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An Integrated Framework for Detection of Car Accident Damage using Deep Neural Networks Model: a Real-Life Case Study

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Abstract

In this study, in the insurance industry, an integrated framework based on the Convolutional Neural Networks method is proposed to estimate the amount of car damage after the accident. This paper aims to analyze the performance of deep convolutional network methods in recognizing and classifying six different damage including surface damage, deep damage, car side mirror damage, glass damage, tire damage, and light damage. Regarding the case study, the required data for this research is obtained from the customers of an insurance company in 2021 and 2022 in Iran. This statistical population is a cross-section of all the pictures of accidental cars in the country and includes 20,000 pictures of people's cars after the accident, of which 4,100 pictures were selected and extracted as the target data of the research from the database of third-party insurance companies. The performance of models based on algorithms such as ConvNeXtBase, ConvNeXtXLarge, ResNet-50, ResNet-101, EfficienetNetB7, EfficienetNetV2L, and EfficientNetV2B0 has been evaluated under criteria including accuracy sensitivity, specificity, precision, and F- score criteria to compare all types of heuristic algorithms. The results of this research show that the performance speed of the models largely depends on the characteristics of the pre-trained models and the accuracy of the models is based on algorithms such as AlexNet, VGG-19, ResNet-50 have been obtained in the range of 0.59 to 0.91, which indicates the acceptable performance of these algorithms based on deep convolutional networks in detecting and evaluating car damage after accidents.

Keywords: Deep learning, Convolutional neural network, Car accident damage, Insurance industry

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1. Introduction

In the real world, after any type of car accident, getting a reliable repair estimate is the essential first step in getting the vehicle back on the road. In this regard, an inaccurate estimate can cause irreparable damage to insurance companies and car service companies (Qaddour & Siddiqa, 2023). On the other hand, in traditional methods, damage estimation often depends on the opinions of experts, and this has created many problems for companies, both in terms of organizing these people and in terms of training and accuracy of these people. In addition, these people create a significant cost burden for insurance companies and car service providers (Kyu & Woraratpanya, 2020).

Moreover, different experts provide different opinions and damage bill for the same accident at the same time. This is because these experts have different tastes and experiences and their experiences play a major role in estimating damages. Also, experts cannot estimate the hidden and indirect damages of an accident visually. The purpose of presenting the damage estimation algorithm is to provide a system framework for damage estimation without the role of humans and experts, which can control human tastes and error in estimation. In order to more precise estimates using image peocessing, we first need to prepare the digital images with high quality using new cameras that automatically output digital images. In the next step, the brightness ,contrast, and noise of images are edited and prepared for image processing to more details of the images can be seen easily. Also, the proposed Convolutional Neural Networks algorithm as a DSS (Decision support system) besides the experts are used for accident damage estimation. That is, the algorithm is trained and tested using a lot of image data under the supervision of experts, and after the validation of the algorithm, it is used practically to estimate the accident damage without expert supervision.

In the process of damage estimation, the estimated amount should be enough to repair the car with the necessary standards. For example, if a piece of vehicle equipment is damaged, the damage estimate made by the provided model is consistent with the estimate of the factory's authorized repair center. The customer is interested in benefiting from the most and most accurate services at the lowest cost. Car service providers and repairers also seek to maximize their profits by providing services within a defined framework. Insurance companies, taking into account their profit, undertake to compensate the possible loss of a customer in the event of an accident in a certain time, or to provide certain services to him. In this way, it reduces the possible risks to customers. Therefore, in the issue of damage to the car, we are facing actors who are each looking for their interests and trying to optimize it from their point of view. Therefore, it is necessary to design and implement an intelligent system to detect the state of car damage that does not have the problems and problems of damage estimation by experts (such as fatigue, emotionality, informal relationships, etc.). To be able to make accurate, quick, and justifiable judgments about car damage away from any irrational human judgments and tendencies.

The aim of this research is to propose a new approach to estimate a vehicle body damage using two-dimensional images using the Convolutional Neural Networks method. Therefore, when the body of the vehicle is damaged in the accident, without the need for the presence of an insurance expert, the user is able to receive the type of damage to his car in the shortest possible time as well as damage report to be received from the insurance. When an accident image is uploaded on a software platform, the proposed algorithm processes the image and detects the the amount and severity of the accident. Finally, by sending a accidenet image on a software platform , the user receives the type of damage caused to the car. The research results can reduce the number of processes followed after the accident and eliminate many of them; As a result, the time and cost spent on car damage estimation along with the accuracy of damage estimation are significantly optimized. This research is a developmental and applied research based on machine learning approaches and methods based on deep learning algorithms, which analyzed and learned using real data of the past two years with the aim of detecting accidental car damage and the type of damage. First, after collecting the desired data, they are divided into two groups of training and test data with a ratio of 70% and 30%. These data are classified based on 6 types of common damage and collective learning algorithms are used to detect and predict the type of damage.

In this paper, seven models under deep convolutional neural networks have been evaluated using the transfer learning method using seven pre-trained networks to perform and classify car damage after an accident. For this purpose, six image data sets of car damage were prepared for training, validation, and testing of the models, and an unequal amount of images including surface damage, deep damage, car side mirror, glass, and car tires were placed. Due to the presence of more than one damage in some images, they have been used repeatedly in other classes as well, and this shared use includes a maximum of ten to fifteen percent of the total data. In this research, seven widely used pre-trained networks were used to build damage detection models, which are: ConvNeXtBase, ConvNeXtXLarge, ResNet-50, ResNet-101, EfficienetNetB7, EfficienetNetV2L and EfficientNetV2B0.

The structure of the present study is as follows. The background on previously conducted literature is provided in Section 2. The proposed models and methods besides the numerical examples are proposed in Sections 3 and 4 respectively. The conclusion is presented in Section 5.

