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Comparison of Deep Learning and Yolov8 Models for Fox Detection Around the Henhouse

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ABSTRACT

Human beings, who have been engaged in agriculture and animal husbandry for centuries, have to constantly track, take care and maintain their own agricultural lands and animals. This requires constant labor and time. The aim and originality of this study is to identify foxes that threaten, harm or kidnap animals such as chickens, geese, ducks and turkeys that live in the coops of individuals engaged in poultry farming. In this way, even if the farmer is not in the henhouse at that moment, material and moral losses to the farmers will be prevented. To achieve this purpose, many images were collected to form dataset. The collected dataset was classified according to whether the fox was in the henhouse or not. Then, the outputs of DenseNet, MobileNet, ResNet50, VGG16, VGG19, Xception and Yolov8 architectures were fine tuned to be performed in transfer learning to detect existence of a fox in the henhouse. Then, the models were trained, and their performances were compared in terms of performance metrics such as loss, accuracy, precision and F1. In the results, Yolov8 architectures generally have demonstrated the best performances.

Keywords: Poultry Farming, Deep Learning, Yolov8

1 Introduction

Human beings started their agricultural activities in 9000 BC in order to survive in many parts of the world, and together with the Sumerians, they carried out many agricultural techniques and plant products as well as animal activities [1]. When the research is examined, crop production activities came before livestock activities [2]. Animals have been the most important source of protein for human beings, who have benefited from animals for centuries. For this reason, animals have been domesticated and made more productive through breeding efforts. Today, livestock activities are grouped as cattle breeding, sheep farming, poultry farming, beekeeping, and aquaculture [2]. In this study, foxes attack especially domesticated poultry, killing or kidnapping poultry, causing financial damage to farmers. In order to

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prevent this, artificial intelligence models DenseNet, MobileNet, ResNet50, VGG16, VGG19, Xception and Yolov8 models for detecting foxes around the chicken coop were trained with the transfer learning method and their performances were compared. In this way, it is aimed to contribute to preventing farmers from suffering material and moral damage.

Livestock has an important place in terms of meeting the nutritional needs of the increasing population and providing a source of raw materials for industrial activities based on livestock. One of the important criteria used in determining the development levels of countries is the amount of animal food consumed per capita [3]. In economically developed industrial countries, there is generally intensive animal husbandry. In this method, meat and milk yield per animal is also higher. In underdeveloped and developing countries, animal husbandry is done using extensive methods. Meat and milk yield per animal remains low, veterinary services are either not provided at all or at a limited level [2]. Poultry farming, which is one of the sectors most suitable for technological developments among animal husbandry activities, has an important place in meeting the need for animal protein. Products such as eggs and white meat obtained from poultry are highly preferred animal foods because they are rich sources of protein and are more affordable [2].

In rural areas, poultry is raised in quantities that meet the needs of each family. Although the income from backyard chickens is lower than that of intensively produced chickens, the costs for housing, disease control, rearing practices and supplementary feeding are very low [4]. Poultry farming, which provides real economic income, is structured in modern large-scale facilities [5]. Except for chicken farms, poultry farming is carried out for subsistence purposes in extensive methods rather than for commercial purposes [6].

Village poultry farming in Turkey is carried out with the aim of producing eggs at a level that meets the needs of the family, having an egg to break and a chicken to pouch when they have guests, and to meet some small needs with excess production [13, 14]. Kristjanson et al. stated that low-income people owning poultry can help them escape poverty [9]. In addition, Riise stated in his study that women's ownership of poultry increases their self-confidence and is effective in increasing their status in society [10] According to Copland and Alders; farms engaged in backyard poultry farming are generally located in rural areas. They are generally family businesses and operate to meet the meat and egg needs of family members. It plays a vital role in the livelihood of families in rural areas. In addition to meeting the egg and meat needs of families, village chickens also meet the family's medicine, clothing and school needs by selling some of them [11].

