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Image Detection for Common Human Skin Diseases in Indonesia Using CNN and Ensemble Learning Method

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Abstract−Skin disease is a common health problem throughout the world which is one of the main causes of global disease. Skin and subcutaneous diseases managed to contribute 1.79% of global diseases and also became the fourth leading cause of the burden of non-fatal diseases and disability in 2013. Indonesia was ranked 29th out of 195 countries in Asia which indirectly contributed to in contributing to the transmission of skin diseases due to several causes such as lack of access to health care services, poor hygiene conditions, and also population density. Based on the information revealed in the book entitled illustrated guide on various skin diseases commonly found in Indonesia, it is stated that skin diseases ranging from herpes, ringworm, chickenpox, scabies, to psoriasis are often found in Indonesia. With current technological advances, it is possible for humans to be able to recognize various skin diseases with the help of the Convolutional Neural Network (CNN) Method. A total of 1203 images containing types of skin diseases such as herpes simplex, pityriasis, psoriasis, tinea corporis, scabies, and also vitiligo will be a class in the classification process, but because most images are still unbalanced and do not have strong object elements, it is necessary to do this. data preparation and data balancing is also needed so that the architectural model will not be difficult to learn. By using k-fold cross validation and carrying out the ensemble method, the results of the model evaluation will be in the form of an accuracy matrix where the results of each model will be compared and it will be determined which model is the best based on the results obtained. The test results that produce Cross Validation show that the RGB image is superior where the accuracy value obtained is 49% and the Grayscale image has an accuracy of 47%. however, when compared with the ensemble results, Grayscale images have superior accuracy results, namely the accuracy results are 93% and RGB images produce only 86.

Keywords: Image Detection; Skin Disease; Machine Learning; Convolutional Network

1. INTRODUCTION

Until now, skin disease is still a problem faced by various countries in the world. Skin diseases have a significant global impact on quality of life, mental health, and loss of income. Skin disease is a common health problem throughout the world which is one of the main causes of global disease. The resulting impact of this skin disease significantly affects people of all ages and cultures. Skin and subcutaneous diseases contributed 1.79% to global disease and also became the fourth leading cause of the burden of non-fatal disease and disability in 2013 [1].

Several countries on the Asian continent, which are included in high income, recorded inflammatory skin diseases such as acne, alopecia areata, atopic dermatitis, contact dermatitis, decubitus ulcers, psoriasis, pruritus, and seborrheic dermatitis, including those with high transmission rates. Indonesia is ranked 29th out of 195 countries on the Asian continent which indirectly contribute to skin disease transmission due to several causes such as lack of access to health care services, poor hygiene conditions, and population density [2].

A study at one of the Islamic boarding schools in South Jakarta, had a prevalence rate of skin disease of 89.7%, with a total of almost 89% of students having poor hygiene behavior and being diagnosed with skin diseases. Only 30% of students have a level of good behavior and clean who do not have skin diseases. In this case, there was a significant difference between skin disease and education level. Where the higher the education of students, the prevalence of skin diseases decreases. It was found that the highest cause of skin disease outbreaks was the lack of hygiene, as well as bad behavior such as frequent exchange of towels, clothes, and the infrequent change of bed linen, leading to high cases of skin disease in one of the Islamic boarding schools in South Jakarta. Seeing from the lack of self-awareness of the dangers of skin disease outbreaks and the lack of appropriate skin disease treatment actions and according to the type of infection, it can cause an outbreak of skin diseases which if left unchecked will have a very crucial impact on Indonesian society such as depression, inhibiting activities. daily life, sleep disturbances, spinal cord and brain damage (Herpes), and so on [3].

Based on information in illustrated guidebooks about various skin diseases that are commonly found in Indonesia, including Dermatitis, Fungal Infections, Bacterial Infections, Virus Infections, Parasitic Infections, to Skin Tumors. These various skin diseases in fact have a major impact on patients both physically and psychologically, speed and accuracy of diagnosis are very important for treatment which will certainly affect the patient's recovery and prognosis [4]. There are previous studies on Skin Disease that prove by building a Methodological Approach for Skin Disease using the Ensemble Method starting from the CART method, then to SVMs, then to DTs, then to RFs, then to GBDTs. Produces a high accuracy rate of 95.90% in the final results in studies related to Skin Disease. However, there is other evidence that several methods produce Classification Accuracy in the form of percentages such as the Convolutional Neural Networks (CNN) method by Ubeyli with a higher accuracy rate of 97.77% [5]. Therefore, by building a system using the CNN method as well as some of the best classification methods or Ensemble Methods, it is hoped that the author will find results based on the level of

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accuracy of the classification process regarding common skin diseases found in Indonesia that can assist diagnoses in dealing with and overcoming skin disease outbreaks in Indonesia.

