ORIGINAL ARTICLE

Comparative Study of the Performance of Skin Disease Detection Algorithms on Visible Light and Infrared Images

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ABSTRACT

Introduction: The aim of this research is to understand the performance comparison of skin disease detection algorithms, identify the advantages of infrared images and visible light images and measure their effectiveness. **Materials and methods:** This research employs a descriptive method with a quantitative approach and metric algorithms. Data collection is conducted to test hypotheses or answer questions about people's opinions on a topic. Statistical analyses were conducted to compare algorithm performance across imaging modalities, providing valuable insights into their effectiveness and reliability in skin disease diagnosis. **Results:** The skin disease detection algorithm in infrared images and visible light images needs to be evaluated comprehensively to understand its performance. Performance metrics such as accuracy, precision, recall, and F1-score can be used to compare detection results between the two types of images while infrared images provide information on skin temperature. The detection algorithm must have sufficient sensitivity to detect changes in both types of images. The analysis of the skin disease detection algorithm emphasizes how crucial it is to thoroughly evaluate how well it performs in both visible and infrared images. Metrics like F1-score, recall, accuracy, and precision offer important insights into how effective it is. By utilizing two senses, the algorithm becomes more sensitive in identifying different skin diseases. **Conclusion:** The reliability of algorithms on infrared images may require special adaptation and performance evaluation involves measuring accuracy, precision, recall, and F1-score on both types of images.
Malaysian Journal of Medicine and Health Sciences (2024) 20(SUPP9): 70-78. doi:10.47836/mjmhs20.s9.12

Keywords: Algorithm, Detection, Infrared, Skin disease, Visible image

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INTRODUCTION

Skin diseases are a serious concern in the context of global health, affecting millions of people worldwide (1). Early detection of skin diseases is crucial because many of these conditions can have a substantial impact on a patient's quality of life if not identified and treated quickly (2). In the early stages of skin disease development, the symptoms are often very subtropical, difficult to identify visually by the human eye (3).

The skin is the largest organ of the body which is located on the outermost part of the human body and functions to cover the entire surface of the human body (4). The skin can be infected with various diseases, ranging from mild diseases that result in itching or more severe ones that can result in death (5). For those who care about the health condition of their skin, a doctor who specializes in skin diseases is needed. However, sometimes people tend to remain silent about this disease, this is due to the shame of being honest and the limited costs for treatment (6).

Factors such as variations in skin color and the complexity of the patterns that may appear add to the level of difficulty in detecting changes that occur (7). Therefore, research and development of skin disease detection technologies has become essential to ensure early detection and effective treatment (8). Skin diseases pose a significant health challenge globally, necessitating early and accurate detection for effective treatment. Although there have been various skin disease detection algorithms developed, there are still limitations in terms of accuracy and efficiency in various image conditions (9). Some algorithms tend to be more effective on visible light images, while others can excel at extracting features from infrared images. Despite advancements in skin disease detection algorithms, challenges persist in achieving consistent accuracy across different imaging modalities.

Variations in algorithm performance across visible light and infrared images present a key challenge in skin disease detection. Comprehensive research comparing algorithm performance on these two types of images is needed to improve diagnostic outcomes. Therefore, in-depth research is needed to compare the performance of detection algorithms on these two types of images. The aim of this research is to understand the performance comparison of skin disease detection algorithms, identify the advantages of infrared images and visible light images, measure the effectiveness and reliability of skin disease detection algorithms on infrared images and visible light images. Existing research has made strides in skin disease detection using various algorithms, with some focusing on visible light and others on infrared images. However, there's a lack of comprehensive comparative studies across both modalities, highlighting the need for this research to inform more effective detection systems.

MATERIALS AND METHODS

Research Methodology

The research method used is a descriptive method with a quantitative approach and metric algorithms. This descriptive method involves collecting data to test hypotheses or answer questions about people's opinions on an issue or topic. (10) Quantitative research is research that is based on collecting and analyzing data in the form of numbers (numeric) to explain, predict and control phenomena of interest (11).

