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Automatic Swimmer Counter for Outdoor Swimming Pool

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Abstract. Swimming is the third most popular sport in Indonesia. Public swimming pools are an option for people who don't have private pools. Unfortunately, there are several dangers lurking in public swimming pools. One of them is the emergence of disease because the urine content is too high in pool water. A solution that can be done is to replace pool water regularly, but changing pool water regularly on a schedule is still not efficient if the number of swimmers swimming is small. An application that can calculate the number of swimmers automatically is needed so that the scheduling of pool cleaning can be dynamic and the addition of disinfectants can run optimally. By utilizing deep learning technology, a system can be created that can detect and count the number of swimmers in a swimming pool. The data used in this study were 343 images. This data is then divided into 263 training data and 80 test data. The test data consisted of 4 groups of data according to the swimming pool conditions at the time the data was collected. While the algorithm used is the 3rd generation You Only Look Once (YOLO) algorithm for object detection. In this study, a system accuracy of 94% was obtained for cloudypool in the morningnoon, 87.8% for cloudypool in the afternoon, 84.9% for cloudy pool in bright afternoons, and 96.5% for clear pool in the morning, with an average accuracy of 90.8%.

INTRODUCTION

Swimming is the third most popular sport for Indonesians after running and cycling [1]. Public swimming pools are the answer for people who want to swim but do not have a private pool. Unfortunately, there are some dangers lurking in public swimming pools [2]. One of them is that pool water can be mixed with various substances, one of which is urine. Urine is dangerous because it can react with disinfectant chemicals in pool water. This can cause irritation of the swimmer's airways so that the swimmer experiences tightness in the chest, throat disorders, coughing, skin irritation, and eye irritation.

The biggest contributor to urine is the swimmers themselves. The solution that can be done to minimize the occurrence of urine contamination is to replace pool water regularly with a fixed schedule, for example once every two weeks. But this method is not efficient because it does not consider the number of swimmers. This scheduled pool water change only adds to the cost if the number of swimmers swimming before the cleanup time is small. On the other hand, if the frequency of swimmers is very large and the pool is not cleaned because the cleaning schedule is still long, it will have a negative impact on the health of swimmers [3]. Therefore, this paper introduces a system that can calculate the number of swimmers automatically so that the scheduling of pool cleaning can be dynamic and the addition of disinfectants can run optimally. Automatic counting program has been previously implemented for example by Zakiyabarsi, et al. [4] for crab larvae counting and by Sitanayah, et al. [5] for vehicle counting.

Counting the number of swimmers manually is not an easy task. On the other hand, technological developments using artificial intelligence methods in the field of computer vision can help detect humans both in a stationary state and in a state of motion. So that this method, in particular deep learning, is used to perform these calculations.

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This calculation system can also help parents who are worried that children are playing and accidentally fall into a private pool in the house. The data for calculating the number of visitors on a regular basis can also be a reference for swimming pool managers to determine peak hours in order to adjust ticket prices and anticipate visitor safety.

RESEARCH METHOD

Swimming Pool

A swimming pool is an artificial construction designed to be filled with water and used for swimming, diving and other water activities. Swimming pools must have an eligibility standard so that pool users and all facilities are safe and protected from various dangers that can threaten their comfort and health [6]. One of the swimming pool feasibility standards is the clarity of the pool water.

Turbidity is an indication of the clarity of pool water. Turbid pool water can look clean with the naked eye, but if the light passes through the pool water the light will scatter because it meets particles in the pool water. The standard for detecting the turbidity of a public swimming pool in addition to using a turbidity sensor is the ability of a person to see the main central pool channel clearly from the edge of the pool [7].

One alternative way to measure pool turbidity is to use a black disc [6]. Swimming pool water is said to be clear if the plate that is placed at the bottom of the pool can be seen clearly from the edge of the pool. In addition, swimming pool water can be said to be clear if the water is sky blue. If the pool water is green, then the PH of the pool water is unstable and contains a lot of green algae [8] In this study, the ability of a person to see the baseline on the swimming pool and the color of the pool water is used for detecting the turbidity. Figure 1 shows the difference between a clear pool and a cloudy pool.

