

IDENTIFYING SKIN CANCER DISEASE TYPES WITH YOU ONLY LOOK ONCE (YOLO) ALGORITHM

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Abstract

The skin is the outermost vital organ and is susceptible to various diseases, including skin cancer. The number of cases of skin cancer around the world continues to increase every year, including in Indonesia. Proper handling is critical to cure skin cancer, and one of the solutions that can be used is the Deep Learning method. This study aims to apply the Deep Learning method, specifically an object detection algorithm called You Only Look Once (YOLO), for early skin cancer detection. The YOLOv5s algorithm is the model for this study because it is accurate and can detect objects in real-time. The research method involved collecting data on skin cancer cases and training the YOLOv5s model. After training, model testing is used to evaluate the ability to detect skin cancer. The test results show that the YOLOv5s model has an accuracy of 89.1% in detecting skin cancer types. This research has important implications in the health sector, especially in early skin cancer detection.

Keywords: Skin, Skin Cancer, Deep Learning, You Only Look Once (YOLO)

Abstrak

Kulit adalah organ tubuh terluar yang penting dan rentan terhadap berbagai penyakit, termasuk kanker kulit. Jumlah kasus kanker kulit di seluruh dunia terus meningkat setiap tahunnya, termasuk di Indonesia. Penanganan yang tepat sangat penting untuk menyembuhkan kanker kulit, dan salah satu solusi yang dapat digunakan adalah metode Deep Learning. Penelitian ini bertujuan untuk menerapkan metode Deep Learning, khususnya algoritma pendeteksian objek bernama You Only Look Once (YOLO), untuk deteksi dini kanker kulit. Algoritma YOLOv5s dipilih sebagai model yang digunakan dalam penelitian ini karena memiliki akurasi yang baik dan mampu mendeteksi objek secara real-time. Metode penelitian yang digunakan melibatkan pengumpulan data kasus kanker kulit dan pelatihan model YOLOv5s menggunakan data tersebut. Setelah pelatihan, dilakukan pengujian model untuk mengevaluasi kemampuan deteksi kanker kulit. Hasil pengujian menunjukkan bahwa model YOLOv5s memiliki akurasi sebesar 89,1% dalam mendeteksi jenis kanker kulit. Penelitian ini memiliki implikasi penting dalam bidang kesehatan, khususnya dalam deteksi dini kanker kulit.

Kata kunci: Kulit, Kanker Kulit, Deep Learning, You Only Look Once (YOLO)

INTRODUCTION

Skin cancer detection is an essential part of preventing and treating this disease. Various methods have been developed to detect skin cancer, especially melanoma, the most malignant type (Setiabudi, Wardhana, Indira, & Puspawati, 2021). However, these methods also have challenges and

limitations that must be understood. Visual Examination is one of the challenges and constraints associated with skin cancer detection methods. Still, the challenges are that the variety of shapes and sizes of skin lesions are complex for health professionals to visually analyze, small lesions or lesions located in hard-to-reach areas can be missed, visual assessment can be affected by the



experience and subjectivity of the examiner, and Dermoscopy also has the challenge of requiring specialized training to interpret dermatoscopic images, distinguishing between malignant and benign lesions can be complicated, especially in complex cases. Dermoscopy results can vary between different observers. (Agustina, 2022)

Based on the explanation of the problem, early detection is needed so that patients can immediately receive appropriate medical treatment. The solution that researchers can provide is to create a model that can detect objects, in this case, skin exposed to cancer cells (Kanwal, Amundsen, Hardardottir, Janssen, & Engan, 2023). One of the most popular identification systems today is the Deep Learning system, part of machine learning. In Deep Learning, the computer learns to process its data, resulting in accurate predictions or decisions using artificial neural network models. (Luqman Hakim, Sari, & Handhajani, 2021)

In this research, the algorithm used is the YOLO (You Only Look Once) algorithm, which is one of the Deep learning algorithms that can detect objects in real time with high accuracy (Mulyana & Rofik, 2022). YOLO has been applied to various fields of life, including the medical field. In contrast to other object detection algorithms, such as CNN, that require several processing stages to perform object detection, YOLO only performs object detection in one processing time, making it faster and more efficient. Based on the problems described above, It is difficult to distinguish the characteristics of the appearance of skin cancer images (malignant and benign), so a model is needed that can help early detection of skin cancer so that sufferers can receive appropriate and rapid medical treatment.