Research challenges found in automating the process include variations in skin color, disease locations, specification of image acquisition systems, and so on. In conclusion, the proposed CNN Classifier yields an accuracy of 98.6% to 99.04% [6].

2. RESEARCH METHODOLOGY

Several stages in this research are using the CNN Resnet50 architecture as the main CNN model to train data obtained from various sources such as atlasdermatologico.com.br, dermnetnz.org and others. Then preprocessing data which consists of removing watermark, object detection, background removal, cropping area implementation, matching its resolutions and normalizing the data, here the author uses k-fold cross validation to separate data with a percentage of 80% for training data, and 20% for test data which will be classified using a CNN model architecture called Resnet50 and evaluated using a confusion matrix. The stages of the research used are as shown in Figure 1.

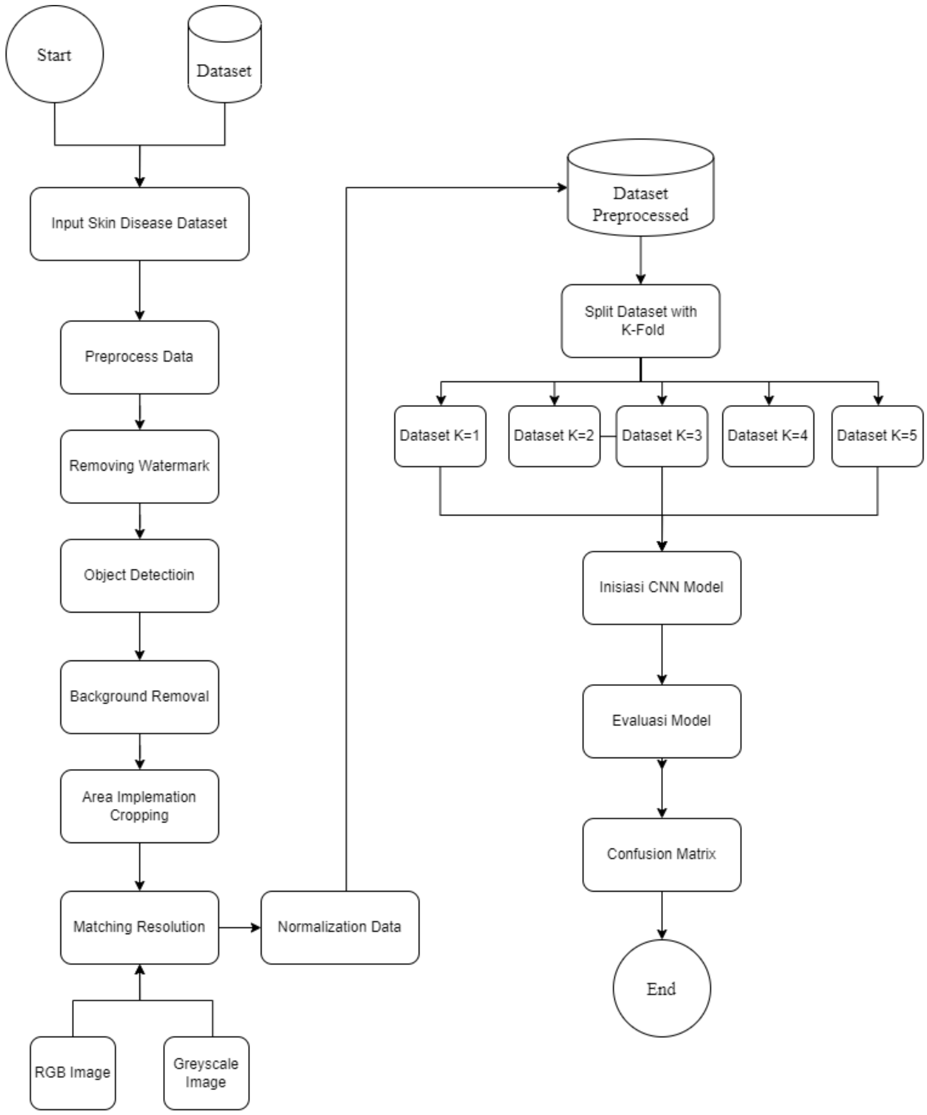

Figure 1. Flowchart System

2.1 Data

The author managed to collect as many as 1203 pictures from the website atlasdermatology.com.br, dermnetz.org, dermatlas.net. Containing types of skin diseases such as Herpes Simplex as many as 222 pictures, Pityriasis 210 pictures, 272 pictures for Psoriasis, 173 Scabies pictures, 160 Tinea Corporis pictures, and also Vitiligo as many as 166 pictures which later became a class in classification process, the following is brief information about the dataset owned.

