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RESEARCH ARTICLE

Determining the Location of Tibial Fracture of Dog and Cat Using Hybridized Mask R-CNN Architecture

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Abstract

The aim of this study is to hybridize the original backbone structure used in the Mask R-CNN framework, and to detect fracture location in dog and cat tibia fractures faster and with higher performance. With the hybrid study, it will be ensured that veterinarians help diagnose fractures on the tibia with higher accuracy by using a computerized system. In this study, a total of 518 dog and cat fracture tibia images that obtained from universities and institutions were used. F1 score value of this study on total dataset was found to be 85.8%. F1 score value of this study on dog dataset was found to be 87.8%. F1 score value of this study on cat dataset was found to be 77.7%. With the developed hybrid system, it was determined that the localization of the fracture in an average tibia image took 2.88 seconds. The results of the study showed that the hybrid system developed would be beneficial in terms of protecting animal health by making more successful and faster detections than the original Mask R-CNN architecture.

Keywords: *Cat, Dog, Fracture, Hybrid, Mask R-CNN, Tibia*

Hibrit Mask R-CNN Mimarisi Kullanılarak Köpek ve Kedi Tibia Kırık Yerinin Belirlenmesi

Öz

Bu çalışmanın amacı Mask R-CNN çatısında kullanılan orjinal omurga yapısını hibrit hale getirerek köpek ve kedi tibia kırıklarındaki kırık bölgelerinin tespitini daha hızlı ve daha yüksek performans ile sağlamaktır. Yapılan hibrit çalışma ile bigisayarlaştırılmış sistem kullanılarak daha yüksek doğruluk oranıyla veteriner hekimlerin tibia üzerindeki kırık teşhislerine yardımcı olması sağlanacaktır. Bu çalışmada üniversitelerden ve kurumlardan elde edilen toplam 518 adet köpek ve kedi kırık tibia kemiği görüntüsü kullanıldı. Bu çalışmanın F1 skor değeri toplam veri seti üzerinde %85.8 olarak bulundu. Çalışmanın köpek veri seti üzerindeki F1 skor değeri %87.8 olarak bulundu. Çalışmanın kedi veri seti üzerindeki F1 skor değeri %77.7 olarak bulundu. Geliştirilen hibrit sistem ile ortalama bir kırık tibia görüntüsündeki kırık yerinin lokalizasyonu 2.88 saniye sürdüğü tespit edildi. Çalışmanın sonuçları, geliştirilen hibrit sistemin orjinal Mask R-CNN mimarisine göre daha başarılı ve hızlı tespitler yaparak hayvan sağlığının korunması açısından faydalı olacağını gösterdi.

Anahtar sözcükler: *Hibrit, Kedi, Kırık, Köpek, Mask R-CNN, Tibia*

INTRODUCTION

Artificial Intelligence (AI) is a term that developed by John McCarthy in 1956 and was briefly defined as "the science and engineering of making smart machines". AI is a system that can deal with complexity and uncertainty, including learning from past experiences, decision-making logic, power of inference and rapid response [1]. AI includes neural networks, deep learning, statistics, machine learning, which are successfully used in many areas such as security, research, robotics, voice recognition, and transportation [2].

Artificial neural networks and deep learning (DL) under AI form the basis of most applications [3]. DL is a complex computational model that uses multiple layers of computing algorithms [4]. The deep learning algorithm extracts the features of the data from the lower layer to the higher layer [5,6]. Deep learning modeling of big data is a machine

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learning technique that has been successfully used in different areas from self-driving cars to medical decisions [4,7]. Diagnosis of cases such as eye problems, malignant melanoma and tuberculosis in medicine with the help of DL has been successfully performed comparable to humans [4,8]. In recent years, there are some studies in the field of orthopedics and traumatology where DL is also used to detect fractures radiographically [5]. Medical images obtained by examinations such as X-Ray, computed tomography (CT), magnetic resonance imaging (MRI), gamma scan (scintigraphy), and ultrasound examinations in the health field are important data for research and clinical applications. These data help automatically detect diseases by minimizing human errors, establishment of study protocols, reduction ofradiation dose by improving image quality, decreasing MRI scanner time, optimize personnel and scanner use, and finally diminish costs [7]. In the field of veterinary medicine, the application of deep learning algorithm is too limited compared to human medicine [9]. In recent years, important legal steps have been taken on animal health and welfare worldwide. In this context, modern techniques are used for more accurate and rapid diagnosis and treatment clinically in animals [9,10]. Tibia fracture is observed frequently in cats and dogs. To diagnose fracture in veterinary medicine, X-ray image is routine and this procedure is always hazardness for operaters [11]. In addition, the increasing demand for radiology services today causes significant pressure on the workforce, and sometimes it can be a difficult and time-consuming process to evaluate medical images. AI helps in solving these problems [5,12]. But there are very few studies in this field. Although there is a study on pig bones using deep learning technology, this study is not about fracture detection, but on classification [13]. The first retrospective study of bone fractures using deep learning technology in animals was conducted on dog tibia [14].

