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REALIZATION OF A YOLO-V3-BASED APPLICATION FOR THE DETECTION OF TICK-BORNE CASES

ABSTRACT

Today, tick-borne diseases have become widespread and pose a significant threat to public health. There are various types of diseases transmitted from ticks to humans. The main of these diseases; Crimean-Congo hemorrhagic fever, Lyme disease, Mediterranean spotted fever and Tularemia can be listed. As with other types of diseases, early diagnosis is important in tick-borne diseases. Therefore, it is necessary to identify ticks quickly and accurately in order to reduce the possible risks of disease in cases of errors bitten by ticks. In this study, Yolo-v3-based deep learning algorithm, which is a subfield of machine learning, was used primarily to detect ticks. For the training and testing of this algorithm, a new data set was created by downloading 1500 different tick images from the internet. Algorithm was trained and tested using this data set. In order to determine that the success accuracy of the Yolo-v3-based deep learning algorithm is superior and to demonstrate its availability in real life, various performance tests were performed and an estimate was made as to whether there were ticks in an image. As a result of the study, in order to reduce the disease risk of patients bitten by ticks and to intervene in a timely manner, tick detection was made effectively by taking only one tick picture.

Keywords: Deep Learning, Convolutional Neural Network, Yolo-V3, Tick Detection, Tick Images

1. INTRODUCTION

Today, tick-borne diseases have become widespread and pose a significant threat to public health. There are various types of diseases transmitted from ticks to humans. The main of these diseases; Crimean-Congo hemorrhagic fever, Lyme disease, Mediterranean spotted fever and Tularemia can be listed. This disease, which was identified in the world in 1944, was first identified in our country around Tokat in 2002 and spread to Erzurum, Erzincan, Sivas, Yozgat, Amasya, Çorum, Çankırı, Karabük, Samsun, Ordu, Giresun, Trabzon, Artvin and Gümüşhane in the next two years. It is thought that the disease reached Turkey by ticks on birds migrating from Russia [1]. As with other types of diseases, early detection is very important in tick-borne diseases. When a person is exposed to a tick bite, he applies to the nearest health institution to find out whether the bitten animal is a tick. However, with the opinion that the bitten animal is not a tick, at that moment the person is trying to get rid of it by his own methods [2].

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In the modern era of science and technology, people widely use the application of image recognition technology in daily life and in various fields of research. Therefore, various cameras are used to capture health-threatening tick images. However, these camera images cannot help people as much as they would like. As a result of a tick bite, it is necessary to establish a system that gives rapid results in order to understand whether the animal that has bitten is a tick or not. This situation both reduces the workload of health personnel and ensures that citizens are conscious at that moment.

Rapid developments in computer vision have allowed the training of new image recognition models [2]. The place of deep learning in the training of image recognition models is indisputably recognized [3]. However, the evaluations on which model will be more effective in tick detection or which should be together have not yet provided the desired level of enlightenment. Deep learning is an emerging member of the machine learning family and has become very popular in recent years [4 and 5]. Deep learning uses many layers of nonlinear processing units for feature extraction and transformation. In deep learning, there is a structure based on learning more than one feature level or representation of data. It is basically based on learning from the representation of data. When a representation is called for an image, properties such as a vector of density values per pixel or edge sets, special shapes can be considered. Some of these characteristics better represent the data [6].

The basic architecture of the deep learning concept is considered to be the Convolutional Neural Network (CNN) architecture [7 and 8]. This architecture uses convolution, pooling, ReLu, dropout, full connectivity and classification layers [9]. In addition, AlexNet, ZFNet, GoogLeNet, Microsoft RestNet and VGG16 architectures, which can be considered as the basic architectures in Deep Learning, are also used [10]. Deep learning algorithms are also very successful for object recognition problems [6]. Object identification is the process of determining where the object is in the image and the boundaries it occupies [10]. In the last few years, deep learning has become a landmark in the field of machine learning, especially in the areas of object detection, classification and image segmentation. The Convolutional Neural Network (CNN) has achieved the best results so far in classical image processing problems such as image segmentation, classification and detection in many applications [9].