Hypothesis Testing and Opinion Analysis

In this study, both visible light and infrared images were gathered to evaluate the performance of skin disease detection algorithms across different imaging modalities. Visible light images refer to images or photos produced by the detection of light that is visible to the human eye, namely in the wavelength range of visible light, namely around 400 to 700 nanometers, were obtained through standard imaging techniques. It covers a color spectrum that includes red, orange, yellow, green, blue, and purple. Detection of light in this range allows us to see objects and the environment around us as we normally observe them every day (12). Infrared imaging is concerned with the detection of light outside the range of light visible to the human eye (13), particularly in the infrared region of the electromagnetic spectrum (14). This imaging modality provides insights into underlying tissue abnormalities not readily visible to the naked eye. Infrared has a longer wavelength than visible light, namely above 700 nanometers.

The performance detection algorithms and analyze data

The performance of skin disease detection algorithms in visible light images depends on a number of factors, and their evaluation involves several metrics that can provide an idea of how well the algorithm is working (15). To analyze the collected data, various metrics were employed to assess the performance of skin disease detection algorithms on both types of images. These metrics include but are not limited to accuracy, sensitivity, specificity, and computational efficiency.

Statistical analyses

Statistical analyses were conducted to compare algorithm performance across the different imaging modalities, providing valuable insights into their effectiveness and reliability in skin disease diagnosis.

RESULTS

Analysis entails checking that results match the initial conditions to verify correctness, counting basic operations to measure efficiency, assessing performance in worst-case scenarios, figuring out optimality by counting the number of operations that are absolutely necessary, and determining a lower bound for operation counts. Images are two-dimensional representations that are acquired by optical equipment and are crucial for visual information. Pre-processing methods include centering for simpler training, switching to grayscale for faster processing, cropping to concentrate on important sections, scaling to conserve memory, and deleting surrounding circles to increase accuracy. Images of visible light with wavelengths ranging from 400 to 700 nanometers are processed to examine colors and textures that are perceptible to humans. With wavelengths longer than visible red light, infrared images offer extra temperature and material property information that is important in a variety of industries. Datasets of tagged skin photos are pre-processed and divided into training and testing sets in order to diagnose skin diseases.

To extract and comprehend characteristics, a Convolutional Neural Network (CNN) architecture including convolution, ReLU activation, and pooling layers is utilized. The accuracy, precision, recall, and F1-score are used to gauge the model's performance during training and validation. For infrared images, data augmentation techniques and a particular model architecture are used, and training and testing procedures guarantee precise illness detection. Through the ability of the models to anticipate skin diseases from fresh photos, both methods improve diagnosis accuracy.

Algorithm

An algorithm is an effective method that is shown in a limited list of commands that have been defined to calculate a function (16). In a computer system, an algorithm is a direct description of the logic written by the software developer to be more effective in achieving the software's targets (17), so that it can obtain output results from the given input (sometimes null) (18). There are five important characteristics that an algorithm must have, namely finiteness, definiteness, input, output and effectiveness (19).

In analyzing an algorithm, we must pay attention to several things, such as (20):

1. Correctness

In proving the correctness of an algorithm, the final result of the algorithm must be checked whether it is in accordance with the conditions given at the beginning of the input (21). To check a complex algorithm, we can divide the algorithm into several small modules, so that if the small modules are correct then the entire program will be correct (17).

2. Number of Operations Performed

Counting the number of operations performed is used to compare the level of efficiency of an algorithm with other algorithms in solving the same problem (22). This is done to obtain an algorithm that can produce faster execution times. The easiest way to compare two algorithms is to count the number of basic operations carried out by the algorithm, because if the comparison is carried out directly on a computer, often the condition of each computer and the way each programming language is read affects the problem-solving time.

3. Worst Case Analysis

Worst case analysis is an analysis used to see the level of effectiveness of an algorithm in solving problems whose input is input that sometimes does not need to be calculated or how to deal with it when the input is possibly wrong (23).

4. Optimality

To analyze an algorithm, it is customary to always use the algorithm class and a measure of complexity, for example, the number of basic operations performed (17). An algorithm is called optimal (for the worst case) if there is no algorithm that can perform fewer basic operations (for the worst case) (24).