2. Literature Review

In recent years, organizations have tried the development of automatic tools to better collect and evaluate information, and extensive research has been done in this field (Dwivedi et al., 2021). Presence in the turbulent market of competition has led organizations to use a new approach to keep current customers and identify and attract new customers. Shortly, the insurance industry will be one of the fastest-growing industries using image recognition. Every day, with the increase in the number of people who drive, the number of accidents and car insurance claims has increased. The lifecycle of registration, processing, and decision-making for each claim includes manual review by the service provider.

Convolutional neural networks (CNN) are among the most important deep learning-based approaches that use various types of data such as text, images, and videos (Bandi, Joshi, Bhagat, & Deshpande, 2021). The insurance industry in Iran is a very old industry with fixed, firm, and framework-oriented rules. For this reason, many activists and enthusiasts of technological technologies have had less entry into the insurance industry than in other fields. We know that the insurance industry, with all the progress it has made since its establishment, is still involved in manual and paper processes. Customers are involved in the administrative process more than expected to receive insurance services and pay extra costs to receive regular services (Marnani et al., 2012; Nozari & Szmelter-Jarosz, 2022). Regarding the scope of the application of artificial intelligence and its derivatives in different industries, many articles have been published during the last decade. Table 1 briefly shows the previous studies of the investigated area of this research in different dimensions.

Table 1: Classification of articles related to this research

Refrences	Method	Attributes													
		Supervised	**Unsupervised**	**Multivariate**	**Univariate**	**Global**	**Local**	**Dynamic**	**Static**	**Splitting**	**Merging**	**Direct**	**Incremental**	**Parametric**	**Non-Parametric**
Tong, Gao, &) (Zhang, 2017	CNN	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×
Vidal, Bruna,) Giryes, & Soatto, (2017	Image processing	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×
Wiatowski &) (Bölcskei, 2017	Information	✓	✓	✓	×	×	✓	✓	×	✓	×	✓	×	×	×
Zhang & Cheng,) (2017	Image ،CNN processing	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×

Dorafshan,) Thomas, & (Maguire, 2018	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Eom & Choi,) (2018	CNN	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Gao &) (Mosalam, 2018	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Kim, Kim,) Hong, & Byun, (2018	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Mohan &) (Poobal, 2018	Information	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Tong, Gao, Han,) (& Wang, 2018	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Riantini,) Subiyanto, & (Adianto, 2019	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Singh, Ayyar,) Pavan, Gosain, & (Shah, 2019	Information	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Li, Wang,) Zhang, Yang, & (Wang, 2020	Image ،CNN processing	✗	✗	✓	✗	✗	✓	✓	✗	✓	✗	✓	✗	✗	✗
Prykaziuk,) Erastov, & (Lobova, 2020	Information	✗	✗	✓	✗	✗	✓	✓	✗	✓	✗	✓	✗	✗	✗
Ranjbar,) Moghaddasnezhad, & ZAKERI, (2020	Information	✗	✗	✓	✗	✗	✓	✓	✗	✓	✗	✓	✗	✗	✗
Han, Pei, &) (Tong, 2022	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Maiano et al.,) (2023	Image ،CNN processing	✗	✗	✓	✗	✗	✓	✓	✗	✓	✗	✓	✗	✗	✗
Crognale, De) Iuliis, Rinaldi, Gattulli, & (Vibration, 2023	Information	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Tian, Zhang,) Chen, Wang, & (Wu, 2023	Image ،CNN processing	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Nisha, Baptista,) Nikhil, & Behl, (2023	Information	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Sajitha,) Sambandam, & (John, 2023	CNN	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗	✓	✗
Wu et al., 2024;) (Nozari et a., 2024	Image ،CNN processing	✗	✗	✓	✗	✗	✓	✓	✗	✓	✗	✓	✗	✗	✗

Naderpour et al.,) (2024	Information	✓	×	✓	×	✓	×	✓	×	✓	×	×	×	✓	×
Kaboodkhani,) Bayesteh, & (Hamidia, 2024	Information	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×	✓	×
This paper	Image ‹CNN processing	✓	×	✓	×	✓	×	✓	×	✓	✓	✓	✓	✓	×

Reviewing the articles in Table 1 of the literature review shows that:

- The deep learning approaches in the automobile industry have not been investigated seriously and considering it to estimate the car damage and its results has been ignored in the related literature.
- Reviwing the literature shows that no paper has been presented on the subject of car damage with deep learning tools. In this research, 6 cases of car damage, including surface damage, deep damage, car side mirror damage, glass damage, tire damage, and light damage have been investigated. Also, seven deep learning algorithms including ConvNeXtBase, ConvNeXtXLarge, ResNet-50, ResNet-101, EfficienetNetB7, EfficienetNetV2L, and EfficientNetV2B0 have been used under criteria including accuracy sensitivity, specificity, precision, and F- score criteria to estimate the accident damage which such a combination of deep learning algorithms are not reported in the previous works.• Real and current data are rarely used in the above articles. The articles that have been worked on a different topic from this research and with the focus on deep learning and related tools have been worked on only one to two tools without analyzing the evaluation factors such as accuracy, sensitivity, etc. of the model. In this research, the data from the last one to two years have been used, and we can have more confidence and trust in its accuracy according to its results.
- According to the study of the previous research in this field, the innovation of the model and one of its distinguishing points is the special attention to the new methods of artificial intelligence in the current situation. Since the most important factor in success on the day of the accident is providing help on time and preventing the creation of traffic to speed up the rescue, this research can have positive financial and life effects by minimizing the time of accident assessment. Therefore, first of all, the proper infrastructure of this platform in the country, and secondly, the use of scientific and specialized capacity in the country can play a significant role in the realization of this great event. From a process point of view, all the activities of one department will have a relative effect on the performance of other departments, and the result of the effectiveness of one part of the process will naturally cause change and transformation in other departments. In general, it can be concluded that machine vision algorithms are of particular importance in insurance companies, and car manufacturing companies, where car damage is one of their key cases, this research can be a good way to enter artificial intelligence and learning in these industries.