RESEARCH METHODS

The research methodology will be conducted in this chapter based on the Cross Standard Industries for Data Mining (CRISP-DM) framework. This methodology is divided into five main completion phases: business understanding and data understanding. Then, in the modeling section, the discussion will focus on designing the stages of Data Preparation, Modelling, and Evaluation. The flow of research methodology using CRISP-DM is seen in Figure 1.

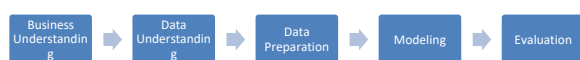


Figure 1. Stages of CRISP-DM Research Methodology

Types of research

These experiments are conducted in a controlled environment, usually in a laboratory, where researchers manipulate one or more independent variables to observe their effect on the dependent variable while controlling for other variables.

Research Target / Subject

At this stage, the researcher conducts data collection. The data used in the study amounted to 3,297 images of skin cancer disease data. This data will then be divided into three types of data, namely training data, validation data, and testing data.

Use training data to train the model to teach the model to recognize patterns and learn the relationship between input and desired output. Use validation data to evaluate and tune model parameters during training and prevent overfitting. Testing data is used to test the final performance of the trained model and provide an objective estimate of the model's ability to make predictions on previously unseen data when this type of data is divided with a ratio of 70:20:10.

Image data was captured from Kaggle with the following link:

<https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign>

A detailed explanation of the number of dataset images used is shown in Table 1.

Table 1. Dataset Image Count Details

Class	Amount of Data
Benign	1800
Malignant	1497

An example of skin cancer image data can be seen in the image below. In Figure 2. a, the image data of malignant skin cancer is shown, and in Figure 2. b, the image data of benign skin cancer is established (Schierbeck, Vestergaard, & Bygum, 2019).

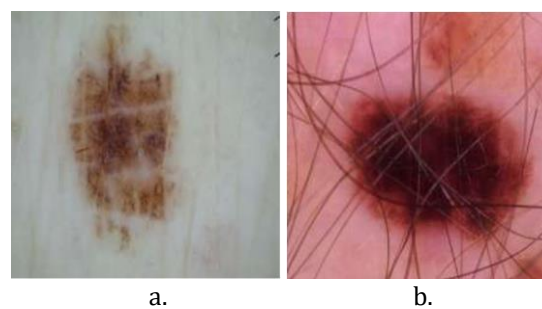


Figure 2. a) Malignant Image Data, b) Benign Image Data

Procedure

At this stage, the image pre-processing stage is carried out, which aims to convert raw data into data that suits the research needs. The pre-processing stage in Object Detection using the YOLO (You Only Look Once) algorithm includes several steps, as seen in Figure 3.



Figure 3. Data Preparation Flow using Roboflow

Data annotation

At this stage, the image data that has been collected is annotated according to its type. Annotation is marking or labelling objects in an image using bounding boxes and annotation tools from Roboflow (Septyanto, Wibowo, & Setianingsih, 2022). The annotation process on YOLOv5 using roboflow goes through several stages as follows:

- a. Firstly, the user uploads the image dataset to be annotated to Roboflow
- b. Second, labelling or grouping the object classes in the image. In this case, the research will use two object classes: the Malignant and the Benign classes.
- c. Thirdly, the user will annotate, giving a rectangular box to the object in the image and associating it with the predetermined label. An accurate and consistent annotation process is essential to train the YOLOv5 model to recognize objects well and produce precise detection results.

Split Data

This stage divides the use of datasets in training and evaluating the YOLO model into training, Validation and Testing data with a ratio of 70: 20: 10. Details of data division in the split data process are in Table 2

Table 2. Split data details using Roboflow

Training	Validation	Testing
2.251	643	322

Resize

At this stage, the previously annotated and divided images are then resized according to the needs of the YOLO model. The image data size is 416 x 416 pixels (Lusiana, Wibowo, & Dewi, 2023). Researchers still use the Roboflow platform at this pre-processing stage, which provides tools to resize images directly. An example of an image data resize scenario is in Figure 4.