5. Lower Bound

To prove that an algorithm is optimal, it is not necessary to analyze each algorithm (17). By proving a theorem that determines the lower bound on the number of operations required to solve the problem, the algorithm that can perform that number of operations is called optimal.

Image

Image is another term for images as a multimedia component which plays a very important role as a form of visual information (25). Image can also be interpreted as an image that has information value (26). Literally, an image is a picture on a two-dimensional plane (27). A light source illuminates an object, the object reflects back as a light beam. This reflection of light is captured by optical devices, for example human eyes, cameras, scanners, and so on. So that the image of the object called the image is recorded (28). In image processing there are several techniques implemented for pre-processing datasets, including (29):

1. Resize

Resize is used to reduce excessive memory usage so that when the image is processed it doesn’t take too long, this resizing process does not lose the quality of the original image. Additionally, resizing ensures optimal performance by reducing the computational load on processing units. This helps maintain the integrity of the image while enhancing efficiency during subsequent operations.

2. Crop

Crop is used to remove the background in a digital image, so that the composition of this image determines how parameters can be used as a reference. Cropping allows for selective removal of unwanted elements from the image, enabling a focus on the subject matter or desired composition. This flexibility in parameter adjustment empowers users to tailor images according to specific aesthetic or functional requirements.

3. Grayscale

Grayscale is used to change images to black and white. The use of greyscale ensures that the processed image does not take too long to execute II-4 because when using an RGB image the process is divided into several layers.

4. Remove Outer Circle

Remove Other circle is used to remove the edge of the circle for the purpose of the training process and reducing parameter errors and detection errors. By removing the edges of the circle, the “Remove Other Circle” function contributes to refining the training process, ultimately minimizing parameter and detection inaccuracies. This meticulous preprocessing step enhances the accuracy and reliability of subsequent analyses or algorithms applied to the image data.

5. Center Placing

This process is used on images to ensure that all images are positioned in the center so that the training process is easier. Centering the images through this process streamlines the training phase by providing a consistent and standardized orientation for analysis. This uniformity enhances model performance and facilitates efficient learning, leading to more accurate and reliable results in subsequent tasks or application.

Visible Light Image

Visible light images are images recorded using light wavelengths that are visible to the human eye (30). These wavelengths range from about 400 to 700 nanometers. This image includes the spectrum of colors we can see, such as red, green, and blue (31). Many conventional cameras and the human eye work in this range (32).

Visible light image processing usually includes analysis of colors and textures that can be seen by the human eye (33).

Infrared Imagery

Infrared images, on the other hand, are recorded using wavelengths of light outside the visible spectrum, specifically in the infrared region (34). These wavelengths are longer than visible red light, ranging from about 700 nanometers to several millimeters (35). Infrared imagery is frequently used in a variety of applications, including remote sensing, agriculture, and machine vision science (14). In infrared images, various objects can emit, reflect, or absorb infrared radiation in different ways, providing additional information about temperature, humidity, or material properties that is difficult to see with the human eye or in visible light images (36).

```
base_dir = '/path/to/dataset'
train_dir = os.path.join(base_dir, 'train')
test_dir = os.path.join(base_dir, 'test')

# Membuat generator data untuk augmentation dan normalisasi
train_datagen = ImageDataGenerator(rescale=1./255,
                                   shear_range=0.2,
                                   zoom_range=0.2,
                                   horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255)

# Menggunakan generator untuk memuat dan augmentasi data
train_generator = train_datagen.flow_from_directory(train_dir,
                                                    target_size=(64, 64),
                                                    batch_size=32,
                                                    class_mode='categorical')

test_generator = test_datagen.flow_from_directory(test_dir,
                                                  target_size=(64, 64),
                                                  batch_size=32,
                                                  class_mode='categorical')

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

# Membuat model CNN
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=(64, 64, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(3, activation='softmax'))  # 3 kelas: normal, jerawat, eksim


Validasi dan Penyetelan Model
# Melakukan validasi menggunakan data pengujian
accuracy = model.evaluate(test_generator)[1]
print(f'Validation Accuracy: {accuracy}')

# Jika diperlukan, lakukan penyetelan model untuk meningkatkan kinerja
              # model.fit(train_generator, epochs=5, validation_data=test_generator)
```

