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Classification of Foot Wound Severity in Type 2 Diabetes Mellitus Patients Using MobileNetV2-Based Convolutional Neural Network

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ABSTRACT

Diabetic Foot Ulcer (DFU) is a serious complication in Type 2 Diabetes Mellitus patients that may lead to amputation if not properly treated. This study employs the MobileNetV2 architecture based on Convolutional Neural Network (CNN) to classify DFU severity into two categories: severe and non-severe. The dataset consists of 1,000 images, divided into 70% training, 20% validation, and 10% testing. Data preprocessing was performed using normalization, augmentation (rotation, flipping, zooming), and dataset balancing to enhance model generalization. The model was trained for 10 epochs with a batch size of 32, learning rate of 0.001, and Adam optimizer. Experimental results show 98% accuracy on validation data with an average precision, recall, and F1-score of 0.98. On the testing stage, the model achieved 94% accuracy with an average precision, recall, and F1-score of 0.94. The confusion matrix also indicates strong performance in distinguishing both classes. This study demonstrates that MobileNetV2-based CNN with proper preprocessing and hyperparameter settings can serve as an effective supporting method for early DFU severity classification, thereby improving the speed and accuracy of medical decision-making.

I. Introduction

High blood sugar levels above normal limits are a sign of a metabolic disease known as diabetes mellitus, also known as diabetes mellitus [1]. Diabetes mellitus is a non-communicable disease belonging to a group of metabolic disorders characterized by hyperglycemia caused by impaired insulin secretion, insulin action, or both. When the body can no longer produce enough insulin to compensate for insulin resistance, a metabolic disorder known as type 2 diabetes mellitus occurs. This type of diabetes increases the risk of heart and kidney disease, as well as stroke [2]. Elevated blood glucose levels are a hallmark of diabetes mellitus. Weight loss, polydipsia, polyphagia, and polyuria are common symptoms experienced by sufferers [3]. One way to control the body's blood sugar levels safely is to take medication regularly [4].

One of the complications that can be experienced by people with diabetes mellitus is the appearance of DM wounds or gangrene and ulcers, which can cause the tissue and skin around the wound to rot, smell, and blacken. These long-term wounds cause nerve damage and poor blood circulation, which can cause painless, sore, and painful feet. Wounds in the feet of people with diabetes are often difficult to heal and risk leading to amputation if not properly treated. Therefore, conventional approaches to identifying wound severity often require complex and time-consuming medical interventions. Therefore, the use of artificial intelligence (AI), specifically Convolutional Neural Networks (CNN), is an innovative solution to improve the accuracy and efficiency of classifying foot wounds in people with diabetes [5].

Approximately 25% of diabetic patients are at risk of developing diabetic ulcers. In more severe cases, diabetic ulcers can lead to partial or complete limb amputation. Classifying diabetic ulcers helps identify the type of wound and select appropriate treatment. For people with diabetes, it is crucial to quickly understand the status or grade of their ulcer so they can receive appropriate medical care. Currently, the Megit-Wagner criteria are one of the classification systems used to determine the grade of diabetic ulcers; they categorize ulcers from grades 0 to 5 and serve as a management guideline that can be given to assess ulcer depth and predict the risk of osteomyelitis [6].

Previous research entitled "Convolutional Neural Network Models for Visual Classification of Pressure Ulcer Stages" in this study used CNN architectures such as AlexNet, VGGNet16, ResNet18, and DenseNet121. The data used consisted of 853 original clinical wound images and was expanded to 7677 images with an augmentation method. The results showed that the DenseNet121 model was the best with an accuracy of 93.71% [7].

Previous research focused on the classification of pressure ulcers using CNN architectures such as AlexNet, VGGNet16, ResNet18, and DenseNet121. However, this study specifically focuses on foot ulcers in patients with type 2 diabetes and uses the lighter and more effective MobileNetV2 architecture for classification purposes. This research focuses on the use of the MobileNetV2 architecture to classify the severity of foot ulcers in patients with type 2 diabetes mellitus. This study proposes the use of a lighter and more efficient architecture to support the development of a classification system that can be applied to systems with limited resources.