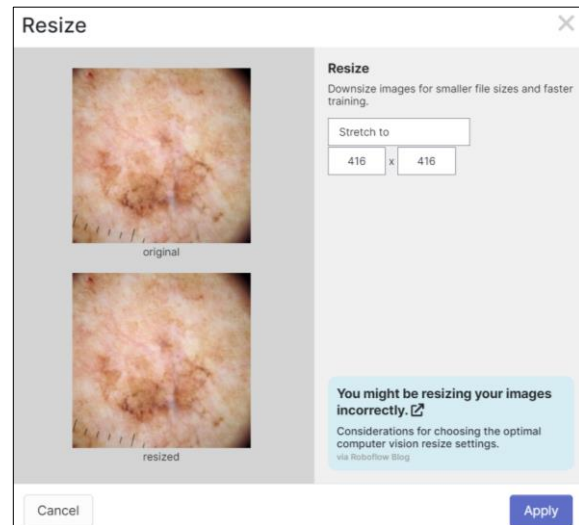


Figure 4. Resize the image using Roboflow

Augmentation

At this stage, image augmentation is performed, where existing image data will be processed to produce new data variations by modifying the original image to increase the amount of training data available (Ieamsaard, Charoensook, & Yammen, 2021). The image data in this research is augmented by rotation and grayscale.

Modelling Phase

The method used in this study's detection and classification process is YOLOv5. The YOLOv5 modelling flowchart is in Figure 5.

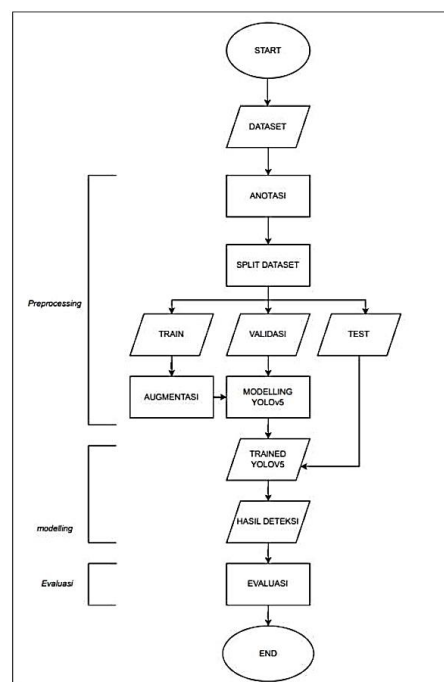


Figure 5. YOLOv5 Flowchart



RESULTS AND DISCUSSION

The data preparation implementation stage will explain the pre-processing of skin cancer image data that has been previously collected. This pre-processing process will be carried out using pre-processing tools from the Roboflow platform;

Annotation

Annotation or object labelling creates a label on the image by providing a bounding box and the object's class name. The object labelling stage is based on skin cancer images from the Kaggle dataset provider platform (Dio, Pratama, Priyatna, Shofiah, & Lia, 2022). Object labelling is divided into two classes, namely Malignant and Benign. The labelling process is carried out on skin lesions that are considered to be affected by cancer cells. The labelling scenario can be seen in Figure 6.

The image annotation process uses the Roboflow labelling platform. This labelling uses annotations in the YOLO annotation format.

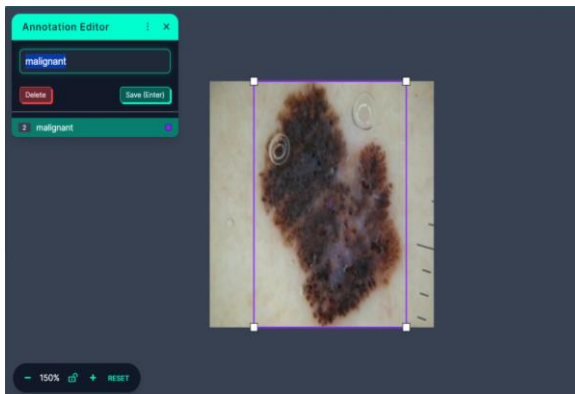


Figure 6. Dataset annotation process using Roboflow

Split Data

The data split stage is carried out to optimize model performance by dividing the data into several sub-datasets (Kumar & Vatsa, 2022). There are no guidelines or metrics regarding how the data should be divided in this data division process. In this study, data that has previously been annotated or labelled will be divided into three sub-datasets, namely, training data (training set), validation data (Validation set), and test data (Test set) with a ratio of 70:20:10 using data splitting tools provided by Roboflow. The data-splitting process can be seen in Figure 7.