3. Research Methodology

Today, using deep learning tools in image recognition applications has become very widespread. Deep learning has significantly improved computer vision over the past few years (Medjdoubi, Meddeber, & Yahyaoui, 2024). Diagnostic imaging in healthcare applications and facial recognition in smartphones are several examples of these deep-learning tools (Mohammadzadeh, Navabakhsh, & Hafezalkotob, 2024). Moreover, neural network approaches apply models that are layered next to each other. This creates each algorithm dependent on the results of the algorithms around it.

In unsupervised learning, the model is provided with unlabeled input data or specified output. The main goal of this method is to extract hidden patterns, structures, and relationships in the data. In this case, the model automatically discovers patterns and semantic relationships in the data without being guided by correct labels or outputs. Deep learning is a subcategory of machine learning under the structure of artificial neural networks. This approach provides powerful modeling to recognize patterns and extract complex features from data (Ramavath & Suryawanshi, 2024). Deep neural networks are based on hierarchical models where each layer is associated with a linear transition after applying a non-linear transformation to the next layer. For example, the input data can be assumed as $X \in R^{N*D}$ where each row of X is data with dimension D such as gray images with D pixels and N is the training number of the network. In this network, W^k is defined as a matrix for linear transfer from layer $k-1$ to another stage to reduce dimensions in layer k.

$$X_{k-1}W^k \in R^{N*d_k} \tag{1}$$

Afterward, a function ψ_k that is non-linear format is used to create the k th layer.

$$X_k = \Psi_k(X_{k-1}W^k) \tag{2}$$

This non-linear function can be defined and used in different forms such as $tanh\ (x)$ or $(1 + e^{-x})^{-1}$ etc. According to the described process, the network output after several layers is:

$$\emptyset\left(X, W^1, W^2, \dots. W^k\right) = \Psi_k(\Psi_{k-1}(\dots.(\Psi_2(\Psi_1(XW^1)W^2)\dots)W^{k-1})W^k) \tag{3}$$

In the above relationship, $\emptyset$ is an $N \times C$ matrix and C is the output dimension of the network, which is considered as the output dimension in a network to classify the number of categories. As an optimization problem, learning the parameters of the deep network concerning N training data is presented. Thus, in a classification problem, each row of X specifies data in R^D and each Y specifies a member of the output classes C. Based on this, the learning process takes place as follows.

$$Y \epsilon R^{N*C} \qquad X \epsilon R^{N*D}$$
$$\mathrm{Min}\,\ell(Y, \emptyset(X, W^1, W^2, \dots.., W^k)) + \lambda\Theta\ (W^1, W^2, \dots., W^k) \tag{4}$$

In the above relation, a predetermined loss function $\ell\ (Y, \emptyset)$ is considered as the difference between the predetermined classes and the predicted classes based on the relation (Θ) to avoid overfitting the model. λ as an adjustment parameter is a positive value. The CNN is one of the most important deep neural networks whose architecture follows a pattern similar to the connection of neurons in the brain and is modeled after the Visual Cortex. Small groups of visual neurons are busy in each part alone, and the combination of these neurons and the creation of interconnected networks make one see an area.

The convolution layer is the backbone of any CNN working algorithm. In this layer, the images are scanned pixel by pixel and a feature map is created to define future classifications. According to Figure 1, the pooling layer is also known as data sampling by bringing the overall dimensions of the images. The feature information of each convolution layer depends on the initial information.

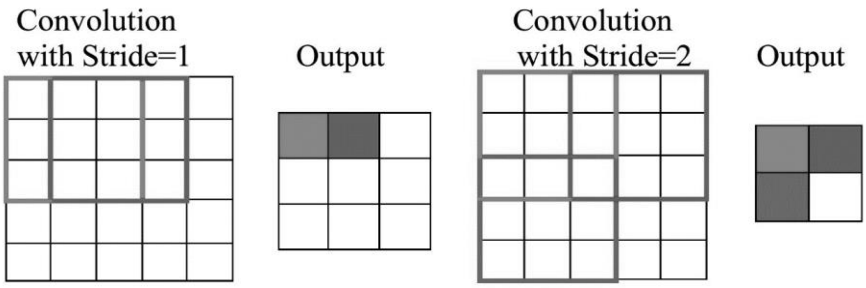

Figure 1: Data convol

For the data of the next layer, the outputs obtained from the last layer are flattened into a vector. The next layer is the fully connected layer. After performing the feature analysis and recording the computation time, this layer assigns a random weight to the inputs and predicts a suitable label. Finally, the output layer is the last layer of the CNN model, which contains the results of the labels determined for classification and assigns a class to the images.

This research is developmental and applied research based on machine learning approaches and methods based on deep learning algorithms, which use real data from the past two years to analyze and learn them to detect accidental car damage and the type of damage. First, after collecting the desired data, they are divided into two groups of training and test data with a ratio of 70% and 30%. These data are classified based on 6 types of common damage and collective learning approaches are used to detect the type of damage. Also, to evaluate the performance of the obtained results, indicators such as accuracy and reliability, weight coefficient, differentiation, ability, and sensitivity have been used. In this article, let's use the transfer learning method with pre-trained algorithms. In this method, the ability to learn and extract basic features in pre-trained networks according to Table 2 (specifications and additional information related to pre-trained networks) is used to retrain the network based on new data. This makes it possible to build the model in less time, with less data and with less processing power.

