val_loss: 0.3411 - val_accuracy: 0.8434
Epoch 98/100
317/317 [=====] - ETA: 0s - loss: 0.3207 - accuracy: 0.8593
Epoch 00098: val_loss did not improve from 0.33544
317/317 [=====] - 1002s 3s/step - loss: 0.3207 - accuracy: 0.8593 - val_loss: 0.3504 - val_accuracy: 0.8406
Epoch 99/100
317/317 [=====] - ETA: 0s - loss: 0.3199 - accuracy: 0.8614
Epoch 00099: val_loss improved from 0.33544 to 0.33226, saving model to model\model1.h5
317/317 [=====] - 1002s 3s/step - loss: 0.3199 - accuracy: 0.8614 - val_loss: 0.3323 - val_accuracy: 0.8486
Epoch 100/100
317/317 [=====] - ETA: 0s - loss: 0.3188 - accuracy: 0.8624
Epoch 00100: val_loss improved from 0.33226 to 0.33206, saving model to model\model1.h5
317/317 [=====] - 1020s 3s/step - loss: 0.3188 - accuracy: 0.8624 - val_loss: 0.3321 - val_accuracy: 0.8525
training took 4:55:0
    
```

Figure 4. Training Log Methodology Steps

Figure 4 is the outcome of recording 100 epochs of steps during the rigorous training procedure by displaying the average accuracy value attained in each step, which is 85%.

### Total Loss

All training and validation loss will be maintained, and the related graph will be visible. The graph of Total Loss is shown below in Keras.

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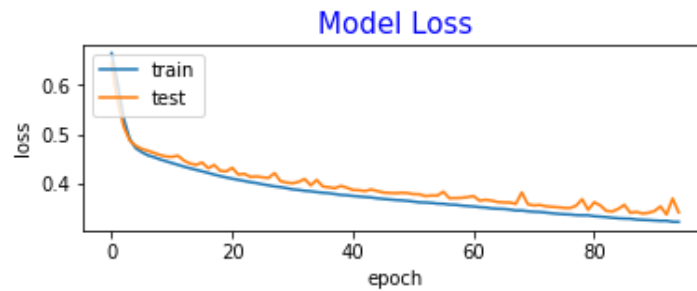


Figure 5. Illustration of Total Loss

Figure 5 is a graph of changes in the total loss value in the training data and testing data. It can be seen that the total loss graph has decreased at each epoch process, while the average decrease is 31% for training loss and 33% for test loss. this shows that the model formed is good because the resulting loss value is getting smaller..

### Confusion Matrix

In the final step of this research, new data for the trial phase are entered. This time, a total of 2529 shots were submitted, comprising 1285 photographs of herpes-exposed skin and 1244 photographs of healthy skin (Mayer-Proschel, Hogestyn, and Mock 2018).

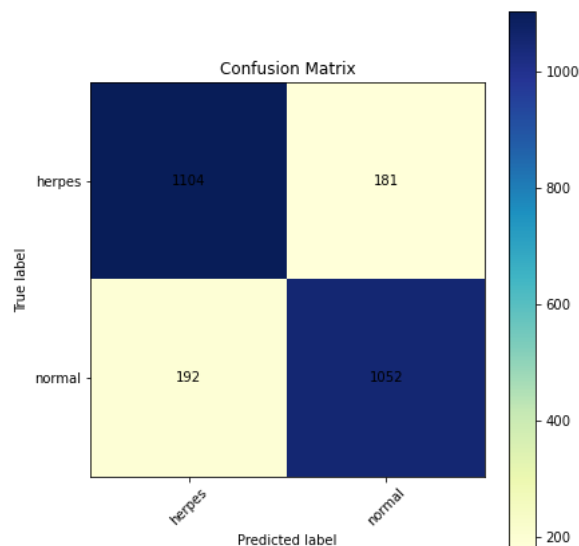


Figure 6. Outcomes of Test Prediction Data

Figure 6 depicts the results of the prediction table for each classification of skin images exposed to herpes and normal skin. According to the results of the prediction class, 1 104 images of skin exposed to herpes are classified as belonging to the herpes class (Lamiell, Ward, and Hilliard 2002), whereas 181 images of skin exposed to herpes illness are classified as belonging to the normal skin class. There are 19 2 photographs of normal skin classified as herpes-exposed skin.

According to these findings, the Convolutional Neural Network (CNN) approach using the pertinent Keras library is applied to photos of herpes-exposed skin and normal skin (Joshi 2022)(TRIPATHI 2019).

## DISCUSSION

### CNN's integration on the Android platform

This is followed by the introduction of the CNN technique for herpes detection on Android applications.