II. METHODS

This study is a quantitative experimental study that aims to use the Convolutional Neural Network (CNN) algorithm to determine the severity of foot wounds in Type 2 Diabetes Mellitus patients.

A. Data Collection

Essentially, a data collection method is a scientific technique for gathering data for a specific purpose [8]. The following are the data collection methods used in this study:

1) Literature Study

Deep learning has emerged as a branch of machine learning within computer vision since 2006. Image processing methods that utilize multiple layers of structure and involve multiple transformation processes are known as deep learning. Image classification is a type of research that uses artificial intelligence to aid in the diagnosis process. This process uses deep learning to identify diseases based on specific characteristics found in a particular image [9].

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that can accept image input and identify objects within the image. CNNs can also use image recognition to distinguish between all existing images. Because of their ability to capture spatial patterns, Convolutional Neural Networks (CNN) have become the primary method for feature extraction in images [10]. The layers that make up a CNN consist of the Convolution Layer, Activation ReLU Layer, Pooling Layer, and Fully Connected Layer [11].

An image is a two-dimensional image plane consisting of many pixels, each pixel being the smallest part of the image. An image consists of a regular rectangular grid, so that the vertical and horizontal distances between pixels are equal. There are two types of images: still images (still images) and moving images (moving images). The row and column index matrix representing the points in the image and its elements is known as a pixel element [12].

Classification is the process of grouping data based on specific criteria and similarities in data variables with the goal of creating a model that can predict new, unknown data classes. The classification process can be performed manually or through the use of computing technology [13]

MobileNetV2 is one of the latest highly effective deep learning models designed to address the problem of consuming large computational resources without sacrificing accuracy. MobileNetV2 uses two types of convolutions: depthwise and pointwise. Both types of convolutions make MobileNetV2 lighter and faster in computation, allowing this model to perform better on devices with limited resources, such as mobile devices or edge devices. A study shows that MobileNetV2 uses fewer resources to provide highly accurate image classification results. Because of these advantages, MobileNetV2 is the main choice for many image processing applications, especially those requiring high performance. MobileNetV2 has a new layer module with inverted residuals with a linear bottleneck. This significantly reduces the amount of memory required for processing [14]. The MobileNet architecture relies on separable depthwise convolution. While standard 2D convolution processes all input channels directly to produce a single output channel by convolving in the depth dimension of the channels, in depthwise convolution, the input image and filter are separated into different channels, then each input channel is convolved with the corresponding filter channel. After the filtered output channels are concatenated, they are then recombined. The advantages of using the MobileNetV2 architecture are high accuracy and a smaller number of training parameters compared to other CNN architectures, which reduces the amount of computation required. Furthermore, the MobileNetV2 model size is small, but still provides good performance [15].

2) Interview

One of the data collection methods used was interviews, which were used to obtain more in-depth information about the classification of diabetic foot wounds. To obtain further information about the classification of diabetic foot wounds, an interview was conducted with Mr. Muhammad Anri Rifai, S.Kep., a nurse who cares for diabetic patients with complicated foot wounds.

3) Data Collection

The total data used in this study amounted to 1,000 images, some of which were obtained from field sources (diabetic foot wound nurses) and the other part of the data was obtained from the open-source platform keggle which provides a dataset of diabetic foot wound images. The dataset used in this study consists of 1,000 images evenly divided into two categories, namely 500 images of severe wounds and 500 images of non-severe wounds. In this study, the process of classifying the severity of foot wounds in patients with type 2 diabetes mellitus using the CNN method with the MobileNetV2 architecture was divided into three data sets, namely (70%) training data, (20%) validation data, and (10%) test data. Training data is used to build or train the model, validation data to optimize the training process, and test data to evaluate the resulting model. Details of the data sets can be seen in Table 1.