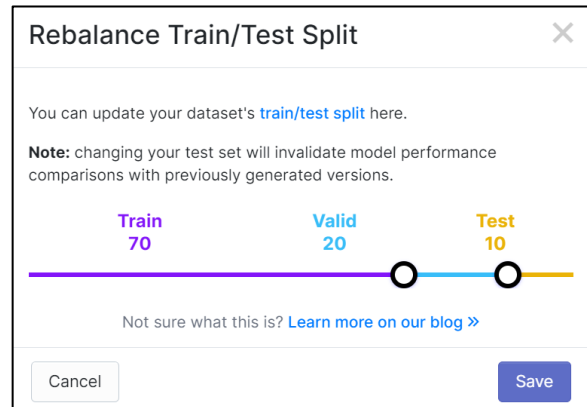


Figure 7. Split data process using Roboflow

Resize

The previously annotated and divided images will remain resized on all image data (Sofia Saidah, Suparta, & Suhartono, 2022). Resizing is resizing image data according to the model's needs, making it easier to adapt to different hardware and enabling more efficient object detection (Ahmad et al., 2020). The initial image data is an RGB image with .jpg format and 224x224 pixels. Furthermore, the image will be resized according to the provisions of the model input data, namely 416x416 pixels. The process of resizing skin cancer images using Roboflow can be seen in Figure 8.

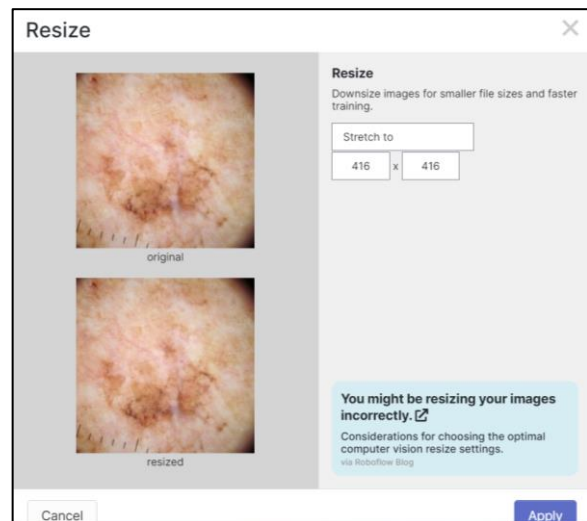


Figure 8. Resizing Image Data to 416x416 size using Roboflow

Augmentation

At this stage, image augmentation is performed, where existing image data will be processed to produce new data variations by modifying the original image to increase the amount of training data available. The process of

determining the type of augmentation is shown in Figure 9. The image data in this study is augmented by rotation and grayscale so that the total image obtained can be seen in Table 3

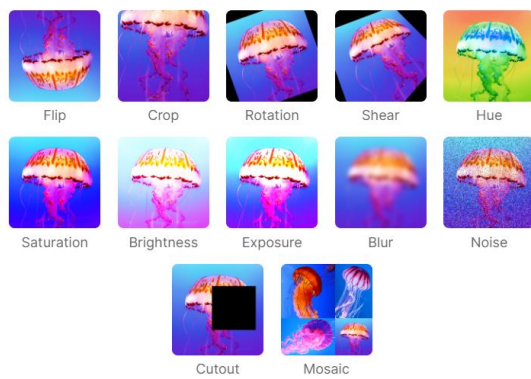
Table 3. Details of the augmented image dataset

Data	Value
Training	6184
Validation	643
Testing	322

Augmentation Options

Augmentations create new training examples for your model to learn from.

