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Shadow Removal in Vehicle Detection Using ResUNet-a

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A B S T R A C T

In traffic monitoring for video analysis systems, vehicle shadows have a negative effect on their performance. Shadow detection and removal are essential steps in accurate vehicle detection. In this paper, a new method is proposed for shadow detection using a novel convolution neural network architecture. In the proposed method, the edges of the image are first extracted. Edge extraction reduces calculation, and accelerates the execution of the method. The background of the frame is then removed and the main features are extracted using the ResUNet-a architecture. This architecture consists of two parts: the encoder and the decoder, which detect the shadow at the decoder output and then remove it. Deep learning is used to detect shadows, which increases the accuracy of the analysis. The ResUNet-a architecture can learn complex, hierarchical, and appropriate features from the image for accurate feature detection and discarding the irrelevant shadow, thereby outperforming conventional filters.The results show that the proposed method provides better performance on NJDOT traffic video, highway-1, and highway-3 datasets than popular shadow removal methods. Also, the method improves the evaluation criteria such as F-measure and runtime. The F-measure is 94 and 93% for highway-1 and highway-3, respectively.

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INTRODUCTION

Detection of moving objects is required in various fields, including traffic monitoring, and is a critical research topic in computer vision [1]. In vehicle detection and tracking, shadows are often identified as a part of the foreground which has movement patterns similar to foreground objects [2].

Shadows are always strong and occupy large areas, especially on sunny days. They usually create severe problems for various applications, such as vehicle tracking and classification [3].

Surveillance cameras often use background subtraction operations to determine the background for motion detection [4]. However, due to changing environmental factors such as background brightness, it is challenging to identify the background of the work accurately. In particular, the shadow is a common barrier that makes it difficult to correctly identify backgrounds and objects [5]. The presence of a shadow can lead to a recognition error, and the object can be identified as a larger object [1, 6].

In a real-time surveillance system, shadow error can cause misdiagnosis. In addition, for vehicles [7], the shadow detection error can cause another problem, and multiple vehicles may be identified as one vehicle [3].

In this paper, a shadow detection method is proposed based on the deep convolution neural network (CNN) [8, 9]. There are several challenges in the discussion of detecting and removing shadows from vehicles: the first issue is that for a vehicle, the intensity and shape of shadows can be different from the environment, which means that the problem of detecting and removing shadows from images is completely changing. The next issue is that it can divide the shadow spatially into two parts of the shadow fixed and moving shadow object divided. It was considering that the shadow of the fixed object is also fixed like the object itself, as a component. It is not detected from the foreground and does not cause a significant problem in surveillance images, and its

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detection is not very important, but this is not the case with moving objects. In recent studies, it has been tried to solve these two tasks independently, but these two are closely related to each other. The intensity of the shadow is not uniform everywhere and gradually changes from the inner area to the edges. Therefore, according to the current needs, it is necessary to use a powerful method such as deep learning to solve the mentioned problems. CNN recognizes the complex features of shadow areas and can remove them.

The most important feature of deep learning is increasing accuracy, which can detect good shadow and discrimination rates. Therefore, performance improvement leads to improved tracking in regulatory scenarios. Our research is novel in several ways compared to previous works:

1. ResUNet-a [10, 11] is one of CNN architecture [12]. This network combines the appropriate specifications of computer vision programs with deep learning and demonstrates competitive performance.

In addition, the network modeling framework has a new loss function; thanks to which classification problems deal well with class imbalances and challenges issues. This architecture has just been introduced and has not been used to remove shadows yet. ResUNet-a is a well- known deep learning method used in the proposed method.

2. Increasing the accuracy is often accompanied by decreasing the speed, which has been suggested to reduce the time of edge detection [13, 14].

3. Eliminating shadows to enhance accuracy is another novel feature of this articles.

4. A decrease in the probability of objects merging, decrease the number of false positives caused by fragmented shadows, and more accurate appearance models with deep learning.

RELATED WORKS

There are several ways to detect shadows. Some methods are based on learning, while others are based on non-learning.

A feature-based classification consisting of four categories was investigated by Sanin et al. [2]. These features included color, physics, geometry, and texture.

The foreground is also used to identify and remove cast shadows. Shi and Liu [3] employed the method of global foreground modeling to detect the background. A Gaussian mixture module, and a Bayesian classifier were used to identify the background.