In Turkey, Bolu and Sakarya are provinces where poultry farming is developed. In this area, there are facilities that make contracted production with large companies in these provinces. Düzce's ease of transportation to both Bolu and Sakarya and to big cities with large market areas positively affects the development of poultry farming in the province [2]. Düzce's ease of transportation to both Bolu and Sakarya and to big cities with large market areas positively affects the development of poultry farming in the province [2].

According to TUIK, data on Meat Poultry and Egg Poultry farming for the years 2013-2023 are given in Figure 1 and Figure 2 [12]. As can be seen, although meat and egg poultry farming has remained stable in recent years, it may increase in the coming years with the increase in population, birth rates and migration.

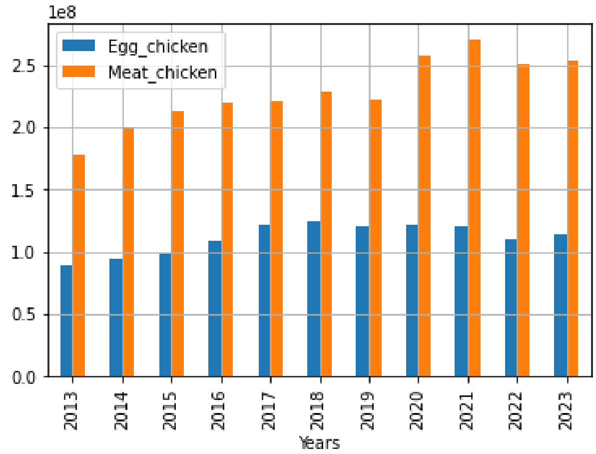

Figure 1: Poultry (Egg and Meat Chicken) Farming data in Turkey

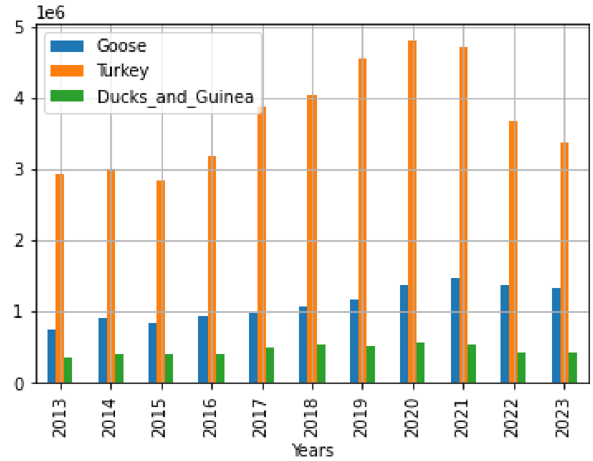

Figure 2: Poultry (Goose, Turkey, Ducks and Guinea) Farming data in Turkey

Permaculture is suitable for places that engage in this type of production, as it is an interdisciplinary system that creates living spaces that have the ability to be permanent in harmony with nature by blending ancient knowledge and experience, technology and science while creating these living spaces [13]. In this regard, combining poultry farming and artificial intelligence technology will increase efficiency. Artificial intelligence is like human brain that learn and make inferences based on data by imitating the human neural structure. Recently, it has become applicable to almost many fields. The success stories of deep learning in various domains include object detection [20, 21], character recognition [16], speech recognition [17], time series prediction [18], [19] and stock market prediction [20], tumor segmentation [21], many more.

In terms of poultry farming, as an image processing and real-time application, Prasetyo et al. stated that the behavior of chickens in the flock is important in determining meat production and stress levels. In this direction, they implemented an application that detects chickens using morphological image processing methods [22]. Karadöl et al. Have implemented a PLC-based and Web-based application to monitor the humidity, temperature and CO2 rates of the environment where broiler chickens are raised [22]. Sasirekha et al. Have implemented an application for monitoring conditions such as internet of things, temperature, humidity, liquid height and servo motor, light and buzzer control in a poultry house [23].