Figure 1: The process of creating and training a Convolutional Neural Network (CNN) model with TensorFlow/Keras, including the use of Image Data Generator for data augmentation and normalization, CNN model creation, and CNN model training using the Adam optimizer

The performance of the skin disease detection algorithm on visible light images is crucial for its applicability in clinical settings. By utilizing the Convolutional Neural Network (CNN) model trained with TensorFlow/Keras, which incorporates advanced techniques like ImageDataGenerator for data augmentation and normalization, alongside the Adam optimizer, we can assess the accuracy, sensitivity, and specificity of the algorithm in detecting various skin conditions under standard lighting conditions. This evaluation ensures the reliability and effectiveness of the algorithm in real-world scenarios, facilitating its integration into diagnostic tools for dermatological practice.

First, a dataset of skin images is collected that includes various conditions and diseases such as acne and eczema. We have images from different sources, and each image is labeled according to the type of skin disease seen in the image.

The next step is data preparation. It involves image pre-processing, such as intensity normalization, contrast adjustment, and dividing the dataset into two parts: training data and testing data. The training data will be used to train the model, while the testing data will be used to test how well the model can generalize on data it has never seen before.

To recognize patterns in skin images, a Convolutional Neural Network (CNN) architecture was chosen. Suppose, we have a convolution layer to extract features, a ReLU activation layer for non-linearity, and a pooling layer to reduce dimensionality. This forms a model that can understand complex features in images.

After model creation, the next step is training. Our model is geared to "learn" from the training data, recognizing patterns related to the type of skin disease. In this process, the model optimizes its parameters using learning methods. To ensure that the model can predict well on data that has never been seen before, we validate it using test data. If necessary, we perform model tuning, which involves adjusting model-parameters to improve its performance on test data.

Performance evaluation is carried out by measuring metrics such as accuracy, precision, recall, and F1-score on test data. This provides an understanding of the extent to which the model can correctly predict and recognize skin diseases. Once the model has been successfully trained and evaluated, we can use it to analyze new images that have never been seen before. By providing images to the model, we can see predictions of the type of skin disease that may be present, helping in the process of identifying skin conditions quickly and accurately.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Path dataset inframerah
base_dir_infrared = '/path/to/infrared_dataset'
train_dir_infrared = os.path.join(base_dir_infrared, 'train')
test_dir_infrared = os.path.join(base_dir_infrared, 'test')

# Membuat generator data untuk augmentasi dan normalisasi
train_datagen_infrared = ImageDataGenerator(rescale=1./255,
                                            shear_range=0.2,
                                            zoom_range=0.2,
                                            horizontal_flip=True)
test_datagen_infrared = ImageDataGenerator(rescale=1./255)

# Menggunakan generator untuk memuat dan augmentasi data inframerah
train_generator_infrared =
train_datagen_infrared.flow_from_directory(train_dir_infrared,
                                           target_size=(64, 64),
                                           batch_size=32,
                                           class_mode='categorical')

test_generator_infrared =
test_datagen_infrared.flow_from_directory(test_dir_infrared,
                                          target_size=(64, 64),
                                          batch_size=32,
                                          class_mode='categorical')

# Membuat model CNN untuk citra inframerah
model_infrared = Sequential()
model_infrared.add(Conv2D(32, (3, 3), input_shape=(64, 64, 3),
activation='relu'))
model_infrared.add(MaxPooling2D(pool_size=(2, 2)))
model_infrared.add(Conv2D(64, (3, 3), activation='relu'))
model_infrared.add(MaxPooling2D(pool_size=(2, 2)))
model_infrared.add(Flatten())
model_infrared.add(Dense(128, activation='relu'))
model_infrared.add(Dense(num_classes, activation='softmax'))  # Ganti
num_classes sesuai dengan jumlah kelas pada dataset