At first, the training data is prepared for model collection and database preparation (data cleaning, normalization, etc.). These data are classified into two main categories of training and testing and 6 subgroups of car surface damage such as scratches, deep car damage such as fractures, car side mirrors, glass, tires, and car lights (Clustering).

Table 2: Information on pre-trained models

# of network construction	*Size /MB*	*# of Parameter (million)*	*# of layers*	*Image dimensions*	*Trained model*
Over a million images in 1000 categories	338.58	88.5	..	227*227*3	ConvNeXtBase
	755.07	197.7	..	224*224*3	ConvNeXtXLarge
	98	25.6	58	224*224*3	ResNet-50
	171	44.7	90	224*224*3	ResNet-101
	256	66.7	438	224*224*3	EfficienetNetB7
	479	119.0	..	224*224*3	EfficienetNetV2L
	29	7.2	..	224*224*3	EfficientNetV2B0

The greater the variety and number of images in each category, the less likely the problem of overfitting will occur. Also, the training time of models and processing power increases. In this research, 4100 images of car damage with average dimensions of 4320x3240 pixels were used (Figure 2).

Figure 2: The study Sample data

Then, the structure of the deep neural network model is defined. This includes the type and order of layers, the number of neurons in each layer, and the connections between layers. Table 3 shows the data used in the field of training and testing.

Table 3: The data used in this research

Category	The number of data	
	Learning operations	
	Education	Test
Car surface damage	12910	2190
Deep car damage	7980	4960
Car window damage	5300	2900
Car side mirror damage	5400	2300
Car light damage	8810	2060
Car tire damage	800	600

The model training phase consists of sending data to the model, calculating the output predicted by the model, calculating the error between the predicted output and the actual value, and using the error backpropagation algorithm to update the weights in the network. This process is repeated and continued until the accuracy of the model increases by taking into account the amount of error and its control. Normally, the captured images do not have the necessary quality to be used as input for the process of making classification models. Over time, the distribution of the pixel values of the image becomes wider and the intensity of the values becomes more balanced, and as a result, it creates images with higher brightness and resolution.

In this research, the performance of the models created by the transfer learning method based on six pre-trained networks for detecting and classifying the types of car damage in accidents has been evaluated. The six algorithms used in this research to identify damage defects are ConvNeXtBase, ConvNeXtXLarge, ResNet-50, ResNet-101, EfficienetNetB7, EfficienetNetV2L and EfficientNetV2B0. As can be seen in Table 3, a total of 4062 images were used in the learning process of the models, of which 3085 images were tested for training and 977 images were tested for validation. The learning tools of this research are Python programming language and Tensorflow, matplotlib, numpy, and glob libraries.

In the model evaluation phase, after training the model, its performance is evaluated using test data. Criteria such as precision, accuracy sensitivity, and other analytical criteria have been used to evaluate the performance of the model. In the stage of model review and improvement, if the performance of the model is not acceptable, you may need changes and improvements in the model structure, training algorithm, or training parameters. In this case, checking the model is done to improve its performance.

In Figure 3, by examining the training process of the models, it can be said that the error rate and accuracy of the models have become stable after 10 to 12 cycles, and the learning process of the models reaches the highest accuracy in each iteration. Based on this, 15 courses seem appropriate in this research.

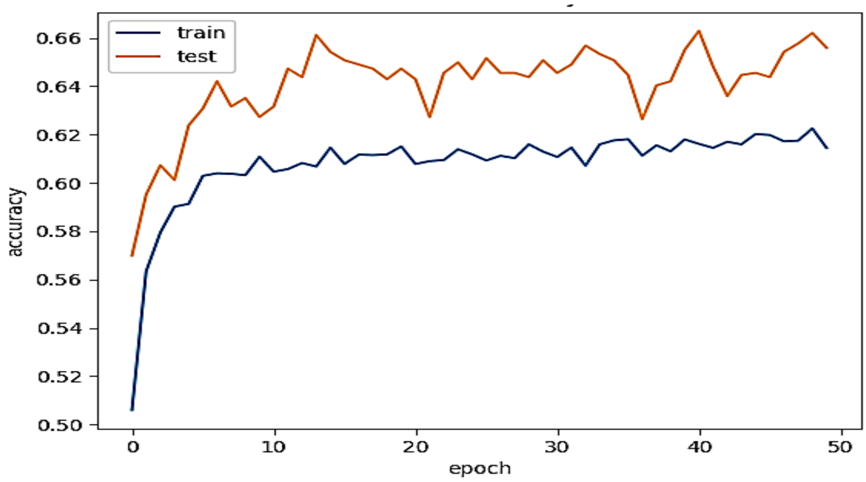

Figure 3: An example of the data training process

Another important parameter that must be determined before starting the model training operation is the number of data in each iteration. The number of samples in each iteration can be chosen between one and the number of training data. A large number of samples per iteration requires a powerful processing system. In this article, according to the processing power, the number of 15 samples per repetition is considered. The repetition number is determined using Equation 5.

$$i = \frac{N}{n} \tag{5}$$

where N is the total number of training data and n is the number of samples (in each iteration). Considering 15 samples in each repetition, 80 repetitions are needed to perform a learning period consisting of 4100 samples (data), and in total, 4100 repetitions must be performed to perform 15 learning periods. It should be noted that if the number of repetitions is too high, it will lead to problems such as overfitting and increasing the processing time.

The learning rate and momentum value are other parameters that have an effect on the learning result and are often considered 0.001 and 0.9 respectively in different studies. In this article, the parameters affecting learning operations are considered the same in all pre-trained models. However for the ResNet-101 model, due to the limited processing power and the high depth and number of model parameters (according to Table 2), it leads to insufficient memory space to perform learning operations.