Current approaches regarding object recognition make great use of machine learning methods. Since the object recognition function is quite complex, the used model must have a lot of data. Convolutional Neural Networks (CNNs) constitute a class of models that are easy to train because they contain fewer connections and parameters [15] The name CNN comes from the mathematical linear operation between matrices called convolution. Generally, CNN is divided into input layer, hidden layer (also known as feature extraction layers) and output layers. Hidden layers consist of multiple layers such as convolutional layer, nonlinear layer, pooling layer and fully connected layer. The number of layers differs for different CNNs [16,17]. CNN is a branch of deep learning technology. Deep learning modeling of big data is a machine learning technique that has been used successfully in a variety of fields, from web search to financial technology banking, from self-driving cars to facial recognition and medical decision support, and has a huge impact on modern society [7]. Mask Regional Convolutional Neural Network (Mask R-CNN) is the one of the most important deep learning object detection methods that detect objects in an image by segmentation with masking method [18].

Most of the hybrid studies are aim to concatenate state of art CNN models instead of using single-handed [19]. The main goal of the scientist in computer science is to solve and improve complex problems by replacing existing algorithms with algorithms that make less computation. This development ensure to solve current problem effectively [20]. In recent years, hybrid models have been applied in different areas to increase performance in deep learning algorithms [6,21,22].

In this study, it was aimed to increase the performance of localization of the fracture of tibia using a new developed hybrid deep learning method.

Material and Methods

Ethical Statement

This study was approved by the Kırıkkale University Animal Experiments Local Ethics Committee (Approval no: 60821397-010.99)

Dataset

The dataset was gathered from tibial fracture of dog and cat. Tibia fracture was obtained from veterinary faculities and Ankara municipality. To have these images, were consulted with Surgery Department of Veterinary Faculties of Ankara, Kırıkkale, Selçuk Universities and Ankara Metropolitan Municipality Sincan Temporary Animal Care Home Rehabilitation Center. 518 fracture of tibial fracture (441 dogs and 77 cats) were used for this research. These radiograph images were taken as Digital Imaging and Communication in Medicine (DICOM) format.

Labeling Fracture Location of Fracture Tibia

LabelImg [23] graphical image annotation software tool was used to annotate 518 fracture tibia images. Fractures oftibia were annotated by veterinarian. Fractures oftibia images were taken into bounding box by using LabelImg. To utilize DICOM images in the computerized system, they were converted to JPEG format. For this process, the Angora Viewer software which works on the institution's computer, was used.

System Architecture of Proposed Framework

In order to localize and detect fracture location of tibia, a new hybrid CNN model was developed on Mask R-CNN. Mask R-CNN [18] is the one of the most robust object detection framework. Original Mask R-CNN framework consists of three part [24]. First part is backbone (ResNet-101, FPN-Feature Pyramid Network). Second part is RPN (Regional Proposal Network). Third part is three branches (Category, Coordinates and Mask). Backbone can be described as the most critic part for Mask R-CNN framework. Because feature extraction process is performed in the backbone section. Whether good or bad of feature extraction results depend on good training of this process. For this reason, it has been thought that hybridization in the backbone will further increase the performance. ResNet model, one of the important CNN models, was used in the backbone part of the original Mask R-CNN framework. ResNet uses skip-connections and identity functions to jump the non-linear transmissions. So, it passes from back layers to front layers via gradient identity function. Nevertheless, it may have a lot of parameters, can block the flow information in the network and have gradient problem disappearing. This can slow down the flow of information and reduce performance due to long training [24]. Since ResNet has been seen to give very successful results in terms of feature extraction [18], instead of removing ResNet completely and using another CNN model alone, the section that may cause slowness in ResNet was improved by using hybrid CNN. Instead of the section that may cause slowness in the network, the "dense block" which contain a narrower network layer and used in DenseNet [24] and "ResNet" turned into a hybrid structure *(Table 1)*. ResNet architecture consists of 5 phases *(Table 1)*. Considering that the 4th phase of the ResNet architecture may cause slowness due to the convulution structure of 23 blocks, it was modified by reducing one block to 22 blocks *(Table 1)*. In the 5th phase, it was aimed to increase the learning performance of the model by accelerating the flow of information in the network by removing a block from the network containing 3 block convolution and adding one dense block, which is also used in DenseNet, instead *(Table 1)*.