Diwan et al. have conducted a review study on Yolov1-v4 models used in object detection. They also mentioned challenges, architectural, successors, datasets and applications about Yolo [24]. Erin et al. Have used YoloV4 model to classify waste and implemented a real-time application. They compared their results in terms of sensitivity, precision F1, IOU and mAP metrics [25]. Bharadiya have explained classification with Convolutional Neural Networks (CNN) in his study. He specifically mentioned that in modeling, transfer learning can be done through models such as AlexNet, GoogLeNet and ResNet50, or points that can be taken into consideration when training models while building them [26]. Şafak et al. have trained deep learning models for fire and smoke detection using transfer learning method MobileNet, original MobileNet, MobileNetV2, EfficientNetB0, ShuffleNet, NASNetMobile and PeleeNet convolutional neural networks [27]. Eryılmaz et al. have trained MobileNetV2, NASNetMobile, Xception and DenseNet121 deep learning models with the transfer learning method for Covid19 detection [28]. Yücel and Çetintas have developed an automatic system using YOLO architecture for classification of blood cell types using blood cell images [29]. Kumral and Küçükmanisa have carried out a study on behaviour of drivers using CNN networks [30]. Dereli et al. have conducted a study on the recognition of jellfish on the shores using data collected from unmanned aerial vehicles. They said that in this system, by using hardware from NVIDIA, it can be used in unmanned aerial vehicles and warn the authorities according to the density [31]. Hussain have gave information about the development and architecture of Yolov8 from Yolov1, which is used in image processing. These methods have given examples of industrial deployment for surface defect detection in the industry [32]. Karaca et al. Have collected data for the classification of waste. They labeled the data they collected and trained them with Yolov3 [33]. Similarly, Uzun and Dilara have collected data for Autonomous Garbage Collection Vehicles. They trained this dataset on SequeezeNet, VGG19 and GoogleLeNet and compared the results in terms of Accuracy, Precision Sensivity and Specificity [34]. Daş et al. Have used the Faster-R-CNN model in the Tensorflow library in Google's open source library. First, they collected data and carried out the labeling process. Then, they trained the images and achieved successful results [Recognition and Tracking of Objects in Pictures and Videos with Deep Learning]. Öztürk et al. have carried out the classification of vehicles, pedestrians and traffic signs on the road using CNN networks [35]. Again, Gülyeter et al. have implemented the lane detection, and detection of vehicle, traffic sign, pedestrian application using the computerized Yolov5 model [36]. Talat and ZainEldin have proposed a fever detection approach for smart cities using the Yolov8 model. They stated that the method they proposed to recognize fires that may occur in smart cities will reduce damage to property and harm to people [37]. Ergönül et al. have classified the traffic in the network in real time using deep learning [38]. On the other hand, Sütçü et al. have estimated the amount of electrical load consumed using deep learning [39].

Bao et al. have carried out to detect sick and dead chickens in chicken farms with artificial intelligence [40]. Triyanto et al. have stated that broiler flock movements and health conditions in the poultry house are generally done manually by the farmers, but this requires a large amount of time and labor. To automate this process, they have developed an automatic recognition and tracking system using the Yolo v4 model [41]. Chen et al. have developed a warning system based on the movements and distribution of poultry in the chicken house using deep learning and machine learning methods [42]. Bingöl and Bilgin have used transfer learning to identify diseased chickens based on their feces on ResNet50, InceptionV3, InceptionResNetV2, Xception and MobileNetV2 architectures [43].

In this study, a dataset containing 1789 images has been collected to identify fox arouund poultry. The collected dataset has been trained to DenseNet, MobileNet, Resnet50, VGG16, VGG19, Xception, Yolo8m, Yolo8n and Yolo8X models via transfer learning. The performances of these trained models were compared and successful results were obtained.