For this reason, the number of samples per iteration of the ResNet-101 model is set at 12. All the processes and calculations performed in this article have been performed using a personal computer with a 64-bit operating system with an NVIDIA GeForce RTX 3060 graphics processor with 12 GB of memory and with image processing operations and deep learning implementation in Python 2022 and GoogleColab software.

4. Research Findings

After carrying out the process of learning the models based on the training data and evaluating the accuracy based on the test data, the obtained results from the evaluation of the learning speed of the models are presented in Table 4.

Table 4: Training time for each image

Model type	training time	Preprocessing time f	Time evaluate models
ConvNeXtBase	0/482	0/5	0/019
ConvNeXtXLarge	0/637	1/2	0/024
ResNet-50	1/944	1/1	0/041
ResNet-101	3/823	4/5	0/054
EfficienetNetB7	61/85	3/4	0/061
EfficienetNetV2L	64/25	8/3	0.056
EfficientNetV2B0	0.55	9/4	0/034

From Table 4, to evaluate the speed of the models, the time spent in the processes of image preprocessing, learning, and evaluation of the models has been examined. Since the pre-processing operation is performed before the training and evaluation of the models, Figures 4 and 5 show the comparison of the performance speed of the models in the learning operation (pre-processing and training) and the evaluation operation (pre-processing and evaluation).

Based on Figure 5, in the learning operation, a small part of the operation time is dedicated to data pre-processing. On the other hand, the image preprocessing process in the operation of learning the performance of the models has taken a significant part of the time. ConvNeXtBase, ConvNeXtXLarge, and EfficientNetV2B0 models have a higher speed than other models in learning and evaluation operations by performing the learning process in less than one second and evaluating new images in less than 0.1 second. Among the evaluated models, the ConvNeXtBase model with a time of 0.482 seconds for each image in the learning operation and 0.019 seconds for each image in the evaluation operation is the fastest, and the EfficienetNetV2L model with a time of 25.64 and 0.056 seconds, respectively. It has performed the slowest for learning and evaluation. Table 5 shows the performance evaluation of the models in general.

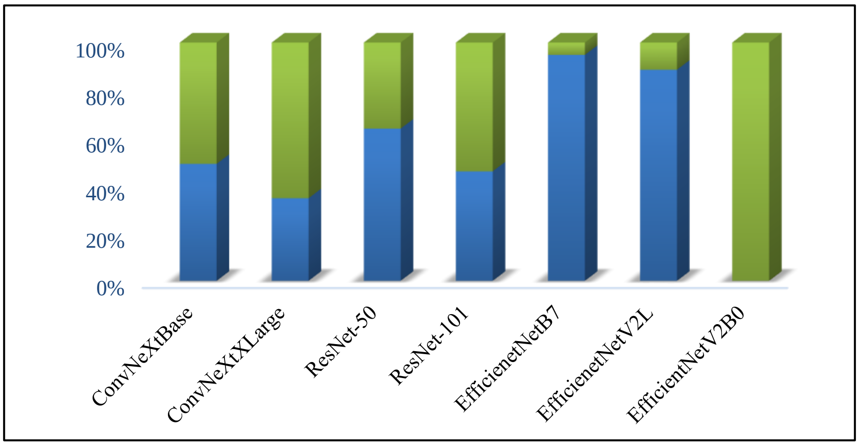

Figure 4: Speed comparison in learning operations

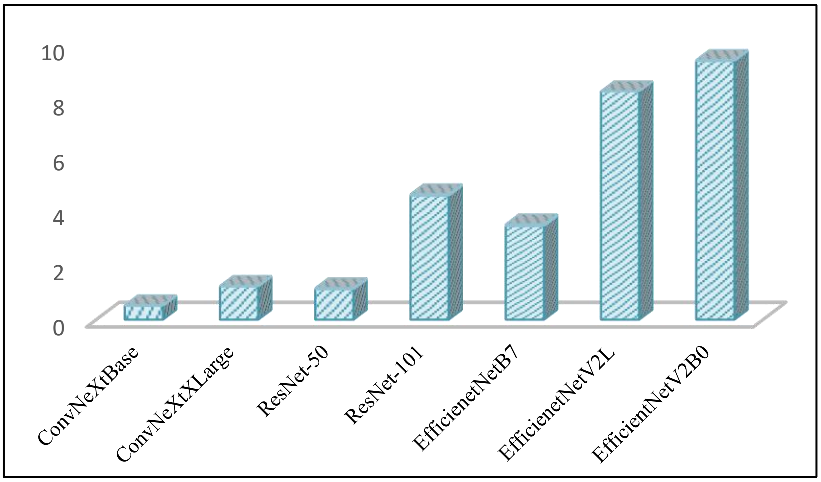

Figure 5: Speed comparison in the evaluation operation

Table 5: Overall evaluation of the models' performance

Model	***Class***	***Accuracy***	***Sensitivity***	***Specificity***	***Precision***	***F- score***
ConvNeXtBase	Deep damage	0/502	0/455	0/51	0/473	0/415
	Car side mirror damage	0/488	0/456	0/414	0/456	0/456
	Glass damage	0/445	0/469	0/414	0/471	0/428
	Tire damage	0/441	0/447	0/412	0/347	0/412
	Surface damage	0/414	0/436	0/435	0/52	0/436
	Car light	0/412	0/428	0/42	0/428	0/428
	Total	0/450	0/449	0/434	0/449	0/429
ConvNeXtXLarge	Deep damage	0/423	0/475	0/434	0/433	0/42
	Car side mirror damage	0/443	0/456	0/455	0/474	0/445
	Glass damage	0/435	0/469	0/414	0/471	0/411
	Tire damage	0/441	0/417	0/422	0/474	0/435
	Surface damage	0/494	0/486	0/435	0/42	0/436
	Car light	0/432	0/448	0/45	0/407	0/428
	Total	0/445	0/459	0/435	0/447	0/429
ResNet-50	Deep damage	0/532	0/511	0/541	0/532	0/57
	Car side mirror damage	0/51	0/544	0/557	0/534	0/524
	Glass damage	0/574	0/511	0/554	0/544	0/554
	Tire damage	0/545	0/521	0/577	0/545	0/545
	Surface damage	0/521	0/53	0/535	0/531	0/545
	Car light	0/523	0/522	0/532	0/554	0/562
	Total	0/534	0/523	0/549	0/540	0/550
ResNet101V2	Deep damage	0/544	0/515	0/512	0/515	0/515
	Car side mirror damage	0/528	0/553	0/554	0/686	0/556
	Glass damage	0/545	0/554	0/514	0/671	0/528
	Tire damage	0/541	0/547	0/512	0/545	0/525
	Surface damage	0/577	0/566	0/554	0/577	0/564
	Car light	0/585	0/574	0/596	0/51	0/528