TABLE 1
DATASET DISTRIBUTION

Class	Training Data	Data Validation	Data Testing	∑
Severe Injuries	350	100	50	500
Injuries Not Severe	350	100	50	500
Total	700	200	100	1000
Percentage	70%	20%	10%	100%

The following is a visualization of a sample wound image for the serious wound class as shown in figure 1.

Figure 1. Sample Dataset of Severe Injuries

The following is a visualization of an example of a wound for the non-serious wound class as shown in Figure 2.

B. Data Pre-Processing

Data preprocessing is crucial to ensure the quality and effectiveness of the developed classification model. This process begins with the collection of images of diabetic foot ulcers of varying severity, achieved by standardizing the image capture to ensure data consistency. Image preprocessing is performed prior to image collection. This includes resizing to standardize dimensions, normalizing pixel values, converting to an appropriate color format, and cropping to remove unimportant areas and focus on the ulcers. Preprocessing aims to improve the quality of the input data, reduce noise, and ensure that the CNN model can effectively learn relevant characteristics in the diabetic foot ulcer images to produce accurate severity classification. The initial stage of data processing in this study is data augmentation.

Figure 2. Sample Dataset of Non-Serious Injuries

This process is carried out to expand the dataset variety, reduce the potential for overfitting, improve model robustness, balance data distribution, and accelerate the training process. After augmentation is performed, the next step is to load the dataset. At this stage, the dataset is entered, separated as needed, and then directories are determined for training, validation, and testing data. This process also includes labeling and data division (dataset splitting) with a proportion of 70% for training data, 20% for validation data, and 10% for testing data.

C. Data Augmentation

Data augmentation is performed to increase the number and variety of images in a dataset, allowing the model to learn various image characteristics. This technique is used to prevent overfitting, a condition where a model performs well on training data but fails to generalize to new data. In this study, augmentation was applied to the model through several image transformations, including horizontal mirroring, 30-degree random rotation, and 20% zoom.

Figure 3. Results of Severe Wound Augmentation

Figure 4. Wound Augmentation Results are Not Severe

D. CNN Model Design

In this study, the CNN model design with the MobileNetV2 architecture aims to produce an efficient, accurate image classification model that can run optimally on devices with limited computing power. By utilizing a depthwise separable convolution structure and an inverted residual block, this architecture is designed to be able to extract important features from images of diabetic foot wounds with a low computational burden without sacrificing accuracy performance. This approach allows the model to be not only fast in the training and prediction process, but also efficient in memory usage.

The use of the MobileNetV2 architecture in this study was carried out with a transfer learning approach with a limited fine-tuning method, rather than using the pure MobileNetV2 architecture. The base MobileNetV2 model that had been pre-trained on the ImageNet dataset was used as a feature extractor with retained initial weights (frozen layers). With this configuration, the initial weights of MobileNetV2 that had been trained on the ImageNet dataset were maintained, so full fine-tuning was not performed. After that, several new layers were added, namely GlobalAveragePooling2D, Dense with ReLU activation, Dropout of 0.5, and Dense output with sigmoid activation. Thus, the final architecture is a combination of MobileNetV2 with additional classification layers, which proved to be more efficient than building a CNN from scratch.

Membangun model MobileNetV2...
Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_3 (InputLayer)	(None, 224, 224, 3)	0
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2,257,984
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1280)	0
dense_2 (Dense)	(None, 128)	163,968
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 1)	129

Total params: 2,422,081 (9.24 MB)
Trainable params: 164,097 (641.00 KB)
Non-trainable params: 2,257,984 (8.61 MB)

Figure 5. Summary Model MobileNetV2

Figure 5 shows an image classification model built using the Transfer Learning approach with MobileNetV2. The model begins with a 224×224 pixel input layer with 3 color channels (RGB). Then, features are extracted using MobileNetV2 (with pre-trained weights) to produce an output of size (7, 7, 1280). This output is then summarized through a 2D Global Average Pooling layer into a 1280-dimensional vector. After that, a dense layer with 128 units and ReLU activation is added, followed by a dropout layer to prevent overfitting. The final layer is a dense layer with 1 unit and a sigmoid activation function used for binary classification. Overall, the model has a total of 2,422,081 parameters, with 164,097 trainable parameters and 2,257,984 non-trainable parameters. This shows that most of the weights come from MobileNetV2 which is frozen to retain features from its initial training, while additional layers are trained to fit the diabetic foot wound classification dataset.