2 Material and Method

2.1 Deep Learning Models

The first structure of CNN modeling was proposed by Fukushima in the 1980s [44]. The concepts of feature extraction, pooling layers, and using convolution in a neural network were introduced and finally recognition or classification at the end was proposed in the Neocognitron. Generally speaking, while conventional neural networks work with one-dimensional feature vectors, CNNs receive data in matrix format and process it with trainable filters in each convolution layer. CNN can successfully capture spatial and temporal dependencies in an image using relevant filters. To create a simple CNN architecture, three main types of layers are mainly used, namely convolution layer, pooling layer and fully connected layer, as shown in Figure 3. CNN processes the input data it receives by using filters in successive layers. Filters learn their values during training and reveal certain patterns in the data. The pooling layer reduces the size of the data coming from the convolution layers using certain methods to ensure ease of processing the data. As the last layer, the obtained data is converted into vectors and the result is obtained using multilayer sensors. An error occurs equal to the difference between the obtained result and the desired result. It is desired that this error to be minimum. To reduce the error by updating the weights, the backpropagation algorithm or others can be used. At last, the error is minimized by updating the weights with each iteration [20, 51, 52].

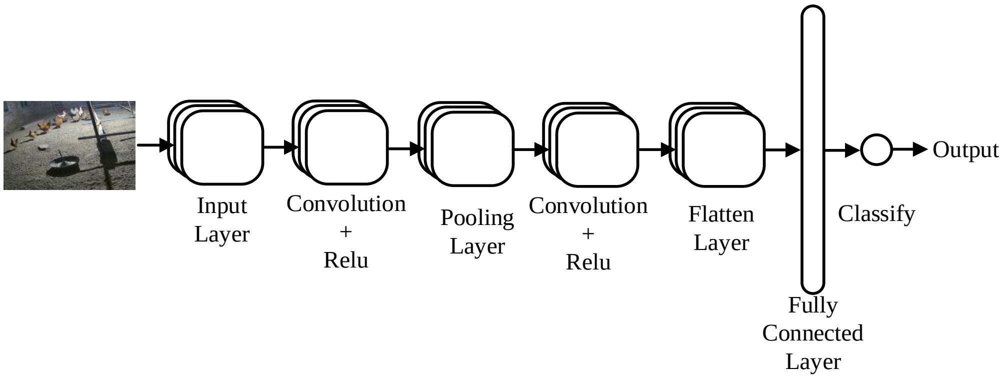

Figure 3: CNN Arhitecture

The main heading of the paper should be written in both Turkish and English if the paper is prepared in Turkish, while it should be written in only English if it is prepared in English. Moreover, the main heading of the paper should be 14 pt and be centered at the top of the paper. VGG (Visual Geometry Group) network architecture is the well-known CNN model. The VGG network has 16 to 19 learnable layers [47]. 19-layer VGG networks were used in this study. VGG19 is a pre-trained 19-layer deep convolutional neural network model that can classify images into several class categories using visual data. With the support of bounding box structures, this model often plays a vital role in image localization and classification. It uses a stacked architecture consisting of 3x3 convolution layers to increase the depth of the model.

ResNet50 (residual neural network) is derived from the ImageNet database [48] is a type of 50-layer residual network trained on at least one million images. To solve the vanishing gradient problem, ResNet uses skip connections, which allow information to pass directly from one layer to the next layer, in addition to regular information flow. Various ResNet model variations exist [45].

In the DenseNet121 architecture, as all layers are interconnected, each layer takes the feature map of the previous layer as input and adds its own feature map to this accumulation and transmits it to the next layer [49]. Continuously growing features make the applicability of the network difficult. In architecture, this problem has been overcome by applying subsampling to feature maps. In this way, feature maps are kept within limits [50].

InceptionV3 is a complex convolutional neural network model trained by GoogleNet on millions of images from the ImageNet dataset. This model can recognize a wider range of images rather than delving deeper into networks. It differs from others in that it can contain several smaller convolutions with restricted parameter types and sizes, and then combine them, instead of larger filter size convolutions [51]. The main goal of the starter module is to replace small kernels with large kernels to learn multiscale representations, simplify the calculation, and use fewer parameters overall [58, 59].

Francois Chollet introduced Xception architecture, an extension of the Inception architecture [54]. The deep convolutional neural network called Xception included new initial layers [55]. The CNN Xception or Extreme Inception model, which has 36 convolution layers and serves as the basis of the feature extraction block, offers an upgraded version of traditional Inception [56]. A linear stack of deeply separable convolution layers with residual connections forms this architecture [52]. Xception's structure consists of 3 streams: input stream, midstream and output stream. If the input image is not 299x299, it must be adjusted before feeding it into the model. A network now connects and separates these convolution layers [56].