(a) (b)

FIGURE 1. A clear pool (a) and A cloudy pool (b)

Dataset

In this study, 342 images of the swimming pool were used. Data were obtained from one public swimming pool and was taken from a variety of different times and conditions. The image used is in the .JPG format with a size of 1920 x 1080 pixels. The first step in data preparation is to do manual labeling for each swimmer in swimming pool area for each image. The data is divided into train and test data. For the training data, 243 data were used. As for the test data, 80 were used.

Image Pre-Processing

YOLO v3 requires input data in the form of an image with a size of 416x416 pixels because this resolution is the optimal resolution for a fast computation process without losing accuracy due to the small size of the input image. This resolution value is also used to anticipate errors that occur in the training process due to a large number of input images with different resolutions. Therefore, the image was resized first before it was inserted into the YOLO neural network. An illustration of the image resizing process can be seen in Fig. 2.

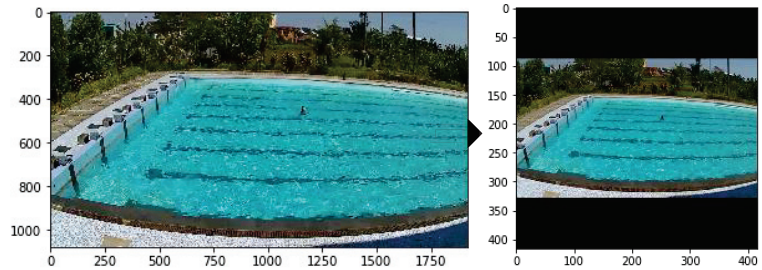
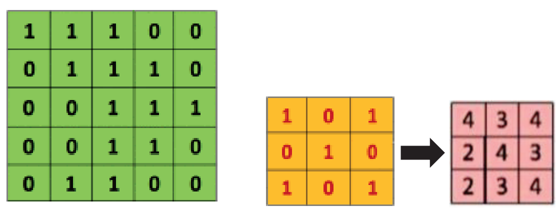


FIGURE 2. Image display before and after resizing

Feature Extraction

Feature extraction aims to get important information from a digital image. In this system, the feature extraction process uses Convolutional Neural Networks (CNN), in which there are 3 processes, namely the convolution process, the ReLu process and the max pooling process [9].

Convolution Layer is the first layer in the feature extraction process from the input image. Convolution maintains the relationship between pixels by studying image features using small squares of input data. The convolution process is a process of mathematical operation of two inputs, namely the image matrix and the filter matrix or kernel. The filter then shifts according to the specified stride value. An example of a convolutional process can be seen in Fig. 3.



(a) (b) (c)

FIGURE 3. Image Matrix (a), Filter Matrix (b), Feature Matrix (c)

ReLUis one of nonlinear activation functions. ReLUstands for Rectified Linear Unit. The process can be seen in Fig. 4.

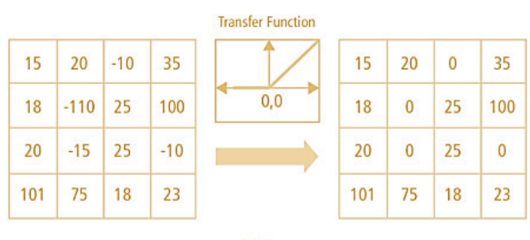


FIGURE 4. ReLU operation

Pooling Layer functions to reduce the number of parameters used when the dimensions of the input image are too large so that the computation process becomes faster. The type of pooling used by YOLOv3 is Max Pooling. Max Pooling works by selecting the largest value of an image area where the area size is determined by the filter dimensions and the filter shifts according to the specified stride value. An example of the max pooling process can be seen in Fig. 5.

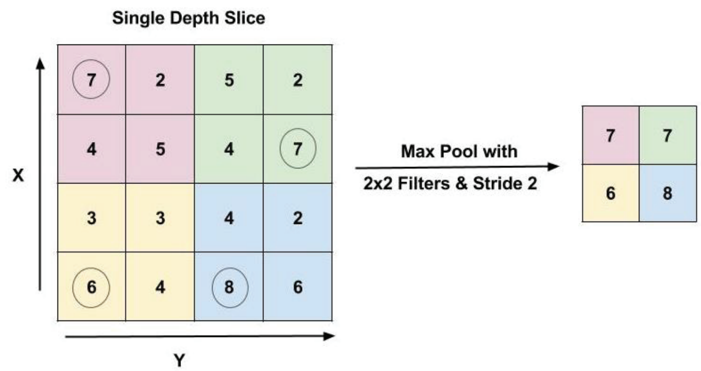
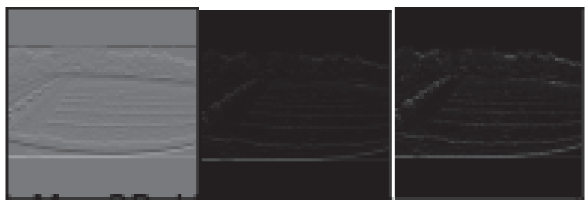


