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Preserving human privacy in real estate listing applications by deep learning methods

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Abstract

The images are important components of real estate applications on the internet to inform users. There are multiple rental and sale properties and many images of these properties on the internet, and it is challenging to control the images of these real estate in terms of time, workload, and cost. Considering the requirements of the problem, Deep Learning (DL), one of the Artificial Intelligence (AI) methods, offers ideal solutions. This study aims to distinguish images that contain humans using deep learning techniques. This will also aid in not violating the privacy of people according to the Law on the Protection of Personal Data in the image content used in real estate applications. For this purpose, firstly, a dataset of real estate images with and without humans called the Real Estate Privacy (REP) dataset was created. The REP dataset was split into 70%, 20%, and 10% for training, validation, and testing, respectively. Secondly, the REP dataset was trained with Inceptionv3, ResNet-50, and DenseNet-169 architectures using transfer learning. Lastly, the performances of the architectures were evaluated by accuracy, precision, recall, and F1-score accuracy metrics. Experimental results indicate that the 52 epoch ResNet-50 architecture is the best for our datasets with 98.45% overall accuracy and 98.00% precision, 98.90% recall, and 98.44% F1-score. The Inceptionv3 model provided the best results on the 55th epoch with 98.27% accuracy, 97.81% precision, 98.71% recall, and 98.26% F1-score. Finally, the DenseNet-169 model produced the best results on the 47th epoch, with 97.81% accuracy, 97.09% precision, 98.52% recall, and 97.80% F1-score. Accuracy assessment shows that the highest accuracy among the three architectures was obtained with the ResNet-50 architecture This study shows that deep learning methods offer a perspective to image content control and can be used efficiently in real estate applications.

1. Introduction

Real estate has a physical and psychological impacts on people, depending on its location, accessibility, and constraints, beyond meeting basic needs [1]. In addition to location, accessibility, and constraints, there are many factors for real estate preferences and prices along with the interior and exterior elements such as wall paint and floor materials, many visual details such as the appearance of the neighborhood, the view seen outside, and the condition of the accessories [2].

Nowadays, Internet technologies are extensively used to advertise real estate [3]. Real estate for sale or rent is usually promoted by using images of a property [4]. The images and digital files of real estate are often uploaded to the systems by users over which the publisher has to check the content of the image manually. Unwanted situations due to this uncontrolled content can cause great material and moral damage to publishers. The images that are made available to many users over the internet must be suitable for the listed real estate. to minimize the damage [5].

According to the Law on the Protection of Personal Data, it is expected that the relevant photos must only contain the properties of the real estate [6]. Considering that a large number of real estate images are uploaded to these portals, people can't control the content of images in terms of time and workload. Since there is a large amount of content that human inspection cannot deal with errors and cost constraints, it is possible

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to perform this inspection automatically using computer vision and artificial intelligence (AI). Recently, deep learning (DL) which is one of the machine learning (ML) methods, has become popular with the graphics processing units that have been developing and increasing in capacity in the AI field [7,8].

Many DL networks have been proposed for image classification in recent years. After the great success of AlexNet on the ImageNet dataset using Convolutional Neural Networks (CNN), DL approaches have become widespread [9]. The architectures and training procedures still need improvements, as they usually work on a patch-based framework. Long et al. [10] proposed fully convolutional networks (FCNs) that improve CNNs. Simonyan and Zisserman [11] and Szegedy et al. [12] proposed VGG and GoogLeNet (Inception) networks, respectively, showing that deeper and wider networks provide increased accuracy. He et al. [13] then presented the ResNet framework, where layers are formulated by learning residual functions concerning layer inputs. The ResNeXt network developed by Xie et al. [14] is built by repeating a building block that combines a series of transformations with the same topology. The main strategy of ResNeXt is "divide-transform-merge", similar to an Inception module. Huang et al. [15] proposed the DenseNet network, which connects each layer to all other layers in a feed-forward manner, with the approach that a more accurate and efficient training process can be realized by having shorter connections between the layers close to the input and the layers close to the output. Zoph et al. [16] proposed the NASNet network that learns model architectures directly on the dataset of interest. The EfficientNet network developed by Tan and Le [17] proposes a new scale-up method called compound scaling to achieve higher accuracy.