Dataset of tibial fracture of dog and cat was trained by using hybridized backbone (Modified ResNet 101 + Dense Block-from DenseNet) Mask R-CNN framework for detection and localization fracture location of tibial fracture. The dataset was divided into two parts as training and testing. This dataset was re-trained with new developed hybrid Mask R-CNN model for the detection and localization of fracture location of fracture tibia. The weights of Mask_RCNN_COCO model were used for training. The configuration values of hybrid Mask R-CNN model were determined as follows: Batch size: 2, learning rate: 0.001, learning momentum: 0.9, weight decay: 0.0001, epoch: 4000. To use different size of images, image was scaled (image_min_dim: 800 and image_max_dim: 1024 pixel). Keras API was used for developing this application. The development system was implemented on 30.5 GB NVIDIA Tesla M60 GPU and Ubuntu 18.04 operating system.

Qualifications of Metrics

Performance metrics are required to qualify the performance of detection and localization of fracture location of tibial fracture. One of the most frequently used metric is Intersection of Union (IoU) to qualify performance of application. In this research, IoU refers that coincide between the ground truth and the bounding box on the fracture tibia image. According IoU threshold value, the result can be whether True Positive or False Positive. In this research IoU was specified as 0.4. False Positive was called when threshold value was less than 0.4. If not, it was called as True Positive. "True Positive-TP" was described as matching up with labelled fracture and detected fracture location by the application. Otherwise, it was described as "False Positive-FP". "False Negative-FN" was described

Table 1. *Architecture comparison of modified ResNet 101 + Dense Block (from DenseNet) and ResNet 101*

Layers	**Modified ResNet 101 + Dense Block (DenseNet)**	**ResNet101** [24]
Convolution	7 x 7 conversion, Stride 2	7 x 7 conversion, Stride 2
Pooling	3 x 3 max pool, Stride 2	3 x 3 max pool, Stride 2
Conv2_X	1x1 conv 3x3 conv x 3 1x1 conv	1x1 conv 3x3 conv x 3 1x1 conv
Conv3_X	1x1 conv 3x3 conv x 4 1x1 conv	1x1 conv 3x3 conv x 4 1x1 conv
Conv4_X	1x1 conv 3x3 conv x 22 **(Modified part of ResNet 101)** 1x1 conv	1x1 conv 3x3 conv x 23 1x1 conv
Conv5_X	1x1 conv 3x3 conv x 2 1x1 conv + **Hybrid CNNs**	1x1 conv 3x3 conv x 3 1x1 conv
Dense Block	1x1 conv 3x3 conv x 1	-
Convolution Layer	3 x 3 conv	3 x 3 conv

as nothing to detect any fracture on image by system but if there was a fracture on image. Confidence score which is another valuable metric for evaluation this application performance, is the possibility of localization and detection fracture on fracture tibia [11]. In order to get overall system performance, F-Score [25] was calculated.

Results

In this research, fractures of fracture tibia were detected using hybridized backbone (Modified ResNet 101 + Dense Block-from DenseNet) Mask R-CNN framework. 518 fracture dataset were split into 415 training (360 dog and 55 cat) and 103 test (81 dog and 22 cat). IoU rate was specified as greater than 0.4. The F1 score of hybrid model on the total dataset were 85.8%. Only 18 images out of 103 could not make a prediction for the detection of fracture on the fracture tibia. The F1 score of hybrid model on the dog dataset were 87.8%. Only 12 images out of 81 could not make a prediction for the detection of fracture of tibia. The F1 score of hybrid model on the cat dataset were 77.7%. Only 6 images out of 22 could not make a prediction for the detection of fracture of tibia. The detected fracture locations of tibia were shown in *Fig. 1* and *Fig. 2*. Fracture location of tibia in 103 test data were detected and localized within 296.64 seconds. It took an average of 2.88 seconds for an image. Fracture location of tibia in 81 dog test data were detected and localized within 233.28 seconds. Fracture location of tibia in 22 cat test data were detected and localized within 63.36 seconds. The metrics of these studies were given in *Table 2*.

Discussion

According to the 2018 data of the World Health Organization (WHO), approximately 34% of human deaths on a global scale may result from misinterpretation of medical data. Therefore, it is important to improve all stages of clinical diagnosis [26]. Recent developments, especially in the field of deep learning, have enabled better perception of images and better interpretation of complex data by machines [5,27]. Convolutional neural network (CNN) is a class of deep neural networks where in deep learning most commonly used to analyze images and video processing [6]. There are several learning methods that have advantages and disadvantages.