FIGURE 5. Max pooling process

Feature extraction process on pool image can be seen in Fig. 6.



(a) (b) (c)

FIGURE 6. Convolution (a), ReLU (b), Max pooling (c)

Classification

Data from the feature extraction process in the form of an activation map will be forwarded to the Fully Connected Layer. In the classification process, the model recognizes whether an object is detected in an image and whether the object is a swimmer or not. The activation map will go through the reshaping process into a vector first, because the FC Layer requires vector input while the activation map is a multidimensional array. The reshape result matrix then becomes the input for the FC Layer. Illustration along with the results of the FC Layer can be seen in Fig. 7.

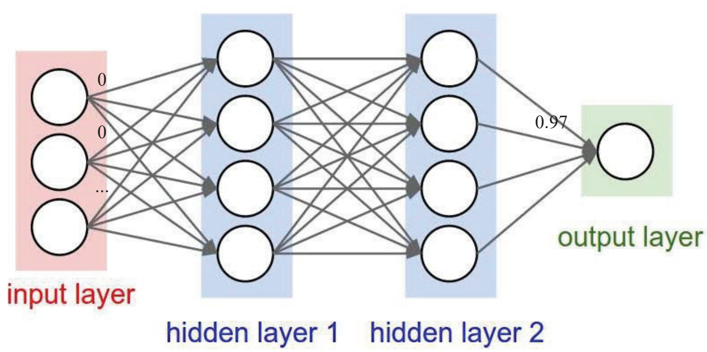


FIGURE 7. Fully connected layer

Output Prediction

YOLOv3 uses 2 approaches to draw bounding boxes, namely Confidence Level and Class Probability Map. In the confidence level approach, the system will divide the image into several grid cells as in Fig. 8, then the grid cells become a reference for detecting objects. Each grid cell will predict and describe the bounding box that has a confidence score for each box.

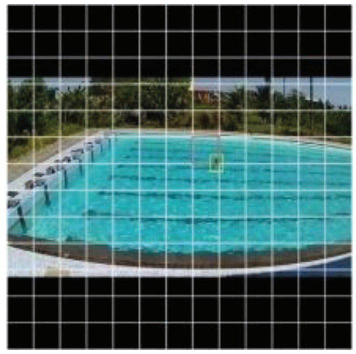


FIGURE 8. Image divided into 13x13 grid

The confidence score represents how high the system believes that the box contains the object you want to detect and how accurately the system predicts the object. In the class probability map approach, each bounding box consists of 5 values: x, y, w, h, and confidence. The x and y values represent the coordinates of the midpoint of the bounding box to the grid cell. The w and h values represent the width and height of the whole image. Meanwhile, the confidence value represents Intersection over Union (IoU) between the bounding box of the predicted object and the original object bounding box [10].

The output from the FC Layer is a matrix containing a grid cell, with parameters for each object detected in a grid cell as shown in Fig. 9.

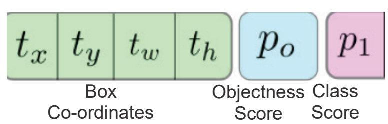


FIGURE 9. Parameters of output matrix

Visualization

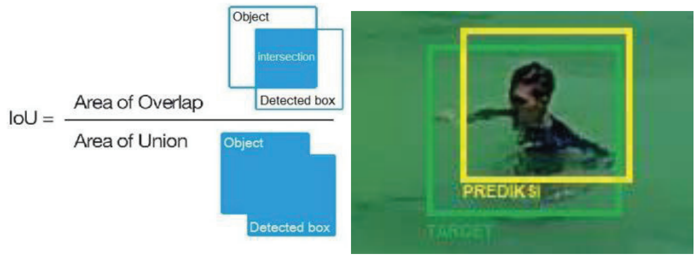
Visualization of system detection results can be displayed in the form of images or videos as needed. The visualization process uses OpenCV which streamlines the data computation process so that the delineation of the bounding box becomes faster.