IMAGE LEVEL AUGMENTATIONS



BOUNDING BOX LEVEL AUGMENTATIONS



Figure 9. Image Data Augmentation Process using Roboflow

Rotation

Rotation is the process of changing the orientation of an image by rotating it around the centre point. This augmentation type helps the model study objects from different viewpoints (Akhyar, Novamizanti, & Riantiarni, 2022). In this research, the rotation process performed is rotating image 90°. The method of skin cancer image data augmented by rotation can be seen in Figure 10.



Figure 10. 90 Degree Rotation Augmentation Process

Grayscale

Grayscale converts a colour image into a grayscale (black and white) image where the colour information is removed, and only the brightness or Light intensity information remains. Grayscale reduces data complexity and saves memory space in model training, especially if the model only needs to capture colour patterns and textures (Aningtiyas, Sumin, & Wirawan, 2020). Grayscale also helps reduce the model's sensitivity to colour variations in objects so that the model focuses more on essential features and designs when detecting objects.

The process of augmented skin cancer data image using grayscale can be seen in Figure 11.

Grayscale

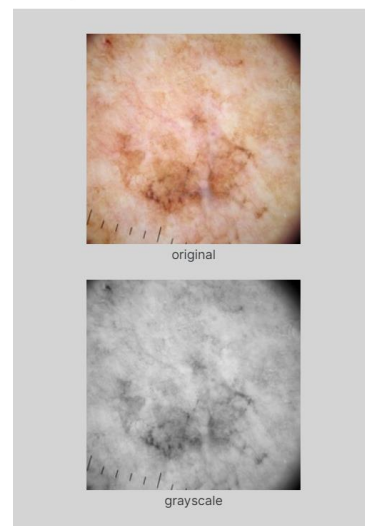


Figure 10. Grayscale Augmentation Process

Implementation of Modelling Phase

After the Data Preparation phase is completed, the next phase is the modelling phase. The YOLOv5 model will be built, trained, and adjusted to the available training data in this phase. In this phase, the YOLOv5 model undergoes a series

of steps that involve creating a model architecture, training using training data, and evaluating model performance. This section uses transfer learning techniques to use the pre-trained weight of YOLOv5. The transfer learning process in YOLOv5 uses a YAML file that contains parameters that describe the network structure, such as input size, number of classes, and others.

Model training

The YOLOv5 model training process uses Google Collaboratory with the YOLOv5-small configuration type. Table 4 will explain the parameters used in this layer structure.

Table 4. YOLOv5s Parameters

Parameter	Note
From	The layer's input, -1, is the last layer, and 1 is the first layer.
Number	Number of modules, the final number of modules = modules * width
Module	Sub-module
Args	Module parameters, channel, kernel size, stride, padding, bias, etc.

The next stage is the YOLOv5s-Small model, which will be tested for accuracy in detecting objects through the epoch-calling process to get the optimal model for skin cancer type detection, and researchers will conduct five experiments with different numbers of epochs, namely 10, 25, 50, 75, 100. The training dataset contains 6184 images of skin cancer images with two classes, namely Malignant and Benign. Each model will be validated with 643 original photos. This validation process will provide precision and recall values for each type individually. The precision value shows the accuracy of the model prediction results against the given data, and the recall value shows how accurate the model is to remember the given object. The results of skin cancer detection experiments using Yolov5-small can be seen in Table 5.

Table 5. Yolov5 Skin Cancer Detection Trial Table

Experiment	Epoch	Precision	Recall	mAP
1	10	0,714	0,766	0,778
2	25	0,789	0,805	0,848
3	50	0,811	0,796	0,866
4	75	0,802	0,855	0,881
5	100	0,798	0,861	0,885

The following explains each experiment in detecting skin cancer types using the YOLOv5-small model in Table 5.

Experiment 1

In this experiment, the model completed ten epochs in 0.170 hours with the following details:

- Precision 0.714 shows that about 71.4% of the model detection results are relevant to skin cancer-type objects according to their class.
- Recall 0.766: The model can remember about 76.6% of the objects detected from everything that should be in the image.
- mAP50 0.778: shows that the model performs well in detecting objects with a confidence threshold above 50%, namely 0.778.