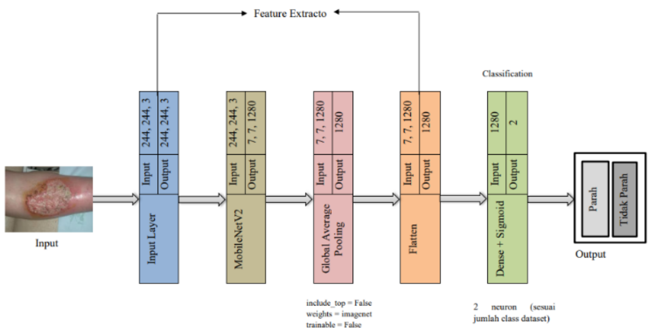


Figure 6. MobileNetV2 Architecture

Figure 6 explains the stages or processes of the MobileNetV2 architecture that will be used in classifying the severity of foot wounds in type 2 diabetes mellitus sufferers.

E. Testing

The model's generalization ability was tested using pre-prepared test data that was never seen during the training process. A CNN model trained to generate severity classification predictions was used to process the wound images in this test data. To assess model performance, various metrics such as accuracy, precision, recall, and F1-score were used. This testing used the Python programming language and Google Colab tools.

F. Model Evaluation

The goal of the evaluation phase of this research is to determine how well a Convolutional Neural Network (CNN) model classifies the severity of diabetic foot wounds. Part of this process involves using test data that differs from the data used to train the model. To assess model accuracy, the trained CNN model predicts wound severity based on the test data. These predictions are then compared with the labels on the actual test data. Model performance is quantitatively measured using metrics such as accuracy, precision, recall, and F1-Score. The evaluation in this study used a confusion matrix to calculate the accuracy, precision, recall and F-1 Score values shown in equations 1-4.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F-1 Score} = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \tag{4}$$

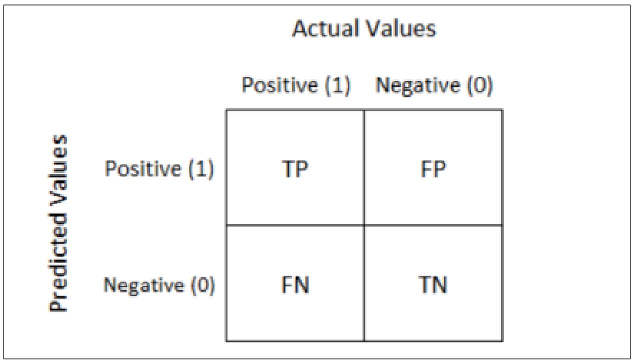


Figure 7. Confusion Matrix

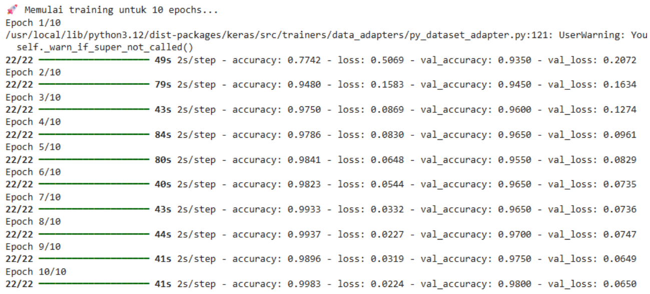
Information:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