MobileNet is an efficient convolutional neural network model used for mobile and embedded image recognition applications. MobileNet convolutional neural network consists of 28 layers and 4,253,864 parameters. MobileNet uses depth-separable convolutions. In this way, the number of parameters has been significantly reduced compared to networks consisting of regular convolutions with the same depth. Depth-separable convolution allows the depth and spatial size of a filter to be separated. Deep convolution applies a single filter to each input channel. MobileNet provides two simple global hyperparameters that efficiently trade off between latency and accuracy. MobileNet network structure is another factor that increases performance. The MobileNet network can be tuned to trade off between width and resolution, and between latency and accuracy. MobileNet has less computational power to run or implement transfer learning [57].

Yolo is an artificial neural network structure developed for instant object recognition by Joseph Redmon and his colleagues in 2016 [58]. Yolo uses the detection task with a single pass of the network and also uses classifier in its output. Unlike Fast R-CNN, regression for the boxes coordinates and classification for the probabilities are performed at the Yolo output. Yolo V2 was also suggested by Joseph Redomond and Ali Fardadi. They have developed a structure that is faster, stronger and more capable than the original. Unlike Yolov1, batch normalization, high-resolution classifier, fully convolutional, use anchor boxes to predict bounding boxes, dimension clusters, direct location prediction, Finner-grained features, multi-scale training features have been changed in Yolov2. Additionally, the backbone structure is used in Yolov2 [59]. Yolov3 was proposed by Joseph Redomond and Ali Fardadi in 2018. Unlike Yolov2, the Yolov3 they recommend has either added or updated features such as Bounding box prediction, Class Prediction, New backbone, Spatial pyramid pooling (SPP), Multi-scale Predictions, Bounding box priors. After that Yolov4, Yolov5, Yolov6, Yolov7 and Yolov8 have been proposed sequencially. Yolov8 has been proposed by Ultralytics company in January 2023. It has reduced the number of box predictions, speeded up the Non-maximum impression (NMS) and used mosaic augmentation during training.

Yolo versions have gained great popularity in the field of computer vision. The biggest reason is due to high sensitivity and accuracy with small models. For this reason, many people can easily use these models for object recognition, classification and segmentation. Yolo V8 model is anchor-free. This means that instead of estimating the distance of an element from a known anchor box, it explicitly estimates the center of the object. Anchor-free detection reduces the number of box predictions, which speeds up Non-Maximum Suppression (NMS), a demanding post-processing procedure that ranks possible detections after inference. YOLOv8 architecture was depicted at Figure 4 [60].