In the literature, the first steps have been taken in the direction of tick recognition. According to the findings of the literature review, "identification of tick images: a neural network approach" [11], "using convolutional neural networks for tick image recognition-a preliminary discovery" [2], "There are different studies such as TickPhone application: smartphone application for rapid tick identification using deep learning" [12], "automatic detection and classification of tick-borne skin lesions using deep learning" [13]. However, it seems that there is not enough number of them.

In the study of identification of tick images, real-time identification of ticks via a smartphone application or similar platform, risk information on ticks encountered, additional data on the geographic range of tick activity to public health agencies, helping to reduce the threat of ticks and meeting the requirements. Model has been proposed. The model was trained using a three-class tick dataset belonging to *Amblyomma americanum*, *Dermacentor variabilis* and *Ixodes scapularis*, and an identification accuracy of 87.8% was obtained [11].

In a study using convolutional neural networks for tick image recognition, ResNet-50 and a new convolutional neural network model were compared to prove the accuracy of the previously trained ResNet-50 model.

In model training, a dataset containing tick species *Ixodes scapularis*, *Dermacentor variabilis*, *Amblyomma americanum* and *Haemaphysalis* sp was used. When the newly developed model is compared with the ResNet-50 model, it has been observed that it has higher training (99.7%) and success accuracy (99.1%) [2]. In the study of smartphone application for rapid tick identification using deep learning, a smartphone-based deep learning algorithm called TickPhone application has been developed for tick identification. With the developed model, approximately 90% training accuracy and 85% validation accuracy were obtained. In addition, the developed TickPhone application was used to identify 31 different tick species, and a success accuracy of 95.69% was achieved with this model [12]. In a different study, automatic detection and classification of tick-borne skin lesions using deep learning, ResNet-34, ResNet-50, VGG-19 and DenseNet-121 convolutional neural network models were trained and combined with DesnetNet-121 model to detect tick-borne skin lesions. A success accuracy of 80.72% was obtained [13].

2. RESEARCH SIGNIFICANCE

In this study, tick images taken from the internet were studied. Using these images, an application was carried out with a Yolo-v3-based deep learning algorithm that detects whether there is a tick in an image. The remainder of the work is organized as follows. In Chapter 2, information about the purpose, target and importance of tick detection is presented. The proposed materials and methods related to the study are described in Chapter 3. In Chapter 4, experimental results and discussions obtained from the study are given. In Chapter 5, conclusions and suggestions were made about the study. Also in this study, a deep learning-based tick detection system based on tick images downloaded from the internet will be implemented. Based on these images, the requirements for the system to be created will be determined and a new framework will be developed for tick detection based on sample tick images. For this purpose, the task effectiveness and efficiency of health officials will be increased. At the same time, health officials will be contributed to reduce the risk of disease of patients bitten by ticks and to intervene in a timely manner.

Highlights:

- Implementation of an application that detects ticks
- A new dataset containing tick images
- Use of deep learning methods in the field of tick detection

3. EXPERIMENTAL METHOD

3.1. System Configuration

The deep learning-based tick detection system implemented in the study shows great changes depending on the tick species. In order to get the most successful results in tick detection in the study, it is necessary to conduct many experiments with deep learning algorithms. Therefore, python programming language was used to implement the Yolo-v3-based deep learning algorithm discussed in the study, analyze the data and obtain the results, and the codes were run in a high-performance Google Colaboratory environment [14].

3.2. Acquisition of Image Data

In this study, different tick images were downloaded from the internet environment [15] and converted into a data set because there is no ready data set for tick detection in this study. There are a total of 1500 images with RGB format in the data set, which includes tick images with different pixel sizes. The images of the tick data set used in the study are shown in Figure 1.

Figure 1. Images of the tick data set

3.3. Yolo-v3 Model Structure

In this study, the YOLO (You Only Look Once) model, which has been using convolutional neural networks in recent years and has shown superior success in the field of object detection, has been used [16]. In order to perform tick detection accurately and quickly with this model, the model diagram given in Figure 2 was used.