III. RESULT AND DISCUSSION

In this study, a series of tests were conducted to obtain the best results from the classification model for the severity of foot wounds in patients with Type 2 Diabetes Mellitus based on the Convolutional Neural Network (CNN) algorithm with the MobileNetV2 architecture. The dataset was divided into three parts: the training dataset, the validation dataset, and the testing dataset. The training dataset was used to train the model to recognize patterns in wound images, while the validation dataset functioned to evaluate the model's performance during the training process. Meanwhile, the testing dataset was used in the final stage to measure the model's performance on new, previously unseen data, so that the results obtained could describe the model's overall generalization ability. The results of the training process were then analyzed through the accuracy and loss values obtained at each epoch, and strengthened by evaluation using a confusion matrix to see the distribution of predictions in each class.

A. *Model Training Results*

The MobileNetV2 model training process was carried out over 10 epochs using a dataset that had been divided into training and validation data. Each epoch generated accuracy and loss values for both datasets, which were then used to monitor the model's performance over time. Detailed results from the training process can be seen in the following output.



```
🚀 Memulai training untuk 10 epochs...
Epoch 1/10
/usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: You
  self._warn_if_super_not_called()
22/22 ━━━━━━━━━━━━━━━━━━━━ 49s 2s/step - accuracy: 0.7742 - loss: 0.5069 - val_accuracy: 0.9350 - val_loss: 0.2072
Epoch 2/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 79s 2s/step - accuracy: 0.9480 - loss: 0.1583 - val_accuracy: 0.9450 - val_loss: 0.1634
Epoch 3/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 43s 2s/step - accuracy: 0.9750 - loss: 0.0869 - val_accuracy: 0.9600 - val_loss: 0.1274
Epoch 4/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 84s 2s/step - accuracy: 0.9786 - loss: 0.0830 - val_accuracy: 0.9650 - val_loss: 0.0961
Epoch 5/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 80s 2s/step - accuracy: 0.9841 - loss: 0.0648 - val_accuracy: 0.9550 - val_loss: 0.0829
Epoch 6/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 40s 2s/step - accuracy: 0.9823 - loss: 0.0544 - val_accuracy: 0.9650 - val_loss: 0.0735
Epoch 7/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 43s 2s/step - accuracy: 0.9933 - loss: 0.0332 - val_accuracy: 0.9650 - val_loss: 0.0736
Epoch 8/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 44s 2s/step - accuracy: 0.9937 - loss: 0.0227 - val_accuracy: 0.9700 - val_loss: 0.0747
Epoch 9/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 2s/step - accuracy: 0.9896 - loss: 0.0319 - val_accuracy: 0.9750 - val_loss: 0.0649
Epoch 10/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 2s/step - accuracy: 0.9983 - loss: 0.0224 - val_accuracy: 0.9800 - val_loss: 0.0650
```

Figure 8. Model Training for 10 Epochs

Although the number of epochs used was relatively small, only 10, this was done to prevent overfitting, as the MobileNetV2 model already demonstrated significant accuracy improvements on both the training and validation data in the initial epochs. Furthermore, regularization techniques such as dropout and data augmentation strategies were applied to maintain the model's generalizability.

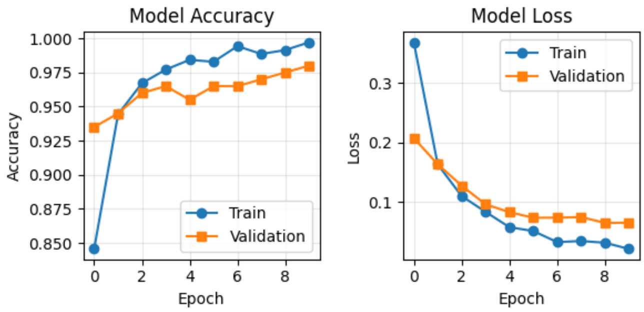


Figure 9. Training Graph Result

The graph shows the comparison of accuracy between training data and validation data during the model training process for up to 10 epochs. It can be seen that the training accuracy increased very rapidly from around 0.85 in the first epoch to nearly 1.00 in the 10th epoch, indicating that the model was able to learn well from the training data. Meanwhile, the validation accuracy also experienced a steady increase from around 0.93 to nearly 0.98, although slightly lower than the training accuracy. This indicates that the model is not only able to memorize the training data but also has quite good generalization ability to data that has not been seen before, with a relatively small gap between training and validation accuracy.