	Total	0/553	0/552	0/540	0/584	0/536
EfficienetNetB7	deep damage	0/574	0/515	0/595	0/575	0/585
	Car side mirror damage	0/685	0/6	0/534	0/556	0/556
	Glass damage	0/575	0/569	0/574	0/579	0/584
	Tire damage	0/621	0/597	0/592	0/547	0/565
	Surface damage	0/524	0/596	0/585	0/566	0/596
	Car light	0/541	0/599	0/54	0/598	0/558
	Total	0/587	0/579	0/570	0/570	0/574
EfficienetNetV2L	Car side mirror damage	0/672	0/655	0/612	0/615	0/655
	Side mirror damage	0/666	0/696	0/654	0/656	0/656
	Glass damage	0/655	0/669	0/674	0/671	0/628
	Tire damage	0/691	0/667	0/642	0/647	0/692
	Surface damage	0/684	0/656	0/635	0/62	0/676
	Car light	0/692	0/628	0/663	0/648	0/628
	Total	0/677	0/662	0/647	0/643	0/656
EfficientNetV2B0	Deep damage	0/892	0/715	0/732	0/705	0/715
	Car side mirror damage	0/858	0/626	0/614	0/616	0/666
	Glass damage	0/805	0/749	0/614	0/521	0/678
	Tire damage	0/541	0/717	0/712	0/617	0/692
	Surface damage	0/904	0/726	0/735	0/72	0/736
	Car light	0/902	0/628	0/74	0/728	0/63
	Total	0/917	0/677	0/721	0/718	0/689

Evaluation of models: Forming a confusion matrix is one of the best methods for evaluating the accuracy of models created for prediction and classification, especially in problems with more than two categories. By comparing the results of the model with reality, this matrix shows the answers obtained from the models in each of the categories with four possible states: correct positive answer (TP), correct negative answer (TN), false positive answer (FP) and checks the false negative answer (FN). After determining the components of the clutter matrix, the efficiency and performance of the models in the classification and correct diagnosis of damages can be evaluated using several basic criteria. Accuracy, sensitivity, specificity, precision, and F-score are among the most widely used criteria in evaluating the performance and accuracy of models in classification and prediction problems. In Table 5, the values of these criteria are presented for each of the models.

Accuracy criterion: This criterion is one of the most common evaluation criteria for models and based on equation 6, it provides an accuracy of models by determining the ratio of correct TP and TN answers to all answers.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Accuracy evaluation and performance comparison of the models for classifying images in defined categories as well as the overall performance of the models based on the accuracy criteria are presented in Figure 6.

Based on Figure 6, all the models have the best performance in classifying and detecting deep damage images, and after that, the most correct answer has been provided in the detection of surface damage. Also, the EfficienetNetV2L and EfficientNetV2B0 models perform better than other models in detecting and classifying images with surface and deep damage. In general, all the models have provided good performance, and the overall performance of the models based on this criterion is in the range of 0.450 to 0.817, which is the best performance of the EfficientNetV2B model and the weakest performance is the ConvNeXtBase model.

Sensitivity criterion: This criterion indicates the sensitivity of the models for correct classification. Regarding Equation 7, this criterion measures the ratio of correct positive answers to the sum of correct positive answers and negative answers.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (7)$$