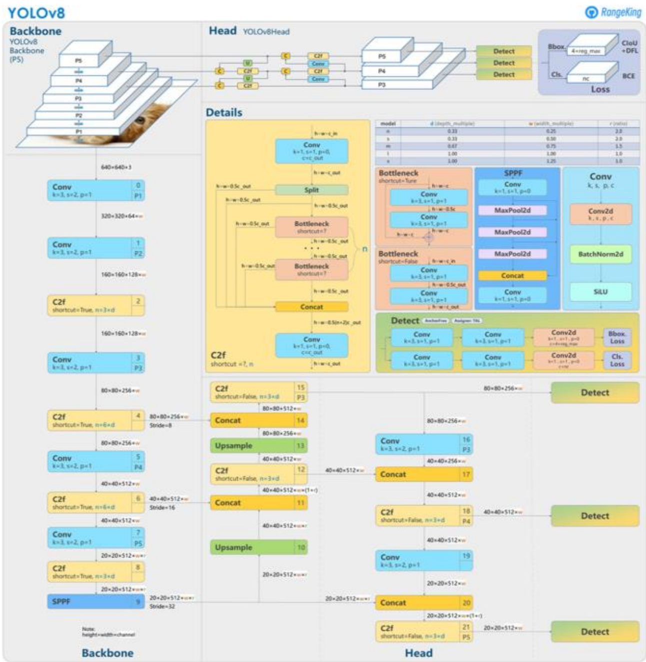

Figure 4: YoloV8 Architecture

2.2 Dataset

In the study, a dataset has been formed to determine the foxes that entered the chicken coop and harmed the poultry. This dataset has been collected especially from videos on the internet and images were taken at regular intervals. A total of 1786 images were obtained. Numerical data regarding the images are given in Table 1. Sample images are shown in Figure 5. After the collected dataset was created, it was classified into 2 categories: tranquil and attack. If there is a fox in the image, the image is classified as "Attacked". If there is no fox in the image, it is classified as "Tranquil". These images were then randomly divided into 20% test and 80% training data to be used in training. Information about the collected dataset is given in Table 1.

Table 1: *Dataset details.*

Classes	Training (Sample, Rate)	Test (Sample, Rate)	Total (Sample, Rate)
Attack	693 %38.8	174 %9.7	867 %48.55
Tranquil	735 %41.1	184 %10.3	919 %51.45
Total	1428 %79.9	358 %20.0	1786 %100

Figure 5: Sample images from the dataset (The ones on the left image there is fox, the ones on the right there is not a fox)

2.3 Transfer Learning

Transfer learning, in which learned knowledge is reused to increase performance on comparable problems, is one machine learning (ML) technique. For example, the artificial intelligence model trained to classify images of cats, dogs, bicycles and cars in Figure 6 can be revised and used to classify just foxes. To achieve this, the output layer of the artificial intelligence model must be revised and learning must be carried out by providing data related to the relevant task. The representative structure of the revised model is again shown in Figure 6. Especially in this study, both the data and the model need to be updated in the context of transfer learning. In this context, the data set collected regarding the problem was given to artificial intelligence models. While performing this process, 1000 neurons were added to the output layers of the DenseNet, MobileNet, Resnet50, VGG16, VGG19 Xception, Yolo8m, Yolo8n and Yolo8X models used in the study and the activation functions were determined as relu. Models were built by assigning a sigmoid function in the output layer. Since classification is a problem, the loss function used in training the models was chosen as binary_crossentropy. For this process, first the model and data set were created as shown in Figure 7. Then the data set was trained. Then the model was tested. As a result of the test, it is determined whether there is a fox in the image.

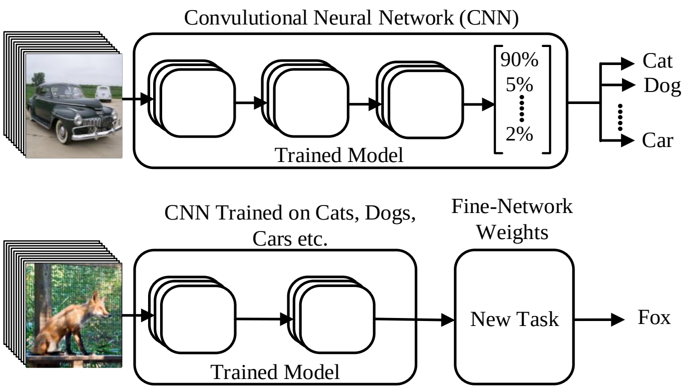

Figure 6: Transfer Learning based on Trained Model

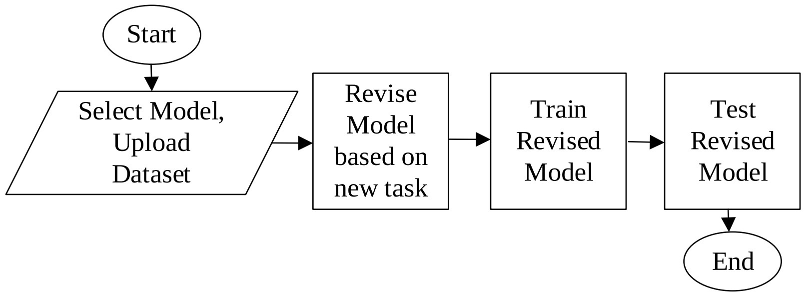

Figure 7: Flow diagram of the process of selecting model, training loading and testing