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Figure 2. Dataset Image Sample

2.2 Pre-processing Data

Before classifying the data, the data still has some elements of noise that can interfere with the model when training the data. Therefore, data pre-processing is required. The first step is to remove the image background so that the image has objects that can help the model better when classifying data. here the author makes two datasets, namely images that have RGB and Grayscale colors. Detailed steps regarding pre-processing data can be seen in the points below.

2.2.1 Removing its Watermark

In the dataset, some images still have a background that will be removed so that the texture or object of the skin disease is more clearly visible without any noise from the existing image. And there are also several watermarks on the image which are usually located at the end of the corner of the image. To remove the watermark, a simple crop will be carried out for several images that have a watermark, to remove the background, it is done by separating the object of the image from the background.

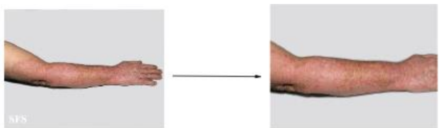

Figure 3. Removing Watermark Process

2.2.2 Gaussian Blur

Some images have light reflection effects that will interfere with the object scanning process, by using gaussian blur, this process will soften the image so that the light reflection effect will be reduced so as to provide a clearer image without making the image blurry [7].

Figure 4. Gaussian Blur Process

2.2.3 Structured Random Forest Edge Detection

After removing the background and doing a gaussian blur, the next process is to detect where the angle of the image is because later, we will crop it so that the skin disease object is more focused and centered on the image. Here, the author uses Structured Random Forest Edge Detection in the hope of detecting the angle of the image [8].

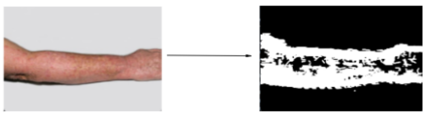

Figure 6. Structured Random Forest Edge Detection Process

As can be seen in the image, the results from Structured Random Forest Edge Detection still have a lot of noise so that noise removal is needed.

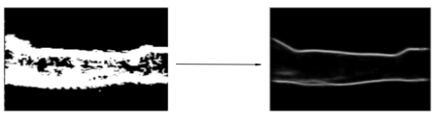

Figure 7. Removing its noise

2.2.4 Find largest Contour

From the results of the Structured Random Forest Edge Detection image, some images have varied sizes and shapes, we can obtain the object using the Find Largest Contours technique by detecting the edge of the image corner so that we can delete or remove objects other than the skin which is smaller.

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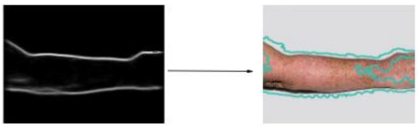

Figure 8. Find Largest Contour Process

Next, we will do masking to get the object that we will save by filling a new layer with white according to the object we already have.

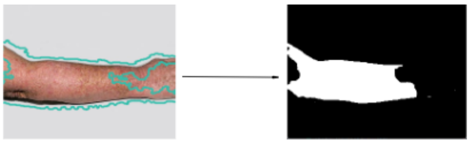

Figure 9. Masking Image Process

We can combine our masking results with the original image by separating the foreground and background so that we will get an image that does not have a background and is more centered on the image object.

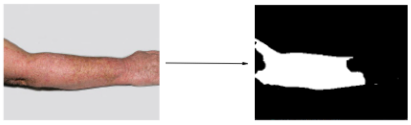

Figure 10. Combining masking result process

Figure 11. Image without its background

2.2.5 Trim to Maximum Square

a. Fuzz

By doing a comparison between the background color of the image with the image that has the object, we know if the maximum distance from the left, right, top, and bottom of the image is so that we will get the size of the image that we can process with the Repage process.