# Mengkompilasi model
model_infrared.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Melatih model inframerah
model_infrared.fit(train_generator_infrared, epochs=10)
```

Figure 2: Creation and Training of a CNN Model for Detecting Skin Diseases in Infrared Images

The performance of the skin disease detection algorithm on infrared images is crucial for measuring its effectiveness in identifying potentially pathological skin conditions. By creating and training a specialized Convolutional Neural Network (CNN) model for skin disease detection on infrared images, as shown in Figure 2, we can evaluate the algorithm's ability to distinguish between various types of skin conditions within the infrared spectrum. This enables more accurate diagnosis and targeted treatment for patients with skin issues, particularly in clinical environments utilizing infrared scanning technology.

Image Data Generator is used to perform data augmentation and normalization. It includes operations such as shear, zoom, and horizontal flip to increase data variation and help the model understand skin disease variations. Conv2D layers to extract features, Max Pooling 2D to reduce dimensions, Flatten to flatten the data, and Dense for fully connected layers. This is a general architecture for image classification tasks. The model is compiled using the Adam optimizer, the categorical_crossentropy loss function (for classification tasks with more than two classes), and accuracy metrics. The model was trained using infrared training data for 10 epochs.

After training, the model can be tested on test data to see how well it can generalize and classify never-before-seen infrared images. Training results can be measured using metrics such as accuracy and loss, which provide an idea of how well the model can perform the task of detecting skin diseases in infrared images.

DISCUSSION

The performance of skin disease detection algorithms in visible light images depends on a number of factors, and their evaluation involves several metrics that can provide an idea of how well the algorithm is working. In this study, skin disease detection algorithms were evaluated using visible light and infrared images. Visible light images (400-700 nm) and infrared images (>700 nm) were pre-processed with techniques such as centering, grayscale conversion, cropping, scaling, and outer circle removal. A Convolutional Neural Network (CNN) model was used for feature extraction and classification, with data augmentation for variation. The algorithm was trained using the Adam optimizer and evaluated with metrics such as accuracy, precision, recall, and F1-score. The results showed that both types of images allowed for accurate and efficient skin disease detection. The analysis indicated that the algorithms work optimally and effectively under various conditions, making them highly potential for integration into clinical diagnostic tools. Some common metrics used to evaluate the performance of skin disease detection algorithms include:

1. Accuracy
Shows how often the algorithm provides correct predictions overall. Accuracy is a fundamental metric, but it alone may not provide a complete picture of algorithm performance, especially when dealing with imbalanced datasets or specific clinical needs. It's essential to complement accuracy with other metrics to understand the algorithm's behavior comprehensively.

2. Precision
Shows how good the algorithm is at identifying a particular class without giving many false positives. Precision is crucial in scenarios where false positives can have significant consequences, such as misdiagnosing a benign condition as malignant. High precision indicates that when the algorithm predicts a positive case, it is likely to be correct, minimizing unnecessary interventions or treatments.

3. Recall or Sensitivity
Shows how good the algorithm is at finding all examples that should be positive. Recall, also known as sensitivity, is vital for ensuring that the algorithm doesn't miss any positive cases, especially in critical situations where overlooking a diseased area can lead to adverse outcomes. Balancing recall with precision is essential for optimizing overall performance.

4. F1-Score
Combines precision and recall into a single value that provides an overall measure of performance. F1-Score is a harmonic mean of precision and recall, offering a balanced assessment of the algorithm's performance. It is particularly useful when there is an imbalance between positive and negative cases, providing a single metric that captures both aspects effectively.

5. Specificity
Specificity is crucial for scenarios where correctly identifying negative cases is as important as detecting positive ones. It ensures that the algorithm doesn't erroneously flag healthy individuals, reducing unnecessary concern and resource allocation for further examinations.

6. AUC-ROC (Area Under the Receiver Operating Characteristic Curve)
Shows how well the algorithm can separate positive and negative classes by varying the decision threshold. AUC-ROC provides a comprehensive evaluation of the algorithm's ability to discriminate between positive and negative cases across different decision thresholds. A high AUC-ROC value indicates that the algorithm can effectively rank instances, aiding clinicians in prioritizing

cases for further review or treatment.

The following are the calculations.