Various image classification techniques have been used for diverse aims in the field of property in real estate agencies. Bappy et al. [3] used long-short-term memory (LSTM) and fully connected neural networks to classify real estate photos according to room types. Koch et al. [18] tested a multi-scale pattern extraction method for the automatic detection of the current condition of a real estate property. Zeppelzauer et al. [19] proposed a two-step approach for real estate age detection. Zhao et al. [20] integrated deep learning and XGBoost methods for automatic real estate valuation with unstructured data. Kamara et al. [21] proposed a hybrid artificial neural network consisting of convolutional neural networks and bidirectional LSTM to predict the advertisement time of real estate in the passive market.

As can be seen from the literature, no study deals with the content of real estate images in terms of protecting people's privacy. The main aim of this study is to conduct human control in image contents used in real estate applications with deep learning techniques. For this purpose, a dataset called Real Estate Privacy (REP) was created using real estate images with and without humans. This dataset was used for the training of deep learning networks named InceptionV3, Deep Residual Network (ResNet-50), and Densely Connected Convolutional Network (DenseNet-169) architectures.

2. Dataset

The REP prepared within the scope of the study is composed of images with and without humans and various factors such as the resolution of the images, the type of human figure, its clarity (blurring ratio), the brightness and tonality of the environment were taken as a basis in the creation of the data set. 495 human-free images were obtained from the real estate images of the project industry advisor the Gayrimenkul Borsası A.Ş. (GABORAS) 2552 human-free images were included in the study from the ADE20K dataset, which consists of 20 thousand scene-centered images in 150 object categories offered as open source [22]. Figure 1 shows examples of image samples from GABORAS Gayrimenkul Borsası A.Ş and ADE20K used in the study.

(a)

(b)

Figure 1. (a) Sample property images of GABORAS Gayrimenkul Borsası A.Ş., (b) Sample images of ADE20K data set

Furthermore, new images from videos of home trips, tours, etc. published on social media platforms were included in the study dataset to complete the missing data. The images were obtained by extracting frames from the videos every 3 second, however, blurring was detected in some frames due to the motion within the videos. For this reason, the average blur rates of each video were calculated. Frames with values greater than the rates were not included in the dataset. The operations were performed using the OpenCV library in a Python environment. Images with different types of people and environments were manually selected to avoid possible overfitting in deep learning algorithms. As a result, 19065 images with people and 2225 images without people were obtained. Images collected from social media platforms are given in Figure 2. The content of the REP data set is shown in Table 1.

19065 images with people and 5272 images without people in different resolutions were obtained. If these images that equal to or larger than 512x512, they were resized as 512x512. However, 5272 images were used for homogeneous data distribution in both classes.

The REP data set was separated into Training, Validation, and Test data for use in DL architectures. 70%, 20%, and %10 of the dataset is reserved for training, validation, and testing, respectively. The number of training data is shown in Table 2.

(a) (b)

Figure 2. (a) Images containing human figures, (b) images without human figures obtained from social media platforms

Table 1. REP dataset content

Class	ADE20K	Gaboras	Social media platforms	Total
Manned	-	-	19065	19065
Unmanned	2552	495	2225	5272

Table 2. Distribution of training data

Class	Train	Validation	Test	Total
Manned	3690	1054	528	5272
Unmanned	3690	1054	528	5272

3. Methodology

AI is a technology that can be created by intelligent systems that can imitate human intelligence. ML is one of the important methods to achieve AI, has enabled machines to learn from past data or experiences without programming. The most popular machine learning technique in recent years has become DL which has provided fast, reliable, and practical solutions using artificial neural networks [23]. DL is one of the rapidly developing methods in big data analytics and has been described as a milestone technology [24].

As can be seen in the literature, many DL networks have been proposed in image classification over time. In this study, Inceptionv3, ResNet, and DenseNet networks are utilized since they are accepted as reference methods in many studies and they achieved great success in the ImageNet dataset. Figure 3 summarizes the whole flow chart of this research.