Experiment 2

In this experiment, the model completed 25 epochs with a time of 0.428 hours with the following details:

- Precision 0.714 shows that about 71.4% of the model's detection results are relevant to skin cancer-type objects according to their class.
- Recall 0.766: This shows that the model can remember about 76.6% of the objects detected from everything that should be in the image.
- mAP50 0.778: The model performs well in detecting objects with a confidence threshold above 50%, 0.778.

Experiment 3

In this experiment, the model completed 50 epochs with a time of 0.922 hours with the following details:

- Precision 0.811 shows that about 81.1% of the model's detection results are relevant to skin cancer-type objects according to their class.
- Recall 0.796: This shows that the model can remember about 79.6% of the objects detected from everything that should be in the image.
- mAP50 0.866: shows that the model performs well in detecting objects with a confidence threshold above 50%, which is 0.866.

Experiment 4

In this experiment, the model completed 75 epochs with a time of 1.380 hours with the following details:

- Precision 0.802 shows that about 80.2% of the model's detection results are relevant to skin cancer-type objects according to their class.
- Recall 0.855 Shows that the model can remember about 85.5% of the objects detected from everything that should be in the image.
- mAP50 0.881: shows that the model performs well in detecting objects with a confidence threshold above 50%, which is 0.881.

Experiment 5

In this experiment, the model completed 100 epochs with a time of 1.605 hours with the following details:

- Precision 0.798 shows that about 79.8% of the model's detection results are relevant to skin cancer-type objects according to their class.
- Recall 0.861: This shows that the model can remember about 86.1% of the objects detected from everything that should be in the image.
- mAP50 0.885: shows that the model performs well in detecting objects with a confidence threshold above 50%, which is 0.885.

The experiment results can be seen in Table 4.5. In this experiment, with a total of five experiments, it was found that the fifth experiment with 100 epochs had the best performance with a mAP50 value of 88.5%.

Implementation of the Evaluation Phase

The value obtained from skin cancer detection training was relatively high in the fifth trial, where the overall mAP value was 0.885 at the 100th epoch.

From these results, it can be seen that the model has increased accuracy when trained for 100 epochs, which can be seen in Figure 11.

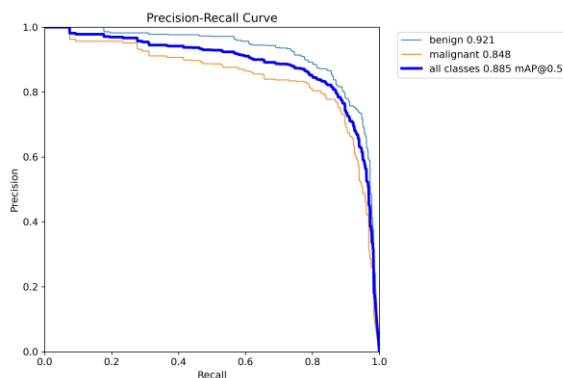


Figure 11. precision Recall Curve

The precision value averages 0.885 against the recall value on the precision-recall curve, which means the weight between the positive rate (True Positive) and the Positive Prediction value for the prediction model using different probability thresholds.

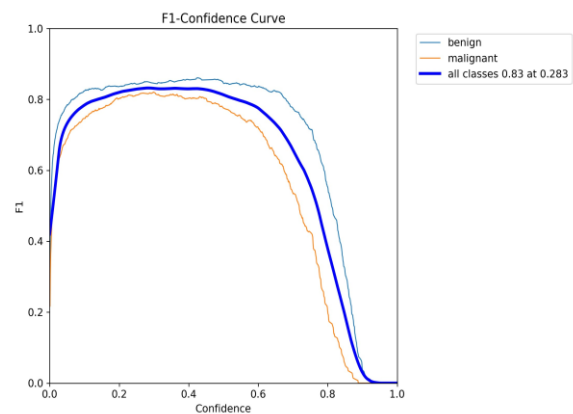


Figure 12. F1 Confidence Curve

The f1-confidence curve shows that the peak value is at 0.83 in the state of a confidence value of 0.283. In other words, about 83% of the objects found by the model at that confidence level are relevant and correct objects. F1 represents the harmonic mean of Precision and Recall.