Figure 12. Fuzz Process

b. Repage

By getting the fuzz result, we can trim or crop the image so that it becomes an image with a maximum square

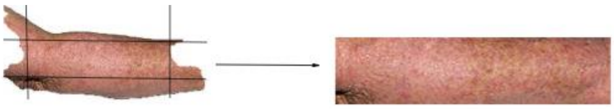

Figure 13. Repage Process

c. Image Size Reduction

After getting an image with a maximum square, by resizing the image size to 100x100 using python library opencv with resize function [9], we will get at least 10000 features in the classification process.

Figure 14. Image Size Reduction

2.3 Normalization

The big reason why data normalization is needed is to avoid the many features or variables in the dataset that we will analyze are deemed to exceed and we cannot analyze optimally [10]. The image has Xmin of 0 and Xmax of

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255. This technique is called Z-Score where later each feature value will be reduced by miu(μ) which is the average value of the feature, then divided by sigma which is the standard deviation where Xi is X.

$$scaled(Xi) = (Xi - \mu X)\sigma X \quad (2)$$

2.4 Data Balancing

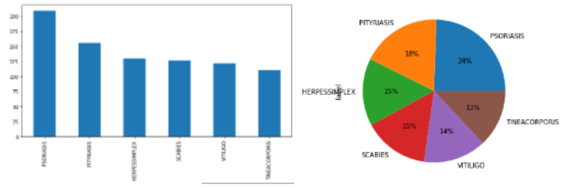

Figure 15. Unbalanced Dataset

As seen in the Figure 15, the dataset that the author has is still not balanced where there is one class that dominates the data and is considered unbalanced, this will affect the final results and also the results of model training when the model is studying unbalanced data resulting in biased accuracy where there is a class that has more data small or minority results in small accuracy results compared to data that have larger or majority data. Therefore, the need for Data Balancing using oversampling.

2.5 Oversampling

By oversampling the data by looking for which class is the majority, later the results from the data that have been oversampled will be combined with the minority class following the number owned by the majority.

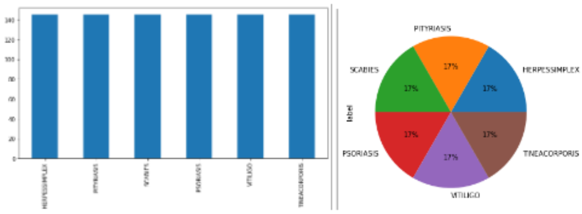

Figure 16. Balanced Dataset

Oversampling is done by duplicating data randomly with the aim of all data in each class being balanced and having the same amount. By oversampling, the data will be overfitting or have the same characteristics and will affect the final result, but by using the model that the author uses, data that have the same characteristics will not be recognized or allowed.

2.5.1 Image Augmentation

Data or Image Augmentation is the process of modifying or manipulating an image [11], so that the original image in standard form will be changed in shape and position, by randomizing the method and the image, the image will increase following the amount of data required. Here the author uses 3 image augmentation techniques, namely Random Flipping Horizontal Augmentation, Random Flipping Vertical Augmentation, and Random Zooming Augmentation.

a. Random Flip Vertical Augmentation

By inverting the image using its columns and rows of pixels, the image will be flipped vertically or by 90°.

Figure 17. Random Flipping Vertical Process

b. Random Flip Horizontal Augmentation

By inverting the image using its columns and rows of pixels, the image will be flipped in the Horizontal direction.

Figure 18. Random Flipping Horizontal Process

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c. Random Zoom Augmentation

By zooming in on the image, the image will feel wider and the pixels will increase, here the author uses a zooming of 1.25 where the image will be zoomed by 25% so that the image does not have a few or low pixels.

Figure 19. Random Zoom Augmentation

2.6 K-Fold Cross Validation

K = 1	Test	Train	Train	Train	Train
K = 2	Train	Test	Train	Train	Train
K = 3	Train	Train	Test	Train	Train
K = 4	Train	Train	Train	Test	Train
K = 5	Train	Train	Train	Train	Test

Figure 20. K-Fold Illustration

K-Fold Cross Validation is an additional method of data mining techniques that aims to obtain maximum accuracy results. Here the author splits the data by 20% for test data and 80% for training data, where as many as 5 tests will be carried out by the author. The main reason for the author to use K-Fold Cross Validation is that the data they have will be divided evenly and each test carried out will have different data and it is hoped that the results of the confusion matrix will be more transparent and also optimal.