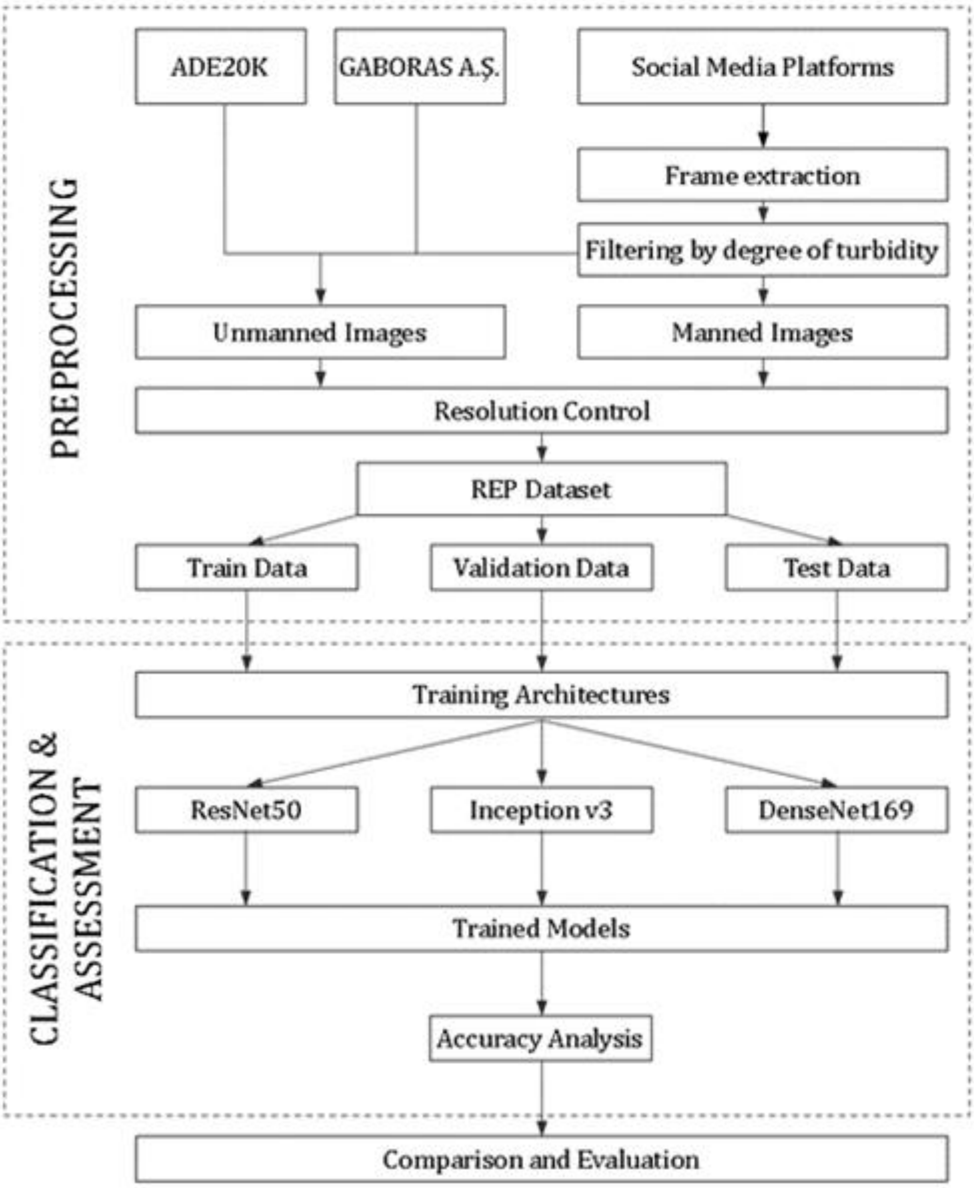
3.1. ResNet

The ResNet [25] network provides a residual learning framework to facilitate the training of significantly deeper networks. ResNet learns residual functions based on layer inputs Instead of learning reference-free functions. Rather than fitting every few chunk layers directly to the desired base mapping, residual networks allow these layers to fit a residual mapping.