3 Results and Discussion

In this study, a computer hardware with an Intel i7 11800H 2.3GHz CPU with Windows 11 Home was used to carry out the training and simulations. The computer has 32GB of RAM and the graphics card is NVDIA Geforce RTX 3070. In the software used, the programming language is Python and the program used is Anaconda. Simulation studies were carried out by writing codes in the Spider IDE of Anaconda. In the Spider sofware, DenseNet, MobileNet, Resnet50, VGG16, VGG19, Xception, Yolo8m, Yolo8n and Yolo8X artificial neural network models were trained to identify a fox entering the henhouse. 300 epochs were selected for training. The model size, parameters, and the results of training of model such as accuracy, loss and training duration are given in Table 2. In addition, the evaluations obtained regarding the data set and training are given in Table 4, Table 5, Table 6.

Model parameter numbers and model sizes for the models are given at Table 2. Additionally, loss, accuracy and training duration information regarding the training results of the models are given at Table 2. When the models are examined, the largest model size is Resnet 50, while the smallest model size is YoloV8n. When examined in terms of training results, Yolo V8M produced the best result with the loss value in the objective function. However, the accuracy metric value gives the accuracy of the model. The Yolov8X model produced the best accuracy value.

Table 2: *Model details and their training results.*

Model	Model Size	Total Parametres	Trainable params	Loss	Accuracy	Training Duration (sec)
DenseNet	229.5 MB	58419780	25691137	0.25753	0.88235	18056.929
Resnet50	494.1 MB	126350212	51381249	0.51188	0.74019	19840.519
VGG16	157.9 MB	40406852	12846081	0.28158	0.86834	37499.622
VGG19	178.6 MB	45716548	12846081	0.31783	0.86064	43852.005
MobileNet	213.6 MB	54611140	25691137	0.20207	0.92577	10068.987
Xception	483.3 MB	123623980	51381249	0.23018	0.90756	21152.228
Yolo v8n	2.90 MB	1440850	1440850	0.02419	0.95531	10943.479
Yolo v8m	30.95 MB	15774898	15774898	0.01902	0.95810	20456.899
Yolo v8X	329.3 MB	56144402	56144402	0.02474	0.96369	22450.812

The confusion matrix for the correct classification and incorrect classification of the model is given at Table 3. In fact, all images in the actual class data column are divided into positive and negative. In predicted class, the image is divided into positive and negative on the raw according to the image result evaluated on the model. If the image is positive in the actual class and positive in the predicted class, a true positive (TP) result appears in the confusion matrix. That means model made a correct prediction. If the image is positive in the actual class and negative in the predicted class, a false negative (FN) result appears in the confusion matrix. That means model made a wrong prediction. If the image is negative in the actual class and positive in the predicted class, a false positive (FP) result appears in the confusion matrix. That means model made a wrong prediction again. If the image is negative in the actual class and negative in the predicted class, a true positive (TP) result appears in the confusion matrix. That means model made a correct prediction.

Table 3: *Confusion matrix.*

<table>
<tr><td></td><td></td><td colspan="2">Actual Class</td></tr>
<tr><td></td><td></td><td>Positive</td><td>Positive</td></tr>
<tr><td rowspan="2">Predicted Class</td><td>Positive</td><td>True Positive (TP)</td><td>True Positive (TP)</td></tr>
<tr><td>Negative</td><td>False Negative (FN)</td><td>True Negative (TN)</td></tr>
</table>

All test data for the actual class and predicted class were evaluated on the models. In addition to TN, FN, FP, TP, the arithmatic mean (mAP) values of the accuracy value for classification are given in Table 4. When the results were examined, Yolo v8m produced the best TN values, while Resnet50 produced the lowest performance. While Yolo v8n showed the best result in terms of TP, MobileNet produced the lowest performance. On the other hand, Yolov8n, Yolov8m, Yolov8X values were close to each other and produced the best results.