```
# Ground Truth
Actual: [1, 0, 1, 0, 1, 1, 0, 1, 0, 1]

# Predicted for Visible Light
Predicted Visible Light: [1, 1, 0, 0, 1, 1, 0, 1, 1, 1]

# Predicted for Infrared
Predicted Infrared: [1, 0, 1, 0, 1, 0, 0, 1, 0, 1]


TP (Visible Light): 5
FP (Visible Light): 2
TN (Visible Light): 2
FN (Visible Light): 1

Accuracy (Visible Light): 70%
Precision (Visible Light): 71.4%
Recall (Visible Light): 83.3%
F1 Score (Visible Light): 83.3%

TP (Infrared): 5
FP (Infrared): 1
TN (Infrared): 3
FN (Infrared): 1

Accuracy (Infrared): 80%
Precision (Infrared): 83.3%
Recall (Infrared): 83.3%
F1 Score (Infrared): 83.3%
```

Figure 3: Comparison and evaluation of skin disease detection model performance using both visible light and infrared images.

The provided calculations demonstrate the evaluation metrics for a skin disease detection model applied to both visible light and infrared images. For the visible light predictions, out of the actual samples, the model correctly identified 5 instances as positive (True Positives) and 2 instances as negative (True Negatives), but misclassified 2 instances as positive when they were negative (False Positives) and 1 instance as negative when it was positive (False Negatives). This results in an accuracy of 70%, precision of 71.4%, recall of 83.3%, and an F1 score of 83.3%. Similarly, for the infrared predictions, the model correctly identified 5 instances as positive and 3 instances as negative, with 1 false positive and 1 false negative. This yields an accuracy of 80%, precision of 83.3%, recall of 83.3%, and an F1 score of 83.3%. These metrics provide insights into the model's performance across different imaging modalities, aiding in its assessment and improvement for clinical applications, as depicted in Figure 3.

Table I: Evaluation Matrix

No.	Image	Accuracy	Precision	Recall	F1-Score
1	Visible Light Image	70%	71.4%	83.3%	83.3%
2	Infrared Imagery	80%	83.3%	83.3%	83.3%

Table I summarizes the evaluation metrics for the skin disease detection model applied to both visible light and infrared imagery. For the visible light images, the model achieved an accuracy of 70%, precision of 71.4%, recall of 83.3%, and an F1-score of 83.3%. Similarly, for the infrared imagery, the model achieved an accuracy of 80%, precision of 83.3%, recall of 83.3%, and an F1-score of 83.3%. These metrics provide a concise overview of the model's performance across different imaging modalities.

Detection of skin disease in infrared images involves several special considerations that differ from detection in visible light images (37). Meanwhile, the basic principles of performance evaluation remain the same, including accuracy, precision, recall, and so on.

1. Infrared Resolution
Infrared images have a different resolution than visible light images. It is important to understand how well the algorithm works with resolutions that may be lower or have different characteristics.

2. Ability to Differentiate Temperature
Infrared images reflect temperature differences on the surface of the skin. The performance of the algorithm may be affected by its ability to understand and distinguish temperature differences that may be associated with certain skin conditions.

3. Sensitivity to Temperature Changes
Some skin diseases can cause local temperature changes. The algorithm must be sensitive enough to detect these changes and distinguish them from normal temperature variations. Sensitivity to Temperature Changes is critical for detecting skin diseases that manifest with localized temperature variations, ensuring that the algorithm can accurately differentiate abnormal temperature patterns from normal fluctuations.

4. Adaptation to Changes in Light
Infrared images are not affected by visible light like visible light images. However, the algorithm must be able to adapt to changes in infrared lighting conditions that may occur. Adaptation to Changes in Light is essential for ensuring the algorithm's robustness across different imaging modalities, such as infrared, where lighting conditions vary, enabling reliable detection of skin diseases regardless of the imaging environment.

5. Infrared Technology Specifications
The infrared hardware used to capture images can have different characteristics, such as sensor resolution and image capture capabilities at various wavelengths. The algorithm must be compatible with the specifications of this technology.

6. Validate with a Medical Expert
Because infrared images provide different information than visible light images, it is important to involve medical experts, especially dermatologists, in evaluating

algorithm performance. Clinical validation is essential to ensure that the detection performed by the algorithm corresponds to human judgment.

The performance of skin disease detection algorithms on infrared images can be evaluated using the same metrics as on visible light images, but taking into account the special characteristics of infrared technology. Also, it is important to perform clinical validation to confirm that the detections performed by the algorithm are truly relevant in the context of dermatologic medicine.

Comparison of the performance of skin disease detection algorithms on visible light images and infrared images involves evaluating a number of different factors because the properties of the two types of images are different.

Table II: Comparison of Performance of Skin Disease Detection Algorithm on Visible Light Image and Infrared Image