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Figure 7. Splash Display



Figure 8. Homepage

Display menu beginning with the current page and splash screen. When the user initially begins an application, the splash screen, as represented in Figure 7, will appear for a couple of seconds before the page beginning application loads. After the splash screen disappears, the page shown in Figure 8 will load. There are four choices on the site, including Herpes Detection, About Herpes, About, Apps, and Exit / Logout. Users can choose the menu that best meets their requirements.

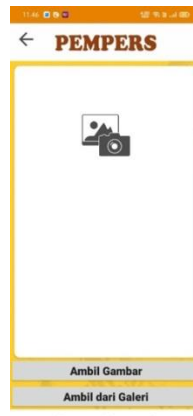


Figure 9. Herpes Diagnosis Menu

When the Herpes Detection menu option is chosen, Figure 9 is displayed. What menu options are available on the herpes detection webpage. Users will identify herpes using a camera smartphone by selecting an image directly from the smartphone's gallery.

If the user chooses to directly detect herpes disease using a smart camera phone, the system instructs the application to open the camera, as shown in Figure 10.

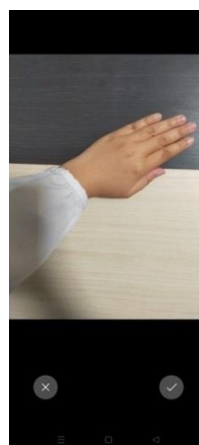


Figure 10. Photographing with a camera

\*name of corresponding author



If a user wishes to take a picture that is already in the smartphone's gallery, the system instructs the application to open the gallery files, as shown in Figure 11.

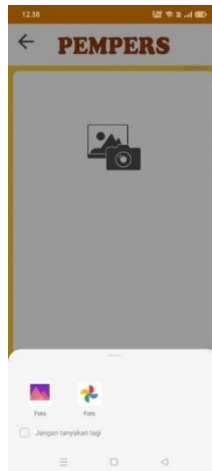


Figure 11. Select a picture from the gallery

After the image has been processed by a smartphone camera or smartphone gallery, the system will determine whether the image depicts an exposed herpes patient or not.



Figure 12. Herpes detected skin



Figure 13. Normal visible skin

Figure 12 depicts the appearance of a system that detects skin-exposed herpes disease and suggests a medication for treating the condition. While Figure 13 depicts the appearance if the system identifies normal skin or no exposed herpes disease, the system will offer herpes disease prevention advice.



Figure 14. Menu About Herpes

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Figure 14 depicts a herpes menu with the submenus Understanding Herpes, Herpes Symptoms, Herpes Medication, and Herpes Prevention.



Figure 15. Herpes definition



Figure 16. Diagram of Herpes Symptoms

Figure 15 depicts the system display when a user selects the Menu about Herpes > Understanding Herpes submenu. Figure 16 depicts the system's display after selecting the Herpes Symptoms submenu.

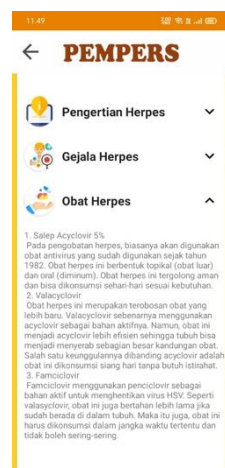


Figure 17. Anti-herpes drugs



Figure 18. Herpes Precautions

Figure 17 depicts the display of the system when the user selects the Herpes menu and the Herpes Drugs submenu. While Figure 18 depicts the display of the system when the Herpes Prevention submenu is selected.



Figure 19. Description of the Menu Application

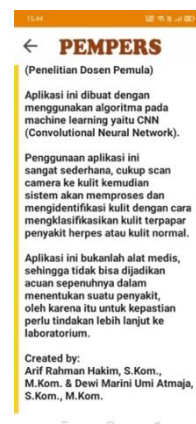
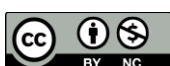


Figure 20. Menu Caring Applications (Continued)

\*name of corresponding author



Figures 19 and 20 depict the system display when a user selects an application-related menu. This menu provides details about the application's construction and purpose.



Figure 21. Menu Exit / Logout

When the user selects Menu Exit / Logout, the system displays Figure 21.

Based on the black box testing that has been done, the features in the application above can run according to their functions.

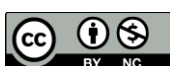
### CONCLUSION

The PEMPERS (Herpes Disease Medical Services) program makes use of the Convolution Neural Network (CNN) method to predict image data of normal skin and skin exhibiting herpes. This application utilizes the Adadelta optimizer, which is quite effective when applied to cases with a small number of classes, such as this study, which consisted of only two classes, namely the herpes class and the normal class. The formed architecture achieves an 85 percent level of accuracy.

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