The problem of detecting and removing shadows from single images was investigated by Guo et al. [15]. In this method, natural scenes different from traditional methods were used, utilizing an area-based approach instead of examining pixel or edge information.

In the continuation of their work, Guo et al. [16] besides considering separate areas, they predicted relative lighting conditions between the divided areas. The positions were used to overcome the problems of shadow recognition [17].

A new random shadow was proposed with recognition, color information, and gradient [18]. In this method, shadow and non-shadow points were detected by dividing the image using a cascade.

A recurrent shadow attention model based on deep learning was also introduced by Zhang et al. [19]. This method included the shadow detection module and different shadow classification modules.

The shadow of pavement images affects the accuracy of road crack detection [20], and a morphological-based shadow separation algorithm component analysis has been proposed to solve the road shadow problem.

CNN FOR SHADOW

Shadows are natural happenings and happen when the light is blocked. Although shadows may interfere with the visual system, they provide some primary information about the environment. If there is less light energy dropping, that range is named a shadow area, and if there is more light energy unconfined, that area is called a non-shadow area. The clarity of images is degraded by shadow [21].

Moving objects may be distorted and can even cause objects to converge because shadows and moving objects have the same characteristics. Shades have their advantages and disadvantages. Sometimes, it provides helpful information about objects. Classifying moving shadow points with moving object points is difficult; sometimes, they may be misclassified. The model-based method, is used for shadow detection through the edges of objects. However, in this method, it is not easy to get the essential information of the object, and it also takes a very long processing time [22]. The feature-based method detects shadows using brightness, texture, color information, saturation, and geometric features. However, if color features are used, it is not easy to classify shadows with objects. CNN, and especially architecture, has high accuracy in classifying objects and hence can provide high-accuracy results ResUNet-a.

This architecture is one of the most popular and widely cited deep learning methods. The reason is to solve two fundamental problems of previous architectures. One of the problems in creating a deeper neural network was that by adding more layers to the neural network, it became more challenging to train, and the accuracy of the network's performance began to decrease. This architecture is a fully convolutional neural network designed to achieve high performance with fewer parameters, which improved over previous architectures.

PROPOSED METHOD

Deep learning is one of the essential elements in data science, which includes statistics and predictive modeling. It is beneficial for collecting, analyzing, and interpreting large amounts of data quickly and easily.

In a way, it can be said that deep learning is the same as machine learning in such a way that it performs learning for the machine at the level of complex tasks, representation, or abstraction. In this way, the machine gets a better understanding of the realities of existence and can identify different patterns. On the other hand, in many applications of intelligent surveillance systems, the shadow is a disturbing factor that causes problems such as wrong identification and tracking of moving objects, disturbances in the segmentation of moving objects, changes in the shape and size of moving objects, and the occurrence of unwanted events such as object distortion and merging. Objects with each other and, as a result of losing objects be made. Therefore, detecting and removing shadows in intelligent systems using deep learning leads to fast and intelligent execution with high accuracy.

Image edges are essential in many image processing applications. The edge detection method will lead to a simple and fast implementation that can be very effective in achieving the desired goals. Edge detection significantly reduces the amount of data and eliminates insignificant information while preserving critical structural properties of the image.

Therefore, an edge detector is used to distinguish the edges of an object from several other objects. Edge detection is extracted using known edges. Deep learning [23–25] is adopted to detect shadow pixels. In the next step, the foreground area is separated using the background image. Because there may be other shadows in the image, such as the shadows of trees, and buildings. However, our goal is only to remove the shadows of moving objects. This stage is detected by background subtraction.

Alghorithm 1. The pseudocode for the proposed method:

START
STEP 1: Read Video
STEP 2: Extract a video frame
STEP 3: Convert into a gray level image
STEP 4: The edge detection
STEP 5: The extraction of essential features with ResUNet-a for s={(x_n, z_n)},
STEP 5-1: Encoder:
input layer
Conv2D layer: size = 3, padding = 1
Conv2DN layer: size = 3, padding = 1
ResBlock layer: The feature map size with:
$OF_{k.l.n} = \sum_{i.j.m}(K_{i.j.m.n} IF_{k+i-1.l+j-1.m})$
STEP 5-2: Decoder:
PSPPooling layer: maximum pooling at four different scales with y= Max (0, x)
Upsample layer,
Combine layer
Output layer:
Calculated the probability of non-shadow and shadow
STEP 6: Shadow removal
END

The pre-trained CNN enters, and the shadow area is detected at the CNN output. ResUNet-a is used in this research. The ResUNet-a architecture model demonstrates the best performance among the current segmentation architectures of deep CNN [8]. The UNet block is the backbone and has a symmetrical and expansive direction for the accurate location of objects.