They stack the residual blocks on top of each other to form a network. ResNet-50 has fifty layers using these blocks. Experiments on the ImageNet dataset have shown that residual networks are easier to optimize and can gain accuracy from significantly increased depth [7].

There are three variants of the ResNet network such as ResNet-50, ResNet-101, and ResNet-152, which are frequently used with increasing depths with an increasing number of blocks [26].

Figure 3. The whole flow chart of this research



3.2. Inceptionv3

Inceptionv3 network is constructed in a step-by-step progressive manner [27,28]. As a first step, convolutions are factored in to reduce the number of parameters in the network, which helps computational efficiency and controls network efficiency. For this purpose, convolutions are factorized in a smaller size and asymmetrically. Secondly, the CNN is added as an auxiliary classifier between the layers during training [29]. While in previous versions of Inception, this was used to create a deeper network, it is used as a regularizer in Inceptionv3. As a final step, the activation plane of the network filters is expanded to avoid the computational bottleneck caused by the pooling process often used in traditional applications. In this way, an effective grid size reduction method is used to design a low computational load and efficient network [30].

3.3. DenseNet

Dense Convolutional Network (DenseNet) was inspired by the Resnet architecture, which aims to eliminate the information loss that occurs as the depth of the networks increases in traditional Convolutional Neural Networks (CNNs) approaches [15]. DenseNet is proposed as a CNNs-based network in which all layers are feed-forward connected to all other layers. Layers receive inputs from each preceding layer and transmit feature maps to the next layers, maintaining the feed-forward structure. Unlike the ResNet architecture's method of transferring them to other layers by collecting features, the features are combined and transferred to the next layers in DenseNet. Since the dense connection model does not relearn unnecessary feature maps, the number of parameters is reduced [31]. Narrow layers add small feature maps to the total information of the network. Classification is performed by deciding on all feature maps in the network. The blocks where the dense connection principle is used include convolution and pooling layers. DenseNet also has versions consisting of 121, 169, 201, and 269 layers. In DenseNet architectures, a 0.2 dropout rate is applied after each convolution layer in all convolution layers except the first. In addition to this, the ReLU activation function is used following the convolution layers [26].

It is aimed to classify images with or without human figures at various angles and indoor-outdoor conditions by using the mentioned deep learning architectures. Table 3 is shown the software and hardware specifications and Table 4 illustrates the used hyperparameters.

Table 3. Used hardware and software

Computer	TUBITAK ULAKBIM High Performance and Grid Computing Centre
CPU	Xeon 6148 2.40GHz - 20 cores x 2 CPU
GPU	4xNvidia V100 GPU
SPECfp_rate_base2006	1400
Theoric Gflops	2048Gflops & 4x7800Gflops
Memory	384 GB & 4x16 GB HBM
Definition	Akya-Cuda Cluster

Table 4. Used hyper-parameters

Models	Resnet50, Inception v3, DenseNet169
Library	Tensorflow, Keras
Learning Rate	0.001
Pooling	average
Optimizer	Adam
Activation Function	SoftMAX
Loss Function	Categorical Cross Entropy
Epoch	100

4. Results and Discussion

In this study, the performance of 3 DL architectures namely ResNet50, DenseNet169, and Inceptionv3 is investigated. Python's Keras library was utilized to implement all of the selected deep CNN architectures [32]. 70% of the dataset was used for training, 20% for validation, and 10% for testing. The training, validation, and test data consists of 3840 images, 1098 images, and 549 manned and unmanned images respectively. Furthermore, trainings were performed to find the combination that obtains the best accuracy result with the ideal hyperparameters in DL architectures. In this part, firstly the best epoch of each training was identified and then the accuracy was analyzed on the test data, finally, the hyperparameter combinations were compared. According to the results, the best combination was determined as the pooling method "Average", the optimization method "Adam", the activation function "Softmax" and the loss function "Categorical Cross Entropy".