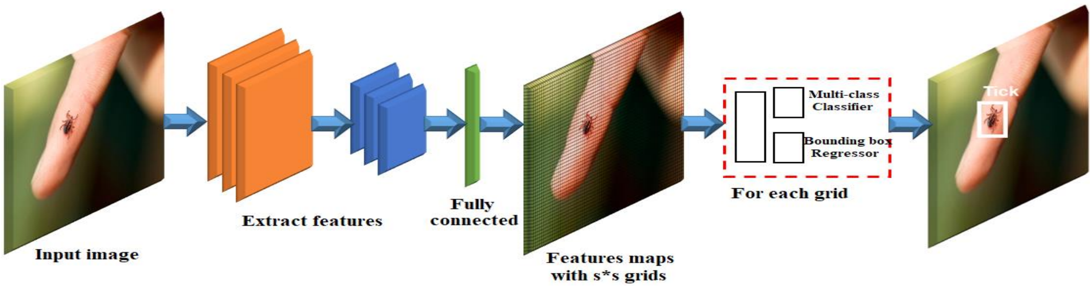

Figure 2. Yolo-v3 model diagram used in tick detection

When the Yolo-v3 model diagram given in Figure 2 is examined, the location and coordinates of the ticks in the image are estimated by passing the input image through the neural network at once. To do this, the input image is first divided into 3x3 grids. However, each grid checks whether the center point is in its area. Deciding that the image has the center point, the grid finds the height and width of the tick and draws a bounding box around the tick.

3.4. Training and Performance Testing

In this study, 300 of 1500 different images containing ticks obtained from the internet were used for model training and the remaining 1200 were used for model performance testing. Tick regions on 300 images were selected and their coordinates were labeled. The resulting 300 coordinate files and tick images were trained by running 1500 epochs with the Yolo-v3 algorithm and the model weights were obtained. These weights were compiled via OpenCv, an image processing library, and tick detection was made on 1200 images allocated for performance testing.

4. FINDINGS AND DISCUSSIONS

In the study, the Yolo-v3 algorithm was trained and weights were obtained using a data set of different tick images taken over the Internet. As shown in Table 1, the data set is divided into two data sets: training and performance testing.

Table 1. Tick dataset

	Training (%20)	Performance Test (%80)	Total (%100)
Number of Images	300	1200	1500

Table 2. Loss values

Loss	Avg. Loss
0.090	0.165

Table 3. Performance test results

Number of Images	Accurate Tick Detection	Success Accuracy
1200	1182	%98.5

A Yolo-v3-based deep learning algorithm was trained with 300 tick images contained in the training dataset. As a result of the training of the Yolo-v3 algorithm, the loss and average loss values given in Table 2 were obtained. However, the model performance was tested december a 50% confidence interval using a performance test dataset containing 1200 tick images and the results are given in Table 3. When Table 2 was examined, an average loss rate of as low as 0.090 and an average loss rate of as low as 0.165 were reached as a result of model training. In addition, when Table 3 was examined, it was seen that 1182 of the 1200 images containing ticks were successfully detected and a 98.5% success rate was achieved. According to the results obtained, it was seen that tick detection was successfully performed with Yolo-v3-based deep learning algorithm and sample images of model performance are given in Figure 3.

Figure 3. Images of the performance test

5. CONCLUSION AND RECOMMENDATIONS

The activities carried out to meet the controls of tick-borne diseases have a positive effect on the disease rate. Public health controls are contributing to a significant reduction in tick-borne disease activity. Early detection of ticks leads to a better understanding of tick-borne diseases and increases the sustainability of health checks.

In this study, using various tick images downloaded from the internet, tick detection was made by means of the Yolo-v3-based deep learning algorithm. This algorithm was trained using a dataset containing 1500 different tick images and tested to demonstrate its usability in real life. As a result of the training of the Yolo-v3-based deep learning algorithm, 0.090 loss and 0.165 average loss values were obtained. In addition, a performance dataset containing 1200 tick images was used for the performance testing and tested at 50% confidence interval. As a result of the test, the location of the tick was determined correctly in 1182 images out of 1200 images of ticks, and the location of the tick was detected incorrectly in 18 images, and a success accuracy of 98.5% was obtained.

As a result, the Yolo-v3-based deep learning algorithm used in the study showed high success performance by estimating whether there is a tick element in a suspicious image. The applicability of deep learning algorithms for tick detection will lead to reductions in the rate of tick-borne diseases and will also make a significant contribution to health institutions.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

FINANCIAL DISCLOSURE

The authors did not receive any financial support in conducting this study.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

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