Many hybrid machine learning methods have been developed to minimize the disadvantages of being used alone and to combine the useful aspects of each [28]. The adaptive neuro-fuzzy inference system (ANFIS) is combined with five different evolutionary algorithms to estimate the diffusion coefficient of carbon dioxide. ANFIS-PSO's hybrid machine learning model outperforms other models (R2: 0.9978) [29]. A hybrid approach based on a new combination of independent component analysis (ICA) and adaptivenoise cancellation (ANC) has been devoleped for Removal of ocular artifacts (OA) in real-time in electroencephalography (EEG) based brain computer interface (BCI) applications. It has been observed that the performance of the hybrid method is better than other compared methods in terms of removal of OA and recovery of the underlying EEG [30]. A new hybrid method which combined VGG Data STN with CNN (VDSNet) have been developed for diagnosis lung disease. VDSNet had been exhibited higher a validation accuracy (73%) than the other methots (vanilla gray, 67.8%; vanilla RGB, 69%; hybrid CNN, 69.5%; VGG, 63.8%) [31]. Brain monitoring combined with automatic analysis of EEGs important for clinicians. However, clinicians had been stated that the sensitivity and specificity of the method should be 95% and below 5%, respectively, for clinical acceptance [32]. Golmohammadi et al.[32] stated that the hybrid structure

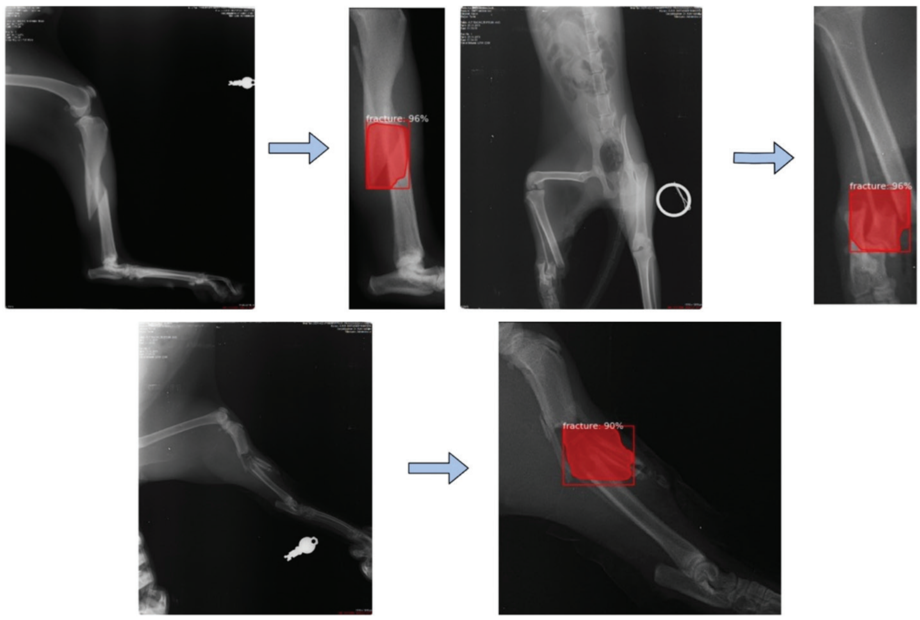

Fig 1. The detected and localized fracture locations on fracture tibia of cats by using Hybridized Backbone Mask R-CNN

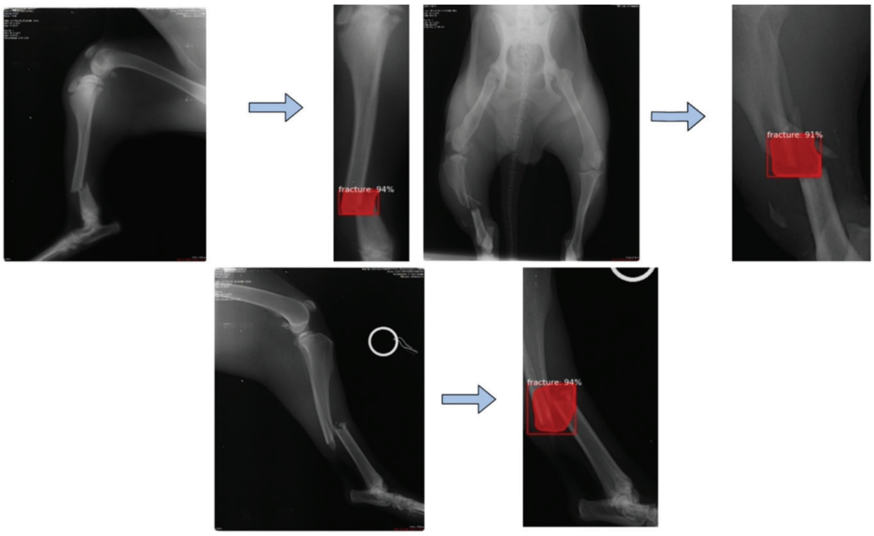

Fig 2. The detected and localized fracture locations on fracture tibia of dogs by using Hybridized Backbone Mask R-CNN