Table 4: *Model training results with respect to to TN, FN, FP, TP and mAP.*

Model	TN	FN	FP	TP	mAP (%)
DenseNet	103	81	92	82	51.5
Resnet50	64	120	36	138	57.0
VGG16	178	6	21	153	92.3
VGG19	113	71	48	126	66.9
MobileNet	159	25	115	59	60.1
Xception	151	33	43	131	78.6
Yolov8n	177	7	3	171	97.2
Yolov8m	179	5	5	169	97.2
Yolov8X	178	6	4	170	97.2

The results of the models in terms of accuracy, Error Rate, Precision, Recall, F1 are given at Table 5. When the results are examined, Yolo v8n, Yolo v8m, Yolov8X showed the best performances in terms of accuracy, Precision, Recall, F1. Although it showed good results in terms of some performance metrics in VGG16, it fell behind the YoloV8 models.

Table 5: *Model training results with respect to accuracy, precision, recall, F1.*

Model	Accuracy	Error Rate / Misclassification Rate	Precision	Recall	F1 score
DenseNet	0.5167	0.4832	0.4712	0.5030	0.4866
Resnet50	0.5642	0.4357	0.7931	0.5348	0.6388
VGG16	0.9245	0.0754	0.8793	0.9622	0.9189
VGG19	0.6675	0.3324	0.7241	0.6395	0.6792
MobileNet	0.6089	0.3910	0.3390	0.7023	0.4573
Xception	0.7877	0.2122	0.7528	0.7987	0.7751
Yolov8n	0.9720	0.0279	0.9827	0.9606	0.9715
Yolov8m	0.9720	0.0279	0.9712	0.9712	0.9712
Yolov8X	0.9720	0.0279	0.97701	0.9659	0.9714

In addition, True Positive Rate, False Positive Rate, False Negative Rate and True Negative Rate as results of the trained models are given at Table 6. When the results are examined, Yolov8n versions and VGG16 showed the best performances in terms of True Positive Rate, False Positive Rate, True Negative Rate.

Table 6: *Model training results with respect to True Positive Rate, False Positive Rate, False Negative Rate and True Negative Rate.*

Model	True Positive Rate	False Positive Rate	False Negative Rate	True Negative Rate
DenseNet	0.5031	0.4718	0.4969	0.5282
Resnet50	0.5349	0.3600	0.4651	0.6400
VGG16	0.9623	0.1055	0.0377	0.8945
VGG19	0.6396	0.2981	0.3604	0.7019
MobileNet	0.7024	0.4197	0.2976	0.5803
Xception	0.7988	0.2216	0.2012	0.7784
Yolov8n	0.9607	0.0167	0.0393	0.9833
Yolov8m	0.9713	0.0272	0.0287	0.9728
Yolov8X	0.9659	0.0220	0.0341	0.9780

4 Conclusion

Animals have been the most important source of food and livelihood for human beings, who have benefited from animals for centuries. Today, livestock activities are grouped as cattle breeding, sheep farming, poultry farming, beekeeping and aquaculture. In this study, a study was carried out to identify the foxes that attack poultry and cause material and moral damage to farmers. In this regard, a data set for foxes attacking poultry was collected and the images were classified. After the classification process, fine tuning was performed on the outputs of the MobileNet, Resnet50, VGG16, VGG19, Xception, Yolo8m, Yolo8n and Yolo8X models. In this method called transfer learning, models with revised outputs are trained on the collected data set and their performances are compared. When the results were examined, YoloV8 models showed higher performance than other models. As a result, in accordance with the purpose of the study, artificial intelligence models have been able to successfully detect whether there were foxes where there were poultry. On the other hand, considering future studies, this proposed method may have the potential to become a commercial product as it is currently a problem for agriculture and livestock. In addition, new deep learning models developed academically in the future can be applied to the same problem.

5 Declarations

5.1 Competing Interests

There is no conflict of interest in this study.

5.2 Authors' Contributions

Corresponding Author Murat Erhan ÇİMEN: Author has organised the article by himself.

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