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Deep-APT: Deep Learning based Efficient Accident Prevention Technique in Fogged Environment

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ABSTRACT

Image defogging is an innovative strategy for recovering images in foggy environments that has gotten a lot of attention in recent years because of its use in surveillance systems. The standard defogging algorithm, on the other hand, has difficulty merging the depth of picture detail and the colour of the picture. In this paper, a novel Accident Prevention Technique (Deep-APT) has been proposed to effectively restore fog-free images and prevent accidents using FasterRCNN network. Initially, a dashboard camera monitors the road ahead of the vehicle and collects video. This video sequence is converted to frames. The transformed images are pre-processed using an Adaptive dual threshold Tetrolet transform that preprocess foggy images to fog-free images it is used to remove noise in the input image. Based on the defogged image, use FasterRCNN technology to detect objects in front of the car. The Deep-APT method has been simulated using MATLAB. The experimental result shows the proposed Deep-APT yields an overall accuracy is 99.52%. As compared to existing techniques, the proposed FasterRCNN network shows better results in terms of precision, F1 score, accuracy, and recall. Using DAWN dataset, the MSE, SSIM and PSNR values for the proposed method are 0.12, 0.65 and 0.12. The Deep-APT network improves the overall accuracy of 15.43%, and 4.72% better than CR-YOLnet, and RDL respectively.

Keywords: Foggy environment, Video sequence, Adaptive dual threshold Tetrolet transform, FasterRCNN network.

1. INTRODUCTION

Fog is an atmospheric phenomenon caused by the compression of large amounts of water vapor. Dust particles dampen the reflected light of the observed object, causing this effect. When fog builds up and hits the image sensor, you get an image with low contrast, low resolution, blurry whites, saturated colors, and degraded colors [1]. However, the tremendous growth of motor vehicle traffic and the automotive industry is having an impact on the freshness of the outside air and ecosystems. Areas of fog on the road affect the driver's visibility. Visibility detachment is a vital metric for drivers to assess the required intervention [2]. Poor visibility due to dense fog is a major factor affecting the efficiency of traffic operations and traffic accidents. Many traffic accidents occur when visibility is poor or the driver is unable to apply the brakes. As a result, providing high-quality images to detection systems can improve the efficiency of vehicle identification and tracking in intelligent visual surveillance systems and autonomous vehicle applications [3,4].

The presence of fog has a direct impact on drivers and their driving behaviour, as evidenced by the high number of traffic incidents, particularly wrecks [5]. As a result, fog collision risk prediction and early warning models are becoming increasingly popular in traffic safety research. Driving in poor weather appears to be an impossible undertaking because it impairs visibility [6,7]. To be applicable to real-time video applications that require resource efficiency, defogging solutions must be fast and close to real-time. While deep learning has long been used in image processing, its use in automotive technology is expanding and becoming more efficient [8]. The whitening effect of fog in the atmosphere obscures and deforms both the foreground and the backdrop. The accumulating veiling effect of distant fog further lowers visibility [9]. Fog image deterioration grows non-linearly with changing distance between camera lens and scene, making accurate defogging difficult [10]. Fog/haze has a substantial impact on the high-level perception functions of self-driving automobiles and surveillance systems in urban environments [11].

Furthermore, even advanced driving assistance technologies find it difficult to avoid the detrimental influence of the foggy environment. The proper perception of the surrounding environment is the concept of helping decision-making [12]. In a foggy environment, however, the detection performance and confidence level of automobile sensors have decreased, with camera sensors suffering the most. The detection model Faster R-CNN, which gave detection results in light, medium, and heavy fog, was used to assess the fog level and camera detection performance [13]. Using deep learning, sharp images are largely derived from atmospheric scattering models that fit the required parameters. As a result, the image fog problem is directly considered as a problem of image reconstruction [14,15]. In this case, the method uses the fog input as acquisition and uses direct reconstruction to sharpen the image. The main contribution of the paper is summarized as follows,

- In this paper, a novel Accident Prevention Technique (Deep-APT) has been proposed to effectively restore fog-free images and prevent accidents.
- Initially, a dashboard camera monitors the road ahead of the vehicle and collects video.
- The transformed images are pre-processed using an Adaptive dual threshold Tetrolet transform that preprocess foggy images to fog-free images.
- Based on the defogged image, use FasterRCNN technology to detect objects in front of the car and show the distance.
- The performance of the Deep-APT method used PSNR, MSE and SSIM.