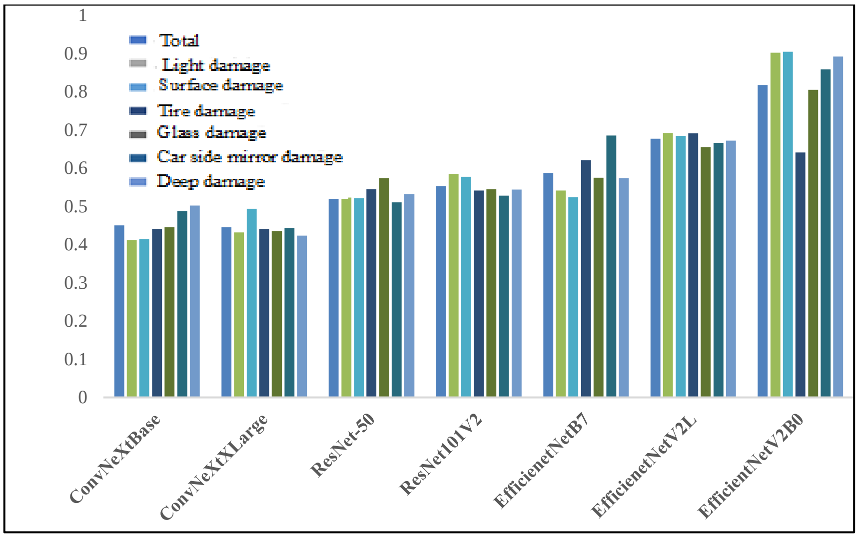

Figure 6: Algorithm performance evaluation based on Accuracy criteria

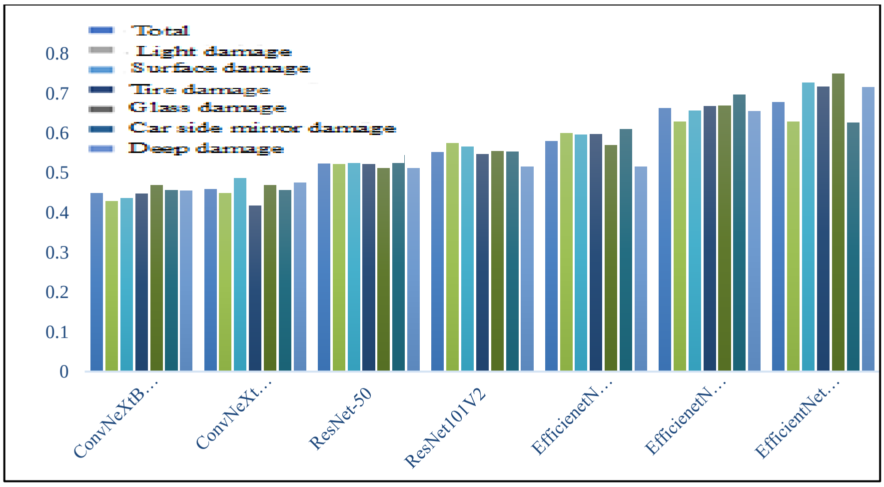

Figure 7: Performance evaluation based on the Sensitivity criterion

The performance evaluation based on the sensitivity criterion is presented in Figure 7. The models evaluated in this research have the highest sensitivity and accuracy in recognizing and classifying car side mirror images. The performance of most models except ConvNeXtBase, and ConvNeXtXLarge in detecting deep damage is better than surface damage. The average sensitivity evaluation of the models in all categories and the placement of values in the range of 0.449 to 0.76 indicates the good performance of the models created with the deep learning technique, and the EfficientNetV2B0 model has the best performance with a sensitivity of 0.76. The EfficienetNetV2L model with an average sensitivity of 0.662 is in the next position and has a better performance than the EfficientNetV2B0 in detecting surface damage images.

Specificity criterion: This criterion determines the ability of models to distinguish between categories by determining the ratio of the correct negative index to the total of false positive and correct negative indexes. The specificity criterion provides a concept similar to sensitivity for negative answers and is also known as the rate of correct negative answers.

$$\text{Specificity} = \frac{TN}{FP + TN} \tag{8}$$

In Figure 8, the performance of the models when they have to give a negative answer has been evaluated. The best performance of the models is in the category of glass images. Most of the models, except ResNet-50, and ResNet-101, have better performance than surface damage in providing the correct negative answer for the car glass and side mirror images.

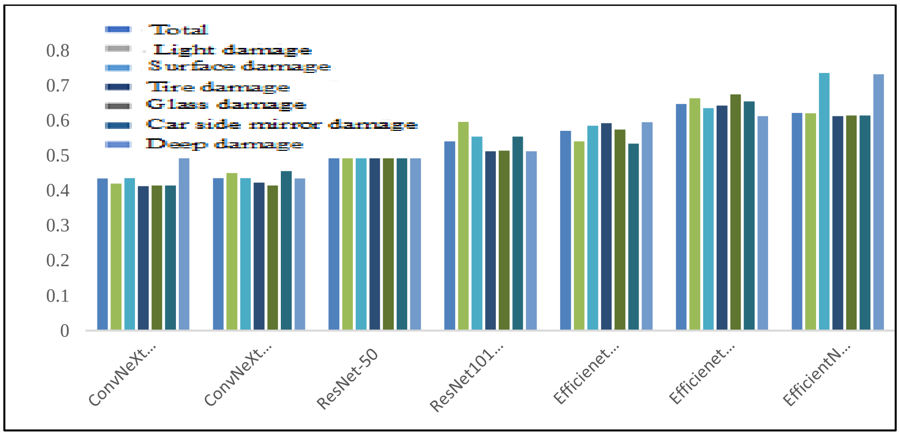

Figure 8: Algorithm performance evaluation based on Specificity criterion

From Figure 8, the EfficienetNetV2L and EfficientNetV2B0 models perform better than other models with an average of 0.647 and 0.621, respectively. Also, placing the values of this criterion in the range of 0.310 to 0.686 and comparing it with the Sensitivity criterion can indicate the better performance of the models in providing a negative answer compared to a positive answer.

Precision criterion: This criterion indicates the accuracy and reliability of the positive answers of the models. This criterion is also known as positive predictive value and is calculated according to Equation 9.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{9}$$