2.7 Convolutional Neural Network

Convolutional Neural Network is included in the type of Deep Neural Network because of its high network depth and widely applied to image data. Technically, Convolutional Network is an architecture that can be trained and consists of several stages, and also CNN has many important layers such as Convolutional Pooling Layer, and Output Layer (*SoftMax*). Max Pooling and Average Pooling are the most frequently used pooling in the process of pooling layers in CNN [12].

2.7.1 Convolutional Layer Process

The convolution process can take advantage of what is called a filter. Like an image, the filter has a certain height, width, and thickness. This filter is initialized with certain values such as random numbers or can use certain techniques such as *glorot* and generate values that become parameters in the update process in learning. Certainly, the image that will be inputted on CNN is always in the form of a box. Where the process for non-rectangular images or images other than square shape is still unknown. The filter also follows the characteristics of the box [13].

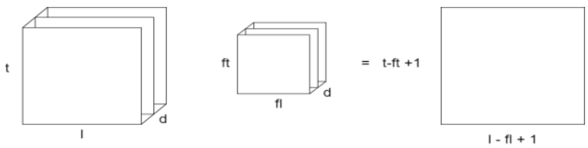

Figure 21. Convolutional Layer Process

Figure 2.2 has an image matrix (volume) with dimensions (t x l x d) with a filter (ft x fl x d) which produces volume dimensions (t – ft + 1) x 1. Looking at Figure 2.2 regarding the process in the convolutional layer, convolutional is the first layer that perform feature extraction from the input image. Convolutional also maintains the relationship between pixels by viewing and studying image features with its small box input data. A number called a dot product will be generated at each image position between parts of the image using a filter, then shifting or convolve the filter in every possible filter position in the image will produce an activation map.

2.7.1 Pooling Layer

The main function of the Pooling Layer process is to reduce the input spatially or to reduce the number of parameters by down-sampling operations. The most commonly used pooling method is max-pooling or taking the largest value from the section. However, there are several other pooling methods that can be used such as average-pooling or L2-norm-pooling [14]. Just like the Convolutional Layer, if we do input to the pooling layer having size W1 x H1 x D1, then the output generated from the pooling layer is:

$$W2 = (W1 - F + 2P) / S + 1 = H2 \quad (1)$$

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Where padding is not commonly done in the pooling layer process but becomes optional to use.

2.9 Ensemble Learning

To overcome the similarities or overfitting in the model, the author uses the Ensemble Learning Bagging method which stands for "Bootstrap Aggregating". Where the results of each K test will produce a model that has been trained or pretrained and will be tested again using K random sample data, then get the average of the ensemble learning results [15].

2.8 Result Evaluation

The results obtained from evaluating the model are accuracy, precision, and recall data. The model also provides accuracy results for test data and also training data which is the result of the number of epochs and batch size [16] The author uses the Confusion Matrix to calculate accuracy, precision, and recall.

a. Accuracy

Accuracy is the percentage of the total data identified and judged correct by the formula:

$$\text{Accuracy} = \sum_{i=1}^{k}\left(\frac{tp_i + tn_i}{tp_i + tn_i + fp_i + fn_i}\right) * 100\ \% \qquad (2)$$

With information: Tp = True Positive, Tn = True Negative, Fp = False Positive, Fn = False Negative, K = Number of Classes

b. Precision

Precision is data taken based on information that is lacking or incorrect or incorrect with the formula:

$$\text{Precision}= \sum_{i=1}^{k}\left(\frac{tp_i}{tp_i + fp_i}\right) * 100\ \% \qquad (3)$$

With information: Tp = True Positive, Fp = False Positive, K = Number of Classes

c. Recall

Recall or Sensitivity is data that cannot be predicted correctly with the formula:

$$\text{Recall} = \sum_{i=1}^{k}\left(\frac{tp_i}{tp_i + fn_i}\right) * 100\ \% \qquad (4)$$

With information: Tp = True Positive, Fn = False Negative, K = Number of Classes

2.9 Standard Deviation

Standard Deviation value is a value used in determining the distribution of data in a sample and seeing how close the data is to the average value. The author uses the Standard Deviation calculation to see the results of the F1 Score from each label or class and each K, which is how many experiments were carried out on the K-Fold Cross Validation [17]. Standard Deviation has the following formula:

$$\text{Standard Deviation } (\sigma) = \sqrt{\frac{\sum(x_i - u)^2}{N}} \qquad (5)$$

With information: x_i = The value of each F1 Score per label or class, u = Average value of Cross Validation, N = Number of trials.