The bounding box displayed is only the bounding box that has the same id as the class id of the desired object. The number of bounding boxes that have the same class as the object in the image is then calculated and displayed at the bottom right of the image or video. An example of a visualization of the output can be seen in Fig. 10.

FIGURE 10. Visualization of system's output

Intersection Over Union (IoU)

Intersection over Union is simply one evaluation measure for object detection algorithms. All algorithms that display bounding boxes can be tested using IoU. Predictions with an IoU value above 0.5 are considered good predictions [11]. Figure 11 shows an overview of IoU calculations.



(a) (b)

FIGURE 11. IoU calculation overview (a), IoU Depiction on swimmer data (b)

Confusion Matrix

The training performance of the swimmer detection and counting system can be measured by calculating the accuracy value using a configuration matrix. The confusion matrix compares the results of the classification carried out by the system with the actual classification [12]. The calculation rules can be seen in Fig. 12.

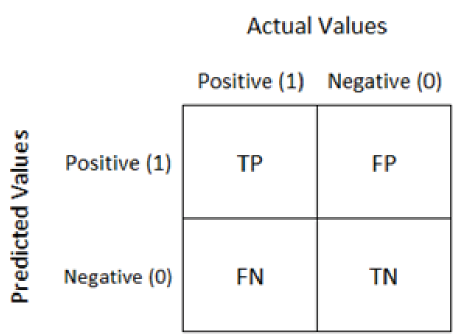


FIGURE 12. Confusion matrix

RESULTS AND ANALYSIS

Results of Training Process

In this study, an experiment was conducted using the parameters such as batch, subdivision, momentum, width, height, channel, learning rate, and default iterations. The standard values of the batch is 64, subdivision is 16, momentum is 0.09, width is 416, height is 416, channel is 3, learning rate is 0.001, and 10000 iterations.

The system then looks for the F1 Score of the test results with IoUvalue of 0.5 to find out how good the system's performance is. The results of system performance can be described in a configuration matrix as in Table 1.

TABLE 1. Calculation of F1 score for IoU 0.5

TP	FP	FN	Precision	Recall	F1 Score
1401	149	105	90%	93%	92%

Results of Testing Process

The system is then tested using test data consisting of 20 images for every 4 categories of swimming pool conditions, namely clear pool in the morning, cloudy pool in the morning, cloudy pool in bright afternoon, and cloudy pool in the afternoon. Cloudy pool categories have been divided into 3 parts according to the time when data was collected. Accuracy tables for each condition can be seen in Table 2.

TABLE 2. Confusion matrix of system performance for several conditions

Condition	TP	FP	FN	TN	Precision	Recall	Accuracy
Cloudy in the Morning	206	1	12	0	99.5%	94.5%	94%
Cloudy in the Afternoon	297	37	4	0	88.9%	98.6%	87.8%
Cloudy in the Bright Afternoon	294	6	46	0	98%	86.4%	84.9%
Clear in the Morning	113	1	3	0	99.1%	97.4%	96.5%

The lowest accuracy is in the cloudy pool conditions on a bright day with a value of 84.9%. This is because in the morning to evening, the position of the sun is behind the camera so that objects in the pool can be seen clearly. At the right place, the sun is in front of the camera so it affects the image quality and around 3:40 PM to 5:00 PM some areas of the air pool reflect sunlight so that objects in that area appear faint and this affects the system. The highest accuracy is in the clear pool conditions from morning to afternoon with a value of 96.5%. This happens because the pool water is clearer when compared to the cloudy conditions of the pool so that the features of the person diving below the surface of the water are clearly visible and this affects the system.

CONCLUSION

The pool counting system was built using the YOLOv3 deep learning algorithm as an object detection algorithm. The results of the accuracy of the system for 4 swimming pool conditions are 94% for cloudy pools in the morning to noon, 87.8% for cloudy pools in the afternoon, 84.9% for cloudy pools in bright afternoons, and 96.5% for cloudy pools. clear pool in the morning to noon, with an average accuracy of 90.8%. Accuracy value is influenced by the camera's location against sunlight.

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