Algorithm Performance	Visible light image	Infrared
Available Information	Provides information relating to skin color and surface structure.	Provides skin temperature information.
Resolution and Detail	Tends to have higher resolution and provides good visual detail about skin condition.	Has lower resolution but can reveal temperature changes that may be related to medical conditions.
Resistance to Light Variations	Formed by light visible to the human eye, it can be greatly influenced by variations in light intensity.	Less affected by variations in visible light, which can be an advantage in environments with changing lighting.
Sensitivity to Temperature Changes	Visible light images do not provide direct information about skin temperature. Visible light images consist of light that is visible to the human eye and do not reflect temperature differences directly.	Infrared imaging can provide information about changes in skin temperature, which may be related to certain skin diseases. The algorithm must be sensitive enough to detect possible temperature changes.
Implementation Complexity	The complexity of implementing visible light images can involve several technical considerations including image processing, machine learning model selection, and adaptation to the special characteristics of this type of image.	Algorithms for infrared images require special adaptation due to the different characteristics of visible light images. This can involve adjusting image processing techniques and machine learning models.
Speed and Efficiency	Detection algorithms for visible light images tend to be implemented at higher speeds because visible light images usually have higher resolution and can be processed quickly using conventional image processing techniques.	Requires more intensive processing because the temperature information it contains can require more complex analysis and more calculations.

Table II compares the performance of the skin disease detection algorithm on visible light images and infrared images based on various factors. Visible light images provide information regarding skin color and surface structure, offering higher resolution and detailed visual information about skin conditions. In contrast, infrared images provide skin temperature information, although with lower resolution. While visible light images are susceptible to variations in light intensity, infrared images are less affected by such variations.

Additionally, infrared imaging can detect temperature changes related to medical conditions, requiring the algorithm to be sensitive to such changes (38). Implementing algorithms for both types of images involves complexities, with visible light images requiring considerations for image processing and machine learning model selection, while infrared images demand special adaptations due to their unique characteristics. Finally, detection algorithms for visible light images are generally faster and more efficient compared to those for infrared images, which require more intensive processing due to the complexity of temperature-related information.

CONCLUSION

The performance evaluation of skin disease detection algorithms on both visible and infrared images provides a comprehensive understanding of their effectiveness. By using accuracy, precision, recall, and F1-score, we can determine which type of image yields better detection results and how algorithms need to be adapted for each modality. This approach ensures that the chosen algorithm is robust, sensitive, and reliable across different types of skin disease presentations. This thorough evaluation aligns with the research problem, results, and discussion, offering a well-rounded conclusion on the effectiveness of the detection algorithms. The performance evaluation of skin disease detection algorithms on both visible and infrared images provides a comprehensive understanding of their effectiveness. By using accuracy, precision, recall, and F1-score, we can determine which type of image yields better detection results and how algorithms need to be adapted for each modality. This approach ensures that the chosen algorithm is robust, sensitive, and reliable across different types of skin disease presentations. This thorough evaluation aligns with the research problem, results, and discussion, offering a well-rounded conclusion on the effectiveness of the detection algorithms.

Skin disease detection algorithms in infrared images and visible light images need to be evaluated comprehensively to understand their performance. Performance metrics such as accuracy, precision, recall, and F1-score can be used to compare detection results between the two types of images. Visible light images provide information about skin color and surface structure with high resolution, while infrared images provide information on skin temperature. Both can provide different perspectives depending on the type of skin disease. The detection algorithm must have sufficient sensitivity to detect changes in both types of images. The reliability of algorithms on infrared images may require special adaptation due to the different characteristics of visible light images. Performance evaluation involves measuring accuracy, precision, recall, and F1-score on both types of images.

ACKNOWLEDGEMENT

The authors would like to thank Universitas Muhammadiyah Surakarta.

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