The model previously generated by the algorithm needs to be evaluated. In this evaluation phase, researchers will analyze the performance of the object detection model using the Confusion Matrix, which consists of four main parts, namely True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN). The determination of this value will later be used in calculating the accuracy of the YOLOv5 model that has passed the training process.

The confusion matrix results of the model results that have been trained can be seen in Figure 13.

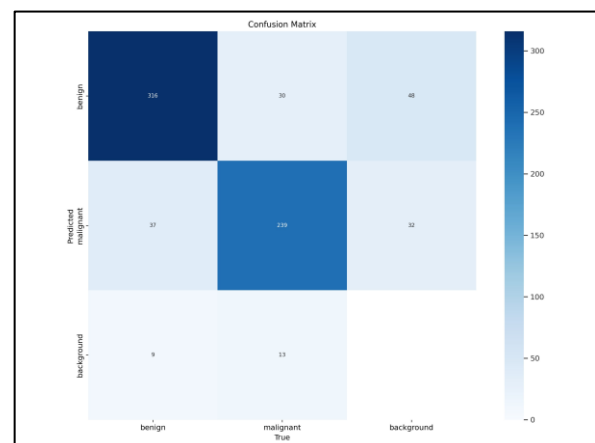


Figure 12. Confusion Matrix for Skin Cancer Detection

From Figure 12, which shows the Confusion Matrix metric for detecting skin cancer types, the True Positive (TP), True Negative (TN), False Negative

(FN), and True Negative (TN) values are generated, which will then be used in the calculation of model accuracy which can be seen in Table 6.

Table 6. Result of Confusion Matrix

Class	TP	FP	FN	TN
Benign	0.87	0.11	0.10	0.85
Malignant	0.85	0.10	0.11	0.87

Table 6 explains that:

1. True Positive value is the number of positive or correct inputs predicted positively by the model. Table 4.6 shows that the model can correctly predict input images for the benign class, 87%, and for the malignant type, 85%.
2. The False Positive value shows how much the model predicts negative input as the correct or positive class. Table 4.6 shows that 11% of false inputs were correctly detected for the benign and 10% for the malignant types.
3. The False Negative value shows the number of positive inputs detected as harmful or wrong by the model. Table 4.6 shows that 10% of correct inputs are detected incorrectly by the model for the Benign class and 11% for the Malignant type.
4. The True Negative value shows the number of negative inputs predicted as unfavourable by the model. Based on Table 4.6, 85% of negative inputs are predicted as damaging by the model for the benign class and 87% for the malignant type.

The values that have been obtained can be calculated with the equation that has been explained as follows.

$$Acc = \frac{TP+TN}{TP+FP+FN+TN} \dots\dots\dots (1)$$

$$relativeAcc = \frac{(0,87 + 0,85) + (0,85 + 0,87)}{(0,87 + 0,85) + (0,11 + 0,10) + (0,10 + 0,11) + (0,85 + 0,87)}$$

$$Acc = 0,89$$

The accuracy obtained for the YOLOv5 architecture on the trained data is 0.891 or 89.1%. This value indicates that the YOLOv5-small model used for training skin cancer type detection is good, as the model accurately detects approximately 80% of the input data.

Testing

The testing phase of the Yolo model will be carried out in two ways: running Inference with Trained-Weight and real-time testing using

Anaconda Prompt. The Trained-Weight Inference stage refers to using pre-trained weights on the Yolo model. Process of using weights that have been previously trained on the YOLOv5-small model.

Figure 13 illustrates the results of the object detected by running inference using the highest training weight from the fifth trial model. The image data used in this testing process uses test data that has previously been divided in the split data process in the pre-processing phase.