B. *Data Testing*

The following shows the results of testing a CNN model on test data with two classes: severe and non-severe injuries. The image shows an example of output, displaying an image of a foot wound along with its predicted class. This prediction is displayed directly in the image with the captions "Prediction" and "Confidence," indicating the model's classification results. This output demonstrates the model's ability to distinguish between two levels of wound severity based on the features extracted from the input image.

In a study using a Convolutional Neural Network (CNN)-based MobileNetV2 for diabetic foot ulcer severity classification, the testing phase included several systematic procedures to evaluate the model's performance. First, the model's generalization ability was tested with prepared test data that had not been seen during the training process. A MobileNetV2-CNN model trained to generate severity classification predictions was used to process the wound images in this test data.

Figure 10. Test Data Results

The test results in Figure 10 on four test data sets show that the MobileNetV2-based CNN model is capable of classification with excellent accuracy. For two samples in the severe wound category, the model provided predictions with confidence levels of 100.00% and 99.79%, while the probability for the non-severe class was at 0.00% and 0.21%. This indicates that the model can consistently recognize the characteristics of severe wounds. Meanwhile, for two samples in the non-severe wound category, the model provided prediction results with confidence levels of 98.00% and 99.91%, with a misclassification probability of only 2.00% and 0.09% for the severe class. The high confidence values in all predictions indicate that the model has successfully learned the fundamental differences between severe and non-severe wounds, making it reliable in the process of classifying diabetic foot wound images.

C. Model Evaluation

The evaluation phase of this study aims to measure the effectiveness of a Convolutional Neural Network (CNN) model with the MobileNetV2 architecture in classifying the severity of diabetic foot wounds. The evaluation was conducted using test data different from the training data to ensure objectivity. The trained CNN model was used to predict wound severity on the test data, then the prediction results were compared with the actual labels. Model performance was assessed quantitatively using evaluation metrics such as accuracy, precision, recall, and F1-score.

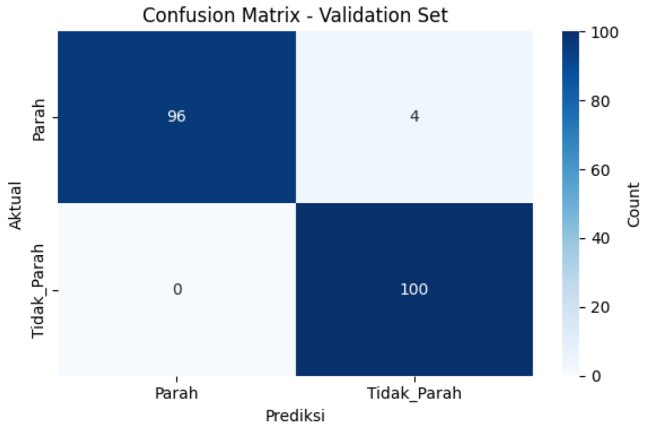


Figure 11. Confusion Matrix in Data Validation

Classification Report (Validation):

	precision	recall	f1-score	support
Parah	1.00	0.96	0.98	100
Tidak_Parah	0.96	1.00	0.98	100
accuracy			0.98	200
macro avg	0.98	0.98	0.98	200
weighted avg	0.98	0.98	0.98	200

Figure 12. Classification Report Model

Figure 11 and 12 shows the evaluation results using 200 validation samples. The CNN model achieved 98% accuracy. For the Severe class, the model achieved perfect precision (100%), meaning all Severe predictions were correct, but recall was slightly lower (96%) due to four Severe data points being missed. Conversely, for the Not_Severe class, recall reached 100% (all data points were detected), while precision dropped to 96% due to several Severe data points being misclassified as Not_Severe. The F1-score for both classes was balanced at 98%, indicating the model was quite stable in recognizing both wound categories. Overall, the macro average and weighted average values were both 98%, reinforcing the model's consistent performance across both classes.