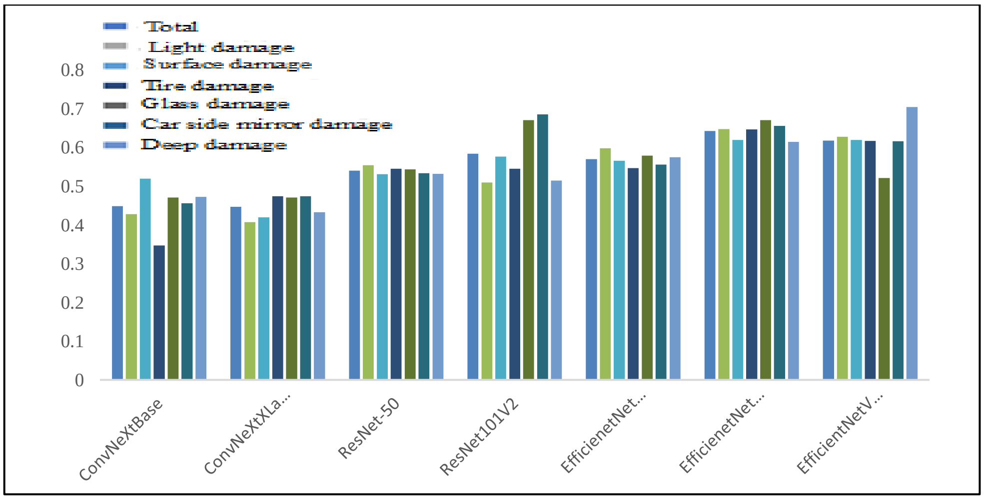

Figure 9: Algorithm performance evaluation based on Precision criteria

According to Table 5, the overall performance of the models is in the range of 0.447 to 0.643 in all categories, which indicates the appropriate performance of the models. In other words, according to the evaluation of this criterion, the positive answers of the created models can be trusted with a high level of confidence. As can be seen in Figure 18, the positive response of the models in recognizing and classifying glass images has the highest value (confidence level) in all models. Also, according to this criterion, the positive responses of the EfficienetNetV2L model with an average of 0.643 have the highest value among the models.

The F-score **criterion**: To evaluate the accuracy and performance of classification models, the F-score criterion is one of the most important criteria. It is determined according to Equation 10 by calculating the average of the weighted coefficients of the Precision and Sensitivity criteria.

$$\text{F} - \text{score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Sensitivity}}\right)} \tag{10}$$

According to Figure 10, the performance of most models in detecting and classifying deep and surface damage images is the same, and the best performance of the models is in the classification of surface images.

Also, the average performance of the models for different categories is in the range of 0.429 to 0.689, which indicates the high ability of the models created with the deep learning technique to detect deep damage. Based on this criterion, similar to other criteria, the EfficientNetV2B0 models with an average of 0.689 achieve tire recognition and classification operations with higher accuracy.

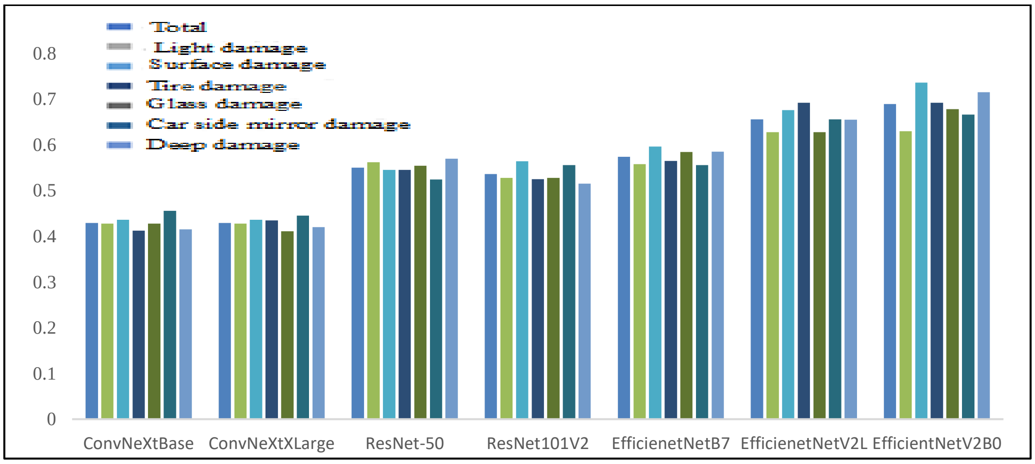

Figure 10: Algorithm performance evaluation based on F-score criterion

Managerial insights: In the communication between the actors on the issue of car accidents and damages, two issues of violation and disagreement between the actors are formed. For example, to maximize their profit, the actors try to maximize their profit or reduce their costs by committing violations such as fake accidents, bribing damage estimation experts, issuing unrealistic invoices, etc. Such issues will spread administrative and systemic corruption in the involved sectors. This research helps the managers to have a uniform and integrated report on the amount and type of damage by creating a suitable and safe platform in the field of activity of their organization and partner organizations, separately according to the equalization of prices in the country.

With the development of this research, managers can have access to fast and correct data and various reports including breakdown of province, damage, year, and type of car. This research can greatly help managers and society by reducing traffic, eliminating paper and manual systems, increasing productivity, social satisfaction with service speed, and controlling repair costs and integrity.

5. Conclusion

Diagnosis of damage and the type of damage in the car, which is mainly caused by the impact of that part on the physical body, play a significant role in various departments of organizations such as the insurance industry, treatment, etc. For this reason, several smart algorithms based on convolutional neural networks were presented in this research to identify and diagnose their problems. According to this smart method, images extracted from urban accidents of the last two years were classified and compared by several proposed deep architectures. This classification included categories of images of surface damage, deep damage, car side mirrors, car glass, car tires, and car lights, which had 61% accuracy. The strengths of this article can be listed in four points: firstly, the proposed deep architecture has more logical complexity and higher acceptability compared to other architectures; Second, while being simple, it has led to higher accuracy than other methods introduced in previous studies and other valid deep architectures. The third case is related to less execution time than other methods. It is expected that using a strong hardware system as well as increasing the number of data according to the project framework and time frame in this project can help to achieve higher accuracy. Also, entering various items in it, including the year of manufacture, cost, and car model, will be very useful and effective in managing this section.

The basic learning parts of each algorithm in machine vision, such as the number of courses, learning rate, number of repetitions, number of parameters, etc., have a great impact on the learning time and the quality of the learning model and are determined experimentally and by trial and error in most studies. and the need is felt to research to optimize these parameters. Comparing the performance of deep convolutional networks used in this article with other approaches such as methods under simple neural networks based on image processing can be a suitable topic for future studies. To increase the applicability of the model, after the appropriate design of the model, it is possible to provide an application of this model for use in insurance and automobile companies.

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