Table 2. *The performance results of detection and localization of cat and dog tiba bone fracture using original mask r-cnn and hybridized backbone Mask R-CNN*

Methods	Dog				Cat				Total			
	P (%)	R (%)	F1 (%)	ART (sec)	P (%)	R (%)	F1 (%)	ART (sec)	P (%)	R (%)	F1 (%)	ART (sec)
Original Mask R-CNN [11]	83.1	91.4	87.1	3.6	65	86.6	74.3	3.6	79.3	90.5	84.5	3.6
Hybridized backbone Mask R-CNN	91.5	84.4	87.8	2.88	87.5	70	77.7	2.88	90.8	81.4	85.8	2.88

P: *Precision,* ***R:*** *Recall,* ***F1:*** *F1 Score,* ***ART:*** *Average Response Time*

based on hidden Markov models and deep learning can approach clinically acceptable performance levels. Although hybrid applications have been made in different fields of medicine, there is no application developed on fracture detection in both medicine and veterinary medicine in fracture diagnosis. Therefore, in this research, it is aimed to develop a hybrid method in the field of AI for better detection of canine and cat tibia fractures.

In the literature searches, retrospective research was not found on bones in which the deep learning method was used for clinical diagnosis in animals. The study of segmentation and classification of spine and limb bones using Computed Tomography (CT) scanned images in pigs is one of several studies of deep learning technology experiments on animal bones. In the study, 3470 CT images were used for spine segmentation, 2000 for spine classification and limb segmentation, and additionally 1428 CT images in the second stage. As a result, according to sagital and coronal, the highest values in the spine classification are cranium (100%) and sacrum + coccyx (100%) for sagittal; the highest value for coronal was found for cranium (99.8%), cervical vertebrae (99.8%) and sacrum + coccyx (99.8%). The highest values in limb segmentation were found for sternum as 84.9% according to sagittal and for right forelimb as 98.2% according to coronal. In limb classification, the highest values were found for scapula as 98.4% according to sagittal and for femur as 95% according to coronal [13]. There are some studies on the detection of bone fractures with CNN in humans compared to animals. 1052 X-ray images were used to test the system in another study performed to detect bone fractures in humans using the two-stage Crack Sensitive CNN system (526 fractures, the remainder without fractures). In the first stage, 20 different bone types were determined from X-ray images using Faster R-CNN. In the second stage, the location of the fracture in the fracture area was determined with CrackNet. As a result, the performance of the two-phase system (F-score) was found as 90.14% [33]. Nine hundered eighty X-ray images were used in the fracture detection of child tibia bones. In this study, Xception-V3 method which is under CNN roof, was applied and the accuracy performance of this method was found as 95.9% [34]. The reason for the low performance of this hybrid study (F-score: 85.8%) in dogs and cats compared to previous studies suggests that the bones belong to different species and the method used is different. However, the result of the fracture detection performance of hybrid study was quite successful compared to the method performed with SSD (68%) in dog tibia fractures [14]. In the study performed with another deep learning algorithm (VGG 16) the performance of fracture detection of Wrist, Hand, ankle (83%) [35] was also lower than this hybrid operation performance (85.8%).

In conclusion, when the original Mask R-CNN framework was compared with hybridized backbone (Modified ResNet 101 + Dense Block – from DenseNet) Mask R-CNN framework for the detection and localization of fractures of tibia, it was observed that the hybridized model (85.8%) gave more successful results than the classical model (84.5%) [11]. Besides, the response time of detection and localization of fractures of dogs and cats tibia using hybridized backbone Mask R-CNN (2.88 seconds) was quicker than original Mask R-CNN (3.6 seconds) [11]. When the performance and response time results of detection and localization of fractures on dogs and cats were examined separately, hybridized model improved results better than the classical model. Briefly, the proposed system showed that the results were promising in terms of detection and localization of fracture tibia in dogs and cats.

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Conflict of Interest

The authors declared that there is no conflict of interest.

Author Contributions

B. Baydan collected data, implemented and developed a new hybrid model. B. Baydan wrote the manuscript. N. Barışçı and H. M. Ünver evaluated the results of study, read and approved final version of manuscript.

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