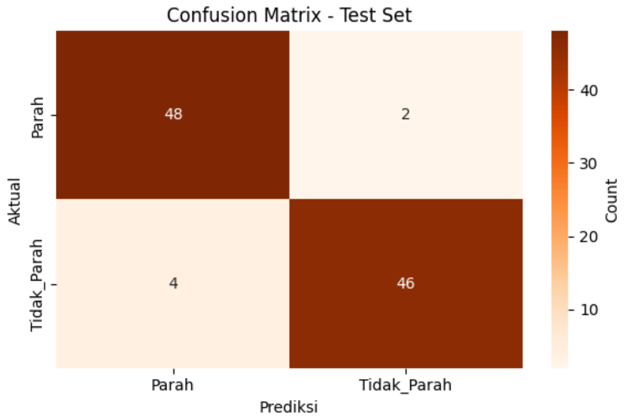


Figure 13. Confusion Matrix on Testing Data

Figure 13 is the confusion matrix from the results of testing the CNN model on the test data set with a total of 100 samples.

```
📊 Classification Report (Test):
              precision    recall  f1-score   support

       Parah       0.92      0.96      0.94        50
 Tidak_Parah       0.96      0.92      0.94        50

    accuracy                           0.94       100
   macro avg       0.94      0.94      0.94       100
weighted avg       0.94      0.94      0.94       100
```

Figure 14. Classification Report Model

Figure 14 shows the classification report results on the test data (test set). It shows that the CNN model achieved an accuracy of 94% with equally high precision, recall, and f1-score values (0.94) for both classes, namely Severe and Not_Severe. The precision value of 0.92 for the Severe class indicates that most of the Severe predictions were correct, while the recall of 0.96 indicates that almost all Severe data were successfully detected. Conversely, for the Not_Severe class, the precision was higher (0.96), meaning the predictions were more accurate, although the recall was slightly lower (0.92). The consistency of the macro average and weighted average values, both of which were 0.94, also shows that the model was able to handle both classes equally without bias. Therefore, it can be concluded that the model has very good and reliable performance in classifying diabetic foot wounds into the Severe and Not_Severe categories.

The performance difference between the validation data (98%) and the test data (94%) shows a small difference of around 4% which does not indicate overfitting, but rather demonstrates the good generalization ability of the MobileNetV2 model. The dataset was divided using a stratified split method with a proportion of 70% training, 20% validation, and 10% testing to balance the class distribution. Evaluation using a confusion matrix shows that prediction errors are more frequent in the severe wound class due to visual similarities with less severe wounds. Overall, these results prove that the CNN-based MobileNetV2 architecture has high performance and great potential as a diagnostic tool for classifying the severity of diabetic foot wounds.

IV. Conclusion

This study demonstrates that the CNN-based MobileNetV2 architecture is capable of delivering excellent performance in classifying the severity of diabetic foot wounds into two categories, namely severe wounds and non-severe wounds. The model drilled with a dataset of 1,000 images and divided into stratified splits (70% training, 20% validation, 10% testing) successfully achieved a validation accuracy of 98% and a test accuracy of 94%, with the confusion matrix results indicating that the model more often misclassifies severe wounds due to visual similarities with non-severe wounds. The difference between the performance of the validation data and the test data was only 4%, which indicates good model generalization ability and no indication of significant overfitting. Compared with results in similar studies using different CNN architectures, the MobileNetV2 model shows higher accuracy even with a smaller amount of data. This confirms the efficiency and effectiveness of MobileNetV2 as a supporting method for early diagnosis, and has the potential to help the medical decision-making process become faster and more accurate. used as a supporting method for early diagnosis in the classification of diabetic foot wounds.

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