In addition, accuracy, precision, recall, and F1-Score metrics were used to analyze the results. Table 5 illustrates the accuracy assessment results. The Resnet-50 architecture obtained a high level of success in all evaluation criteria for test accuracy, precision, recall, and F1-Score. The test accuracy, average precision, average call, and F1-score results were calculated as 98.45%, 98.00%, 98.90%, and 98.44%, respectively.

Table 5. Accuracy assessment results for the REP dataset

Deep Learning Model Used	Test Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet-50 (Epoch 52)	98.45	98.00	98.90	98.44
Inceptionv3 (Epoch 55)	98.27	97.81	98.71	98.26
DenseNet (Epoch 47)	97.81	97.09	98.52	97.80

Table 6. Confusion matrix from three architecture

Architecture	Classification Data	Reference Data	
		Manned	Unmanned
ResNet-50	Manned	538	11
	Unmanned	6	543
Inceptionv3	Manned	537	12
	Unmanned	7	542
DenseNet-169	Manned	533	16
	Unmanned	8	541

The confusion matrix shows the relationships between the test classes as a result of the prediction of the data whose real classes were known. The matrix results for the best epochs of the experiments with Resnet-50, Densenet-169, and Inceptionv3 models are given in Table 6.

The observations on confusion matrices show that Densenet-169 was the model with the most misclassifications. Although the Inceptionv3 and Resnet-50 models had similar results, the Resnet-50 had the best result among them. The Resnet-50 classified all test images as 538 true positives (TP), 6 false positives (FP), 543 true negatives (TN), and 11 false negatives (FN). True and false terms are logical results of classification assessment. Positive and negative are also meant images that are with and without people. If images with and without people were classified as true, they were called TP and TN, were classified as false, they were called FP and FN. Some FP and TN image examples of Resnet-50 architecture are respectively shown in Figures 4 and 5.

Furthermore, Table 7 is shown the training times for the three DL architectures. While the training time of DenseNet-169 was the longest, the ResNet-50 was the shortest training time for the REP dataset.

Investigations on false positive images revealed that does not contain a real person and contain human-like materials such as a painting with human figures, plastic mannequins, and sculptures and these images were misclassified by the models. If the misclassified images are removed from the model, there will be no effect on the accuracy of the classification. Because the model will encounter these images in the training process, it will not be able to learn that they are non-human images. If the number of similar images in the dataset is increased, the problem may be solved.

Figure 4. Examples of incorrect (FP) prediction images

Figure 5. Examples of the correct (TN) prediction images

Table 7. Training times of DL models

Model	Training Times(hour)
Resnet-50	~10
DenseNet	~18
Inceptionv3	~11

5. Conclusion

In this study, it is aimed to distinguish images with people among real-estate listing images to preserve human privacy. For this purpose, we applied three state-of-the-art DL architectures namely ResNet, DenseNet, and Inceptionv3 using our novel REP dataset. The results of the study show that the highest accuracy among the three architectures was obtained with the ResNet50 model. The average accuracy of training with all architectures was approximately 98%.

This study can be used at the national and international levels, including the production of all kinds of spatial services and goods for the protection of personal data. For example, it has the potential to produce solutions that can be used effectively by various industries such as tourism, real estate, warehousing, logistics, construction, and the civil and official authorities that supervise them. Moreover, tools such as room classification, price and building age estimation from images can be among the innovative solutions in this sector. In future studies, we aim to separate the images of people and their body parts in photographs to be used in real estate advertisements through digital services and to improve image quality.

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Author contributions

Bülent Bayram: Conceptualization, Methodology, Writing-Reviewing and Editing. **Tolga Bakırman:** Conceptualization, Methodology, Software,Writing-Reviewing and Editing. **Raziye Hale Topaloğlu:** Writing-Reviewing and Editing. **Hilal Adıyaman:** Data curation, Software, Validation, Writing-Original draft preparation. **Yunus Emre Varul:** Data curation, Software, Validation, Writing-Original draft preparation. **Elif Alkan:** Investigation, Data curation, Validation. **Sevgi Zümra Karaca:** Investigation, Data curation, Validation.

Conflicts of interest

The authors declare no conflicts of interest.

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