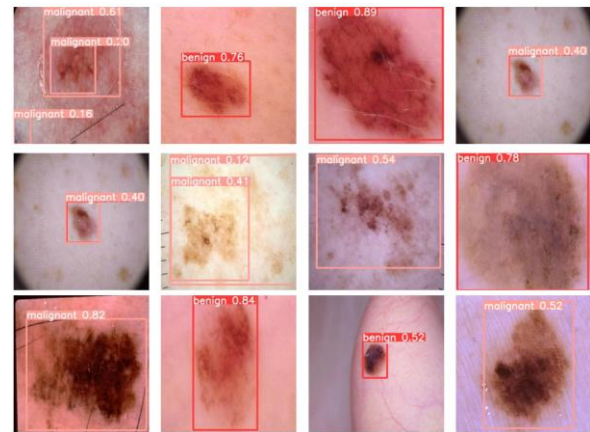


Figure 13. Skin Cancer Object Detection Display Result

Real-time object detection testing using anaconda Prompt. At this stage, researchers will conduct real-time testing with Anaconda Prompt on the YOLOv5-small model that has been previously trained. This YOLOv5 model will be stored in the best.pt file. The results of this detection process can be seen in Figure 14.

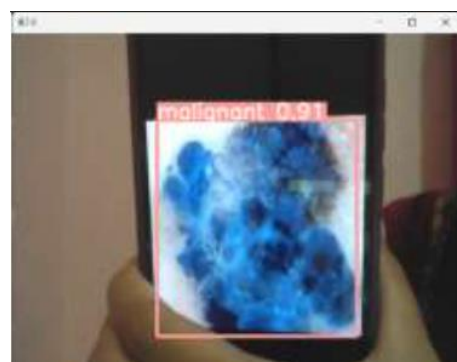


Figure 14 Real-time detection results using Anaconda Prompt

Image 14 shows that the system can detect skin lesions exposed to cancer, as evidenced by the model's confidence level towards the detected object at 0.91. The detection speed is also recorded at around 436.3 milliseconds, indicating that the model can detect objects displayed in real-time.



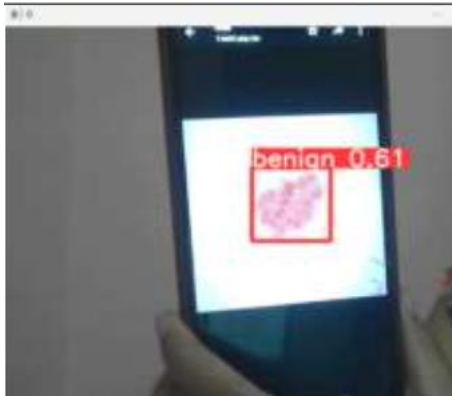


Figure 15 Real-time detection results using Anaconda Prompt

Figure 15 shows that the model can detect images of skin lesions exposed to benign skin cancer types with a confidence level of 0.61 percent, indicating that the model performs sufficiently well in identifying objects according to their correct class. The model's speed in detection reaches 406.1 milliseconds, showcasing its remarkable swiftness in identifying input in the form of cancer-affected skin lesion images. This impressive performance underscores its potential in aiding timely and accurate skin cancer diagnosis.

Figures 14 and 15 show that the model has successfully detected the type of skin cancer tried on images that the model has not seen before. The results of the test show that the model stored in best.pt has been able to detect the type of skin cancer based on its class, namely cancer (malignant) and benign cancer (benign), with detection speeds ranging from 300 milliseconds to 400 milliseconds. This shows that the model can detect objects in real-time, in this case, the type of skin cancer disease. However, if you look at the difference in the confidence value, the confidence value refers to the probability or confidence of the model in object detection. It can be seen in the figure that the confidence value when identifying the malignant class is much higher in the range of 0.83 to 0.91, while in the benign course, the confidence level is still below 0.71. The webcam quality, lighting, and image quality cause the low confidence value.

CONCLUSIONS AND SUGGESTIONS

Conclusion

Based on the study's results, it can be concluded that the difficulty of distinguishing the characteristics of the appearance of skin cancer

images can be overcome by building a model that can help early detection. In this case, the YOLOv5-small model can detect objects. The YOLOv5 model in this study has an accuracy value of 89.1% and a True Positive value greater than False Positive, showing that the system can detect objects well. However, detection also depends on the quality of the image or video. The higher the rate, the higher the detection result will be.

Suggestion

Suggestions that can be given based on the results of this study are to add image datasets with more variations and optimization algorithms that can improve the accuracy of the models that have been made. It continued the development stage so that the model created could be used for early skin cancer detection.

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