The structure of the ResUNet architecture consists of two parts: the encoder part and the decoder part (Figure 1). The encoder part includes the input layer, Conv2D layer, Conv2DN layer, and ResBlock-a layer. This part is displayed in Figure 2.

The input layer receives the input image. The Conv2D layer is a standard 2D convolution layer with kernel size=3, and padding=1. The Conv2DN layer is a 2D convolution layer in which kernel size=3, and padding=1, followed by a batch of a normalized layer.

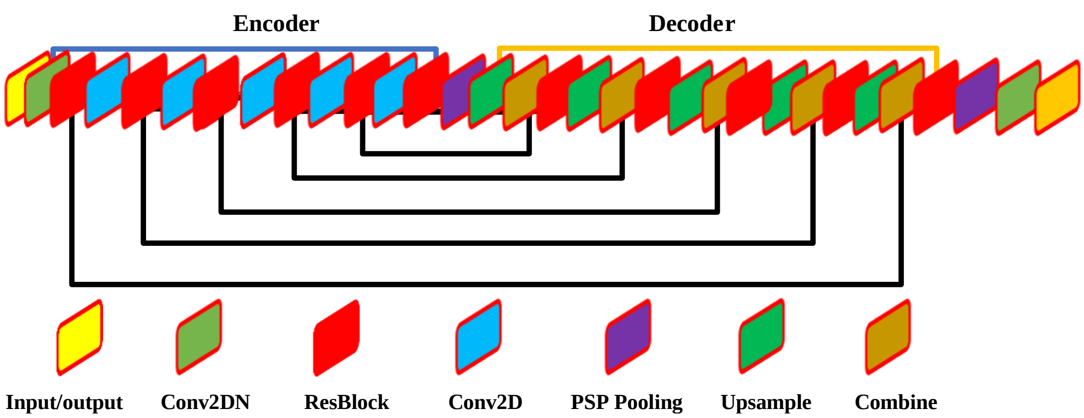


Figure 1. Architecture of ResUNet-a

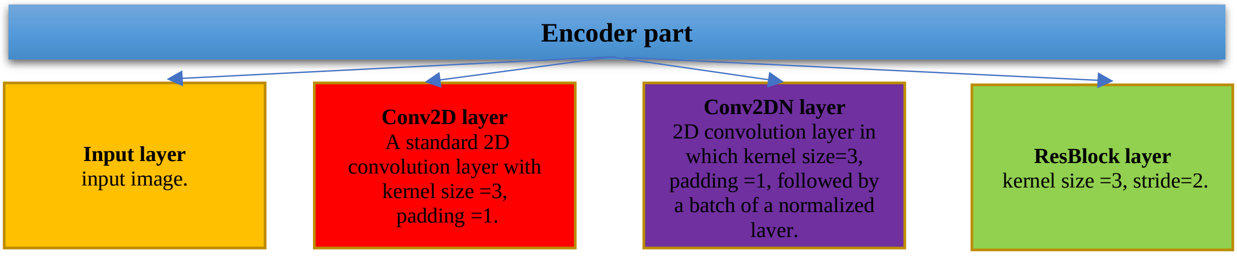


Figure 2. Architecture of encoder

The ResBlock layer follows the physiology of the remaining units, the units placed between the connections, i.e., between the first and last layers. Instead of having a single residual branch consisting of two consecutive convolution layer branches, there are up to four parallel branches so that the input is processed simultaneously in several fields of view. The feature map size is determined based on Equation [1]:

$$OF_{k.l.n} = \sum_{i.j.m}(K_{i.j.m.n} IF_{k+i-1.l+j-1.m}) \qquad (1)$$

In this Equation, $IF_{k+i-1.l+j-1.m}$ is the input feature map of size. $OF_{k.l.n}$ is the output feature map of size, and $K_{i.j.m.n}$ is the size convolution kernel.

The decoder includes the PSP Pooling layer, Upsample layer, Combine layer, and Output layer. This part is illustrated in Figure 3.

The Pooling layer in the PSP Pooling layer scans a pyramid that delivers information using maximum Pooling at four scales. The first scale is maximum Pooling global. In the second scale, the feature map is divided into four equal areas, and maximum Pooling is performed in each of these areas expressed as follows [2]:

$$y = Max(0.x) \qquad (2)$$

where x and y are the input and output values of the ReLU function, respectively. The same applies to the following two scales. As a result, this layer encapsulates feature information.

The upsample layer contains a prototype of the feature map, followed by the Conv2DN layer. The size of the feature map is doubled, and the number of filters in the feature map is halved. The combine layer receives two inputs identical to the number of filters in each feature map. This layer connects them and outputs with the same number of filters as each input feature map is produced on the same scale.

The output layer is a multi-tasking layer that generates four output layers. These layers consist of the extent mask, the boundary mask, the distance mask, and the reconstructed image of the input image. This layer is calculated as the probability of non-shadow, and shadow.

EXPERIMENTAL RESULTS

In this section, the performance of the proposed method is described. For this purpose, we need videos that can

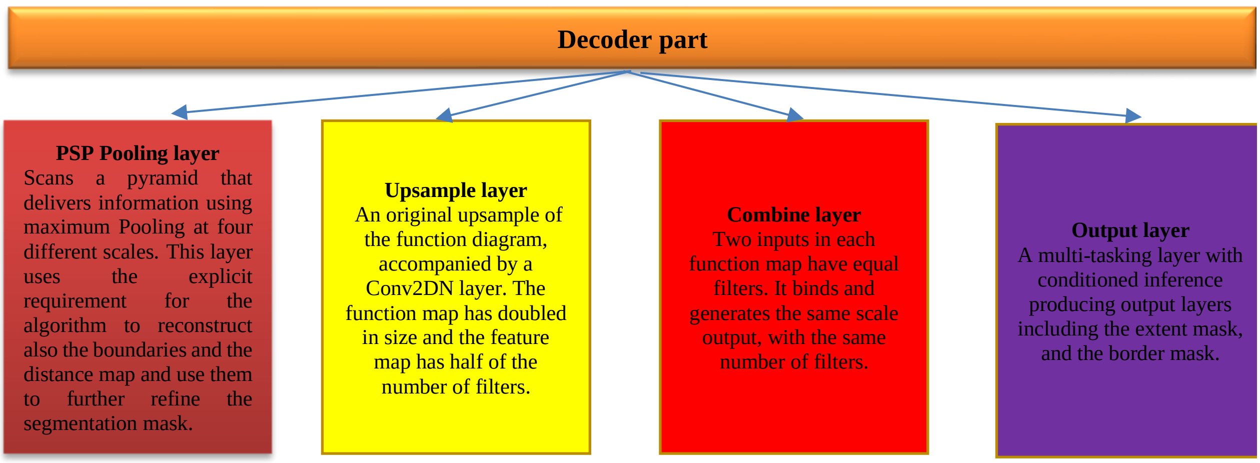


Figure 3. Architecture of decoder

test the algorithm's performance on problematic factors. The public video data ‘Highway-1’, and ‘Highway-3’ are used for the experiments [3].

According to the extraction of the background, the moving object, that is, the vehicle, is extracted. First, the moving object is detected along with the shadow [22]. The bounded domain is marked for comparison with the entire foreground region. The alignment curve of the moving target is extracted and the direction of the shadow is checked according to the alignment curve. Then, the pixels are classified as shadow pixels or non-shadow pixels. Finally, the identified points are removed as shadows.

Figure 4 depicts part of the detection results of the proposed method. Based on the figure, this method has succeeded in detecting in cloudy conditions, the incomplete appearance of the vehicle, the presence of traffic leading to vehicle stacking, and when only part of

A

B

C

D

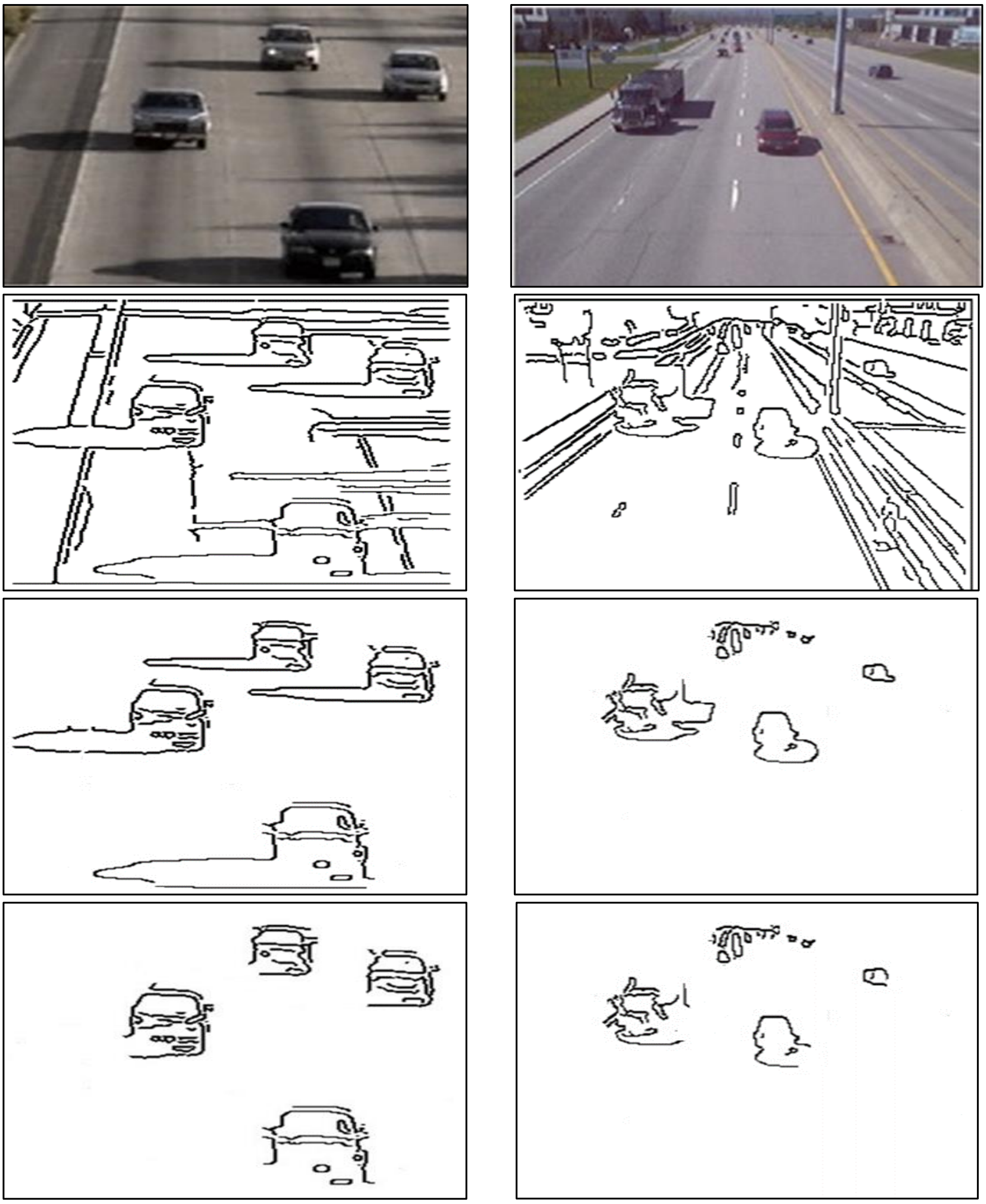


Figure 4. The part of the detection results of the dataset on proposed method. A: Two video frame from Highway-1, and highway-2, B: Edge detection for A, C: vehicle detection, D: Shadow removed

the vehicle is visible in the image. This method does not detect stationary vehicles such as those parked on the side of the road.

The criteria used for the study are expressed by the following equations [26]:

$$TNR=(TN)/(TN+FP). \quad (3)$$

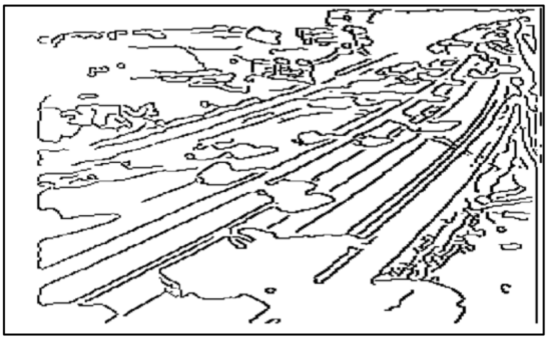
$$TPR=TP/(TP+FP). \quad (4)$$

$$F\text{-}measure=2\,(TNR\times TPR)/(TNR+TPR). \quad (5)$$

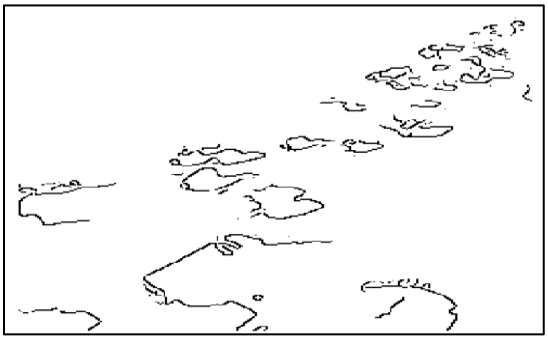
where, TP is actual positive samples, TN is actual negative samples, FP is false positive samples, and FN is false negative samples. The F-measure is a popular metric used to quantify shadow removal performance.

Figure 5 presents the shadow detection results on the NJDOT traffic video, Figure 5B the edge detection for A, Figure 5C for: vehicle detection and Figure 5D for the shadow removed.

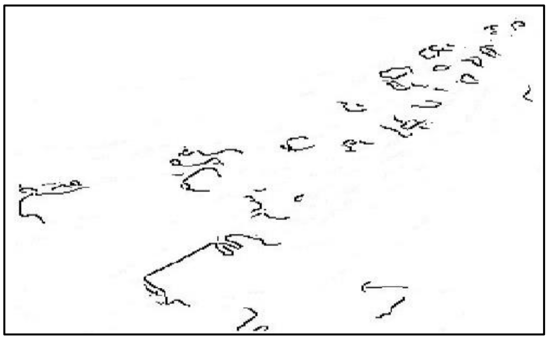
A



B



C



D

Figure 5. A: A video frame from the NJDOT traffic video, B: Edge detection for A, C: vehicle detection, D: Shadow removed

Table 1 shows that the proposed method has achieved the highest value of F-measure, TNR, and TPR, which is the best among other methods.

Table 2 demonstrates the quantitative shadow detection result of some popular methods and the

Table 1. The quantitative shadow detection result of some popular methods [4], and proposed method for Highway-1

Popular methods	F-measure	TNR	TPR
Sanin et al. [2]	0.88	0.82	0.94
Guo et al. [15]	0.67	0.61	0.76
Russell et al. [17]	0.82	0.72	0.95
Guo et al. [16]	0.71	0.68	0.75
Gomes et al. [18]	0.91	0.88	0.94
Zhang et al. [19]	0.53	0.95	0.36
Shi and Liu [3]	0.91	0.89	0.94
Proposed method	**0.94**	**0.91**	**0.97**

Table 2. The comparative shadow detection proficiency of proposed method for Highway-3

Popular methods	F-measure	TNR	TPR
Sanin et al. [2]	0.74	0.62	0.91
Guo et al. [15]	0.54	0.39	0.86
Russell et al. [17]	0.69	0.80	0.61
Guo et al. [16]	0.55	0.42	0.82
Gomes et al. [18]	0.75	0.65	0.90
Zhang et al. [19]	0.46	0.88	0.32
Shi and Liu [3]	0.83	**0.90**	0.76
Proposed method	**0.93**	**0.90**	**0.97**

proposed method for “highway-3”. The proposed method reaches the highest F-measure score of 93%, compared with the popular shadow detection methods.

After the proposed method, Shi's method has the highest values of F-measure=0.83, TNR=0.90, and TPR=0.76. The results of the proposed method show that the values of the evaluated criteria have improved compared to the other methods, especially the criterion of “F-measure” and “TPR” whose values have reached 92% and 97%, respectively.

Table 3 presents the comparative running time of the proposed method and some popular shadow detection methods.

As seen in Table 3, the running time of the proposed method is 19 milliseconds, so the proposed method has an acceptable speed and can be used in real-time applications. After the proposed method, the methods proposed by Shi and Liu [3] and Hsieh et al. [27] with a running time of 24 milliseconds are the fastest.

The proposed method was examined on different videos, and based on the results, we have:

- It can identify the shadow correctly.
- F-measure has been improved to 0.94.
- The computational capacity of CNN is higher than many other algorithms, but the execution time is reduced by edge detection.
- In shadow detection, the proposed method can be directly used for detection without training and guarantees the constancy of like regions to a specific region.
- In shadow removal can reduce the effect of the shadow removal procedure on other features in the shadow region.

The proposed method works well in detecting, and removing the shadow, but it has many limitations and it is possible to improve it. Therefore, the approach of future research can be the following.

1. Improve vehicle accuracy further away, which is reduced due to shrinking.
2. Shadow detection is usually very accurate, but its removal is limited, which needs to be discussed in the next works.
3. The more the proposed method is trained with more diverse data sets, the more satisfactory the results will be and the more results will be obtained.

Table 3. The comparative running time of our proposed method and some popular shadow detection methods

Popular methods	Running time
Barcellos et al. [28]	27
Hsieh et al. [27]	24
Huang and Chen [29]	26.5
Sanin et al. [2]	33.5
Shi and Liu [3]	24
Proposed method	**19**

CONCLUSION

In this paper, a method for vehicle detection based on a deep convolutional neural network architecture is presented. The accuracy of detection is reduced in complex conditions such as climate change, the presence of noise and shadows, and low-quality image resolution, and it is necessary to provide methods with acceptable results in these conditions. The ResUNet-a architecture is a deep convolution network architecture. This architecture has high accuracy in vehicle detection. ResUNet-a is a pyramid scene parsing, pooling, and multi-tasking inference. It sequentially infers the boundary of the objects, the distance transform of the segmentation mask, the segmentation mask, and a colored reconstruction of the input. This architecture establishes a conditioned relationship between various tasks. The use of edge detection reduces the computational load of the proposed method. Shadow removal is another benefit of this method, which leads to improved results and increased accuracy. The results reveal the performance improvement of the proposed method.

Shadow removal results in reduced merging and overlapping of vehicles, which can significantly promote accuracy in tracking applications. Therefore, this method can be adopted to improve vehicle tracking and counting. It can also be used in self-driving vehicles that require higher accuracy. In tracking algorithms, it leads to the reduction of the error caused by the interference of shadows, and it foregrounds objects and divides them into separate areas.

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Persian Abstract

چکیده

در سیستم‌های تحلیل تصویری نظارت بر ترافیک، سایه‌های وسیله نقلیه، اثرات منفی روی عملکرد آن دارند. تشخیص و حذف سایه یک مرحله مهم در شناسایی صحیح وسیله‌ی نقلیه به شمار می‌رود. با استفاده از یکی از معماری‌های جدید شبکه‌ی عصبی کانولوشن، روشی برای تشخیص سایه و بهبود عملکرد آن، پیشنهاد شده است. در روش پیشنهادی ابتدا لبه‌های تصویر استخراج می‌شود. استخراج لبه منجر به کاهش محاسبات و افزایش سرعت اجرای روش پیشنهادی می‌شود. در ادامه پس‌زمینه حذف شده و ویژگی‌های اصلی با استفاده از معماری ResUNet-a استخراج می‌شوند. این معماری شامل دو قسمت کد کننده و کدگشا است که در خروجی کدگشا سایه تشخیص داده می‌شود. برای تشخیص سایه از یادگیری عمیق استفاده شده که دقت تشخیص را افزایش می‌دهد. معماری ResUNet-a قادر به یادگیری ویژگی‌های پیچیده سلسله مراتبی مناسب تصویر برای تشخیص دقیق ویژگی‌ها و حذف سایه‌های نامربوط است و در نتیجه از فیلترهای معمولی بهتر عمل می‌کند. نتایج به‌دست‌آمده نشان می‌دهد که روش پیشنهادی عملکرد بهتری روی مجموعه داده‌های ویدیوی ترافیک NJDOT، بزرگراه-۱ و بزرگراه-۳ در مقایسه با روش‌های معروف حذف سایه دارد و معیارهای ارزیابی مانند F-measure و زمان اجرا را بهبود می‌بخشد. F-measure برای بزرگراه-۱ و بزرگراه-۳ به ترتیب ۹۴٪ و ۹۳٪ بدست آمد.