The remaining portions of this work are laid out as follows. In Section II, discuss literature survey in the area of vehicle object detection. The proposed Deep-APT model is then presented in section III. To test the viability of proposed concept, design and carry out an experiment as part of Section IV. Next, the outcomes of the experiment are analyzed. The results of this study are finally thoroughly explained in Section V.

2. LITERATURE SURVEY

Recently, researchers have presented several systems based on deep learning and machine learning, for defogging in unclear weather patterns, such as fog, haze, and snow sceneries based on the pH value, soil nutrients, and moisture have been presented by the researchers. Some of the recent studies are provided a brief overview in this section.

In 2023, Ogunrinde, I.O. et al., [16] design a CR-YOLOnet network using A multi-sensor fusion network based on YOLOv5 that combines radar object recognition with camera image bounding box. To train and test our multisensor fusion network using CARLA simulator clear and multi-fog weather datasets. The proposed model improves the detection of both distant and small objects significantly. The simulation results yield the accuracy and speed are both 84.9%.

In 2022, Liao, J., et al., [17] suggested an MSP-DSCNN is used to reduce fog and improve image quality. Using parallel depth and shallow channels, the texture feature extraction module extracts texture feature details at various scales from fog photographs, as well as high-dimensional and low-dimensional features. The experimental findings shows that the suggested MSP-DSCNN can complete the image defogging task more quickly and accurately.

In 2023, Pal et al., [18] Convolutional neural networks (CNNs) are used in a proposed robust deep learning (RDL) model to categorize inputs as clear or foggy. Regarding training time complexity and prediction time complexity, the proposed deep neural network (DNN) architecture is effective and precise enough to categorize images as foggy or transparent. In both qualitative and quantitative evaluations, experimental findings are encouraging. Using the SOTS dataset as a benchmark, the model's accuracy is 94.8%.

In 2023, Huang et al., [19] proposed a YOLOX-L and anti-fog algorithm for forest fire detection. To acquire a clear view before the fog lifts, use the dark channel. GXLD can identify forest fires in real time and with great accuracy. After Ghost Net, depth-separable convolution, and SENet have marginally enhanced it, get the YOLOX-L light and use it to locate forest fires in clear images. The advantages of the suggested strategy include defogging excellent target integrity and target confidence.

In 2018, Chen, Y., et al., [20] suggested dark channel prior (DCP) with colour fidelity to improve the image dehazing process. It was used to fine-tune the first transmission map generated by the dark channel. The real-world image shows that it is successful in reducing haze and preventing colour distortion caused by excessive dehazing, resulting in recovered photographs with clear, realistic colours and increased details.

In 2019, Liu, X., et al., [21] suggested a GridDehazeNet for defogging single images is divided into three sections: post-processing, pre-processing and backbone. Because of the generic nature of its structural systems, the suggested GridDehazeNet is to be suited for a large variety of picture recovery issues. GridDehazeNet generates both real-world images and synthetic based on experimental results.

In 2022, Liu, R.W., et al., [22] proposed a TSDNet to increase the picture quality in foggy environment. TSDNet is primarily composed of a multi-scale attention module that predicts the distribution of fog in an RGB image and a branch extraction module that learns the hazy properties. Several testings on real-world imagery and synthetic settings have been conducted. TSDNet's experimental results from several cutting-edge methodologies in quantitative and qualitative analysis.

In 2023, Zhang et al., [23] suggested an enhanced cycle-consistent attacker network-based image-defogging system. Then, to enhance the network's capacity for feature extraction, the self-recognition module and the multi-scale feature fusion module for atrous convolution are built on the conventional Cycle GAN network. A perceptual loss function is added to the model's loss function to improve the generated images' textural quality. Finally, evaluate the suggested defogging model on both a qualitative and quantitative level.

In 2022, Li et al [24] suggested a hybrid image-defogging approach using a Vision Transformer and a convolutional neural network. The pre-processing function first extracted the flat features of the hazy image. The global and local characteristics of the haze image were recorded using a vision transformer branch and a CNN. Convolutional layers were used to merge aggregated characteristics in order to cover the global representation while retaining local features. To get feature information, the encoder and decoder's captured features were combined.