3. RESULTS AND DISCUSSION

3.1 Testing Scenario

The CNN Architecture Model already has a convolutional layer, Pooling Layer, and Fully Connected Layer, where there is a Kernel Size on the Convolutional Layer, Pool Size on the Pooling Layer, and dense Size on the Fully Connected Layer which is the testing parameter used. And there's also an Epoch value to determine how many tests to try. Batch size, which is how much data in one epoch iteration, the results obtained from the test will be compared with the F1-Score for each class in the test, and also the results of Cross Validation.

In this test, the author uses the CNN Resnet50 Architectural Model which was selected by the author based on the study reference. The author will also see how the comparison between 2 image characteristics is to find out which one is more optimal for classifying, the 2 image characteristics consist of RGB Images and Grayscale Images.

3.2 Evaluation Result Model with RGB Datasets

Table 2. Cross Validation Results

Class Name	F1-Score	Precision	Recall
Herpes Simplex	0.582	0.596	0.577
Pityriasis	0.471	0.451	0.5

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Volume 3, No. 4, August 2022, Page 527−535
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Class Name	F1-Score	Precision	Recall
Psoriasis	0.430	0.470	0.411
Scabies	0.454	0.468	0.45
Tinea Corporis	0.514	0.521	0.544
Vitiligo	0.514	0.521	0.544
Average	0.509	0.497	0.495

Table 3. Ensemble Results

Class Name	F1-Score	Precision	Recall
Herpes Simplex	0.904	0.891	0.916
Pityriasis	0.85	0.772	0.944
Psoriasis	0.918	0.894	0.944
Scabies	0.779	1	0.638
Tinea Corporis	0.805	0.805	0.805
Vitiligo	0.868	0.916	0.891
Average	0.872	0.861	0.858

Table 4. Ensemble Evaluation Results

	F-1 Score	
Evaluation Results	**Cross Validation**	**Ensemble**
Minimum F1-Score	0.430	0.779
Maximum F1-Score	0.582	0.918
Standard Deviation	0.504	0.056
Accuracy	0.497	0.861

3.3 Evaluation Result Model with RGB Datasets

Table 5. Cross Validation Results

Class Name	F1-Score	Precision	Recall
Herpes Simplex	0.522	0.552	0.505
Pityriasis	0.459	0.444	0.477
Psoriasis	0.446	0.497	0.411
Scabies	0.447	0.457	0.461
Tinea Corporis	0.464	0.465	0.483
Vitiligo	0.470	0.463	0.488
Average	0.427	0.439	0.435

Table 6. Ensemble Results

Class Name	F1-Score	Precision	Recall
Herpes Simplex	0.945	0.921	0.972
Pityriasis	0.891	0.868	0.916
Psoriasis	0.942	0.970	0.916
Scabies	0.931	0.918	0.944
Tinea Corporis	0.929	0.942	0.916
Vitiligo	0.942	0.970	0.916
Average	0.930	0.932	0.930

Table 7. Ensemble Evaluation Results

	F1-score	
Evaluation Results	**Cross Validation**	**Ensemble**
Minimum F1-Score	0.446	0.891
Maximum F1-Score	0.522	0.945
Standard Deviation	0.327	0.020
Accuracy	0.471	0.930

After evaluating using the confusion matrix, there is a very significant difference in the results of cross validation with the results of the ensemble, where the ensemble results have a higher accuracy value than the results of cross validation accuracy.

4. CONCLUSION

From all the experimental results and tests using the CNN Resnet50 architectural model, with a total of 6 classes of skin diseases, namely Herpes Simplex, Pityriasis, Psoriasis, Scabies, Tinea Corporis, and also Vitiligo. The results of Cross Validation show that RGB images are superior, with an accuracy of 49% and where using Grayscale images, an accuracy of 47% is obtained. And also the results from the Ensemble Model have comparable results where Grayscale images are superior with an accuracy of 93% compared to RGB images which have an accuracy of 86%. Thus, it can be concluded that using K-Fold Cross Validation on RGB datasets will be superior to Grayscale, but Grayscale datasets can be far superior when using Ensemble Methods. However, there is a significant difference in the results of cross validation accuracy when compared with the results of ensemble accuracy, this happens because the author did not prepare validation data so that it can be said that the ensemble method is overfitting because the model takes the highest results when training data that has been used. By providing validation data to measure how optimal the model used for the next research is.

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