In 2021, Van Nguyen et al., [25] suggested an Illumination Decomposition-based Single Marine Image Removal Algorithm. The optimisation variables are updated with the closed solution. The fog component is subsequently removed from the glow-free layer using the defogging method. Lastly, a compensation scheme is used to restore the natural light to the phosphor layer to obtain a haze-free final image.

From the above literature, a various deep learning and ML networks focus on defogging approaches but the existing methods yield poor accuracy. So, in this paper a novel Deep-APT method for effectively restore fog-free images and prevent accidents in foggy weather condition.

3. DEEP-APT METHODOLOGY

In this section, a novel Accident Prevention Technique (Deep-APT) has been proposed to effectively restore fog-free images and prevent accidents in foggy weather condition.

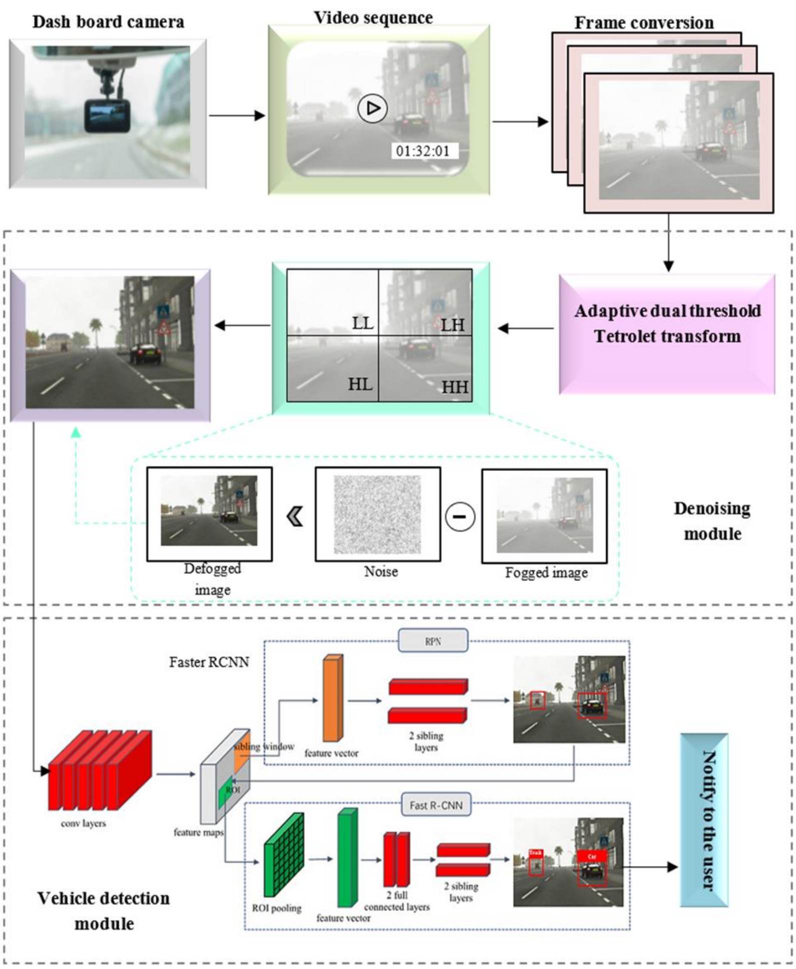


Figure 1. The overall workflow of the Deep-APT model

Initially, a dashboard camera monitors the road ahead of the vehicle and collects video. This video sequence is converted to frames. The transformed images are pre-processed using an Adaptive dual threshold Tetrolet transform that preprocess foggy images to fog-free images it is used to remove noise in the input image. Based on the defogged image, use FasterRCNN technology to detect objects in front of the car and monitor the distance of the car. Figure 1 shows the overall flow of the proposed Deep-APT technique.

3.1. DAWN dataset

The DAWN dataset is made up of 1000 photos from real-world traffic situations that are separated into four weather conditions: fog, snow, rain, and sandstorms. The dataset is labelled with object bounding boxes for situations including autonomous driving and video surveillance. The DAWN dataset was created to investigate the efficacy of vehicle recognition and classification algorithms on a broad set of real images of traffic scenes in the cross-generalization of unfavourable weather conditions, which are divided into four weather groups. Vehicle type, size, orientation, posture, illumination, position, and occlusion are all factors to consider all vary significantly in the DAWN dataset. The Faster R-CNN network can be trained on this dataset image.

3.2 Adaptive Dual Threshold Tetrolet Transform (ADTTT)

Traditional wavelet de-fogging algorithms employ a single threshold to allow the propagation of sub-band constants. Because of its multi-resolution, low entropy, de-correlation, and tetrolet basis variety, the ADTTT was a major success. To purify the information anchored in the primary intensity and functional solid threshold to de-noise the unique signal, the new dual threshold de-fogging approach with a twofold judge role is supported. The LSE (Least Square Error) criterion is used to evaluate the threshold value. The suggested work specifies that the utility's energy is concentrated in only a few coefficients in the tetrolet domain.

Tetrolet Transform (TT) is an adaptive haar wavelet transform it works on the principle of tetromino partition. The tetrominoes are made up of four similar squares, each of which is joined to at minimum one other square around its boundary. Normally tetrominoes are formed in 5 different shapes (O, I, L, T, S) shown in figure 2. This TT has a highly de-noising property thus provide enhanced image quality also has less hardware complexity.

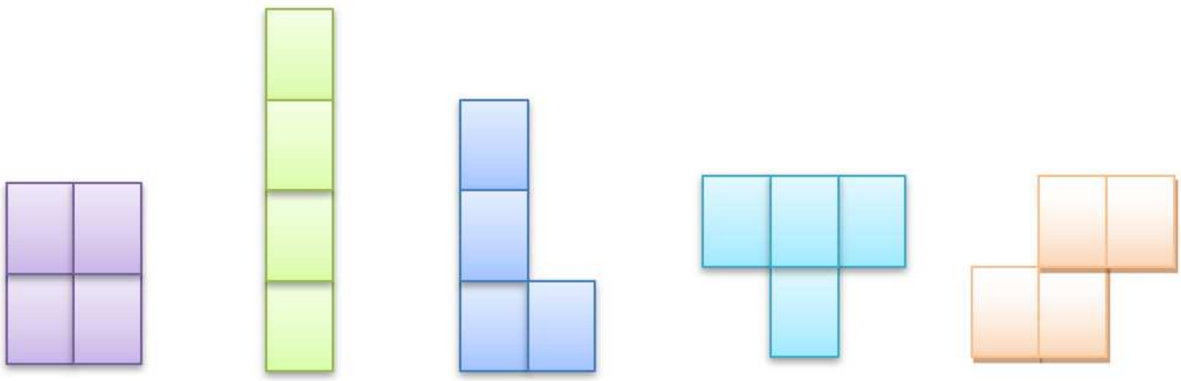


Figure 2. Different forms of free tetrominoes

In TT, given endoscopy each YUV components is divided to 4×4 tetrimino blocks which can created 22 fundamental shapes then using rotation and reflection 117 solutions are formed. 8×8 boards may form more solutions (1178) but it makes complexity so here we neglect it. Tetromino partition determined for each 4×4 block that is tailored to the image geometry in that block. Then the output low pass and high pass coefficients are rearranged into 2×2 block. Tetrolet coefficients are stored and low pass coefficients send to further processing. It is necessary to define the index sets and their appropriate neighbour hoods before applying the algorithm to two-dimensional data.

A prominent image processing mathematics method is the adaptive dual threshold tetrolet transform. The goal of this conversion is to employ high pass and low pass filters to split a signal into different resolutions. Dimensionality plays an important role in image de-noising. Eqs. 1 and 2 give the coefficients of dimensionality reduction, which is an important aspect of de-noising.

$$P[f] = \sum_m a[m] \times i[2f - m] \qquad (1)$$

$$D[f] = \sum_m a[m] \times j[2f - m] \qquad (2)$$

Where $i[m]$denotes a half band low pass filter, $j[m]$ denotes a half band high pass filter $a[m]$-

discrete form of image. $P[f]$ stands for low pass filter and $D[f]$ stands for high pass filter. Equation 3 represents the wavelet transform:

$$[W_{\psi}f](p,q) = \frac{1}{\sqrt{|p|}} \int_{-\alpha}^{\alpha} \psi\left(\frac{X-p}{q}\right) f(x)dx \qquad (3)$$

The proposed dual threshold tetrolet transform scheme utilizes dual adaptive thresholds for signal and noise is expressed by Eq 4 & 5,

$$\mathrm{T_s} = \max_{\mathrm{c-f}}\left(1 - \frac{\max_{\mathrm{c-f}}}{2\pi}\right) \exp(-\mu) \qquad (4)$$

$$T_n = \hat{\sigma} \log(2\pi) \qquad (5)$$

Where Ts represents signal threshold, $\max_{\mathrm{c-f}}$ denotes largest value of the tetrolet coefficients in a particular sub band, μ denotes data around, $\max_{\mathrm{c-f}}$, T_n denotes the noise threshold, and ˆσ approximation of the noise variance in the DTT sub-band. The thresholds are of the exponential family, which allows it to have continuous derivatives and to be optimized accordingly.

3.3. FasterRCNN technique

Deep-APT detects the object and distance of the car using a Faster RCNN net. The CNN and RPN integrated with Faster RCNN network to extracts the relevant properties from gait images. Faster RCNN uses CNN and RPN to extract relevant features from gait patterns. Using the feature map, the CNN layer extracts the most relevant features and creates a bounding box for the extracted features using RPN. As one of the object detection algorithms, the image feature map is first obtained using a series of simple ReLu with pooled layers and conv using Faster R-CNN. The fully linked layer and RPN layer feature maps are identical. CNNs have both pooling and convolutional layers. The Faster RCNN structure is depicted in Figure (3).

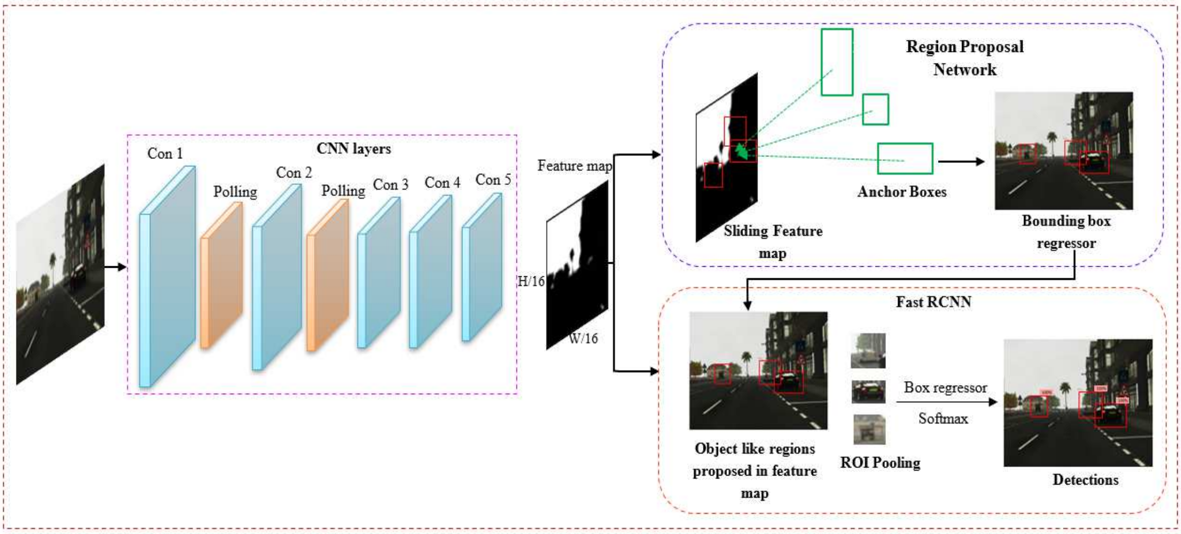


Figure 3. Structure of Faster RCNN

3.3.1. Region Proposal Network (RPN)

RPN was used to set the region of interest and anchor for each feature map. Proposals are created by sliding a small network over the fold feature map to generate a set of rectangular object recommendations containing object scores. The concept of anchor boxes was developed to avoid filter pyramids and photo pyramids. Each region is provided with its own reference anchor box, allowing object detection at different scales. The anchor is placed in the center of the sliding window and linked to scale and aspect ratio. Thus, the foreground and background values of the gait pattern were determined. Anchors used RPN predictions to establish optimal boundaries for gait patterns and adjusted their size and location. After collecting the final region proposals and sending them to RoI Align, we capture the anchors with the highest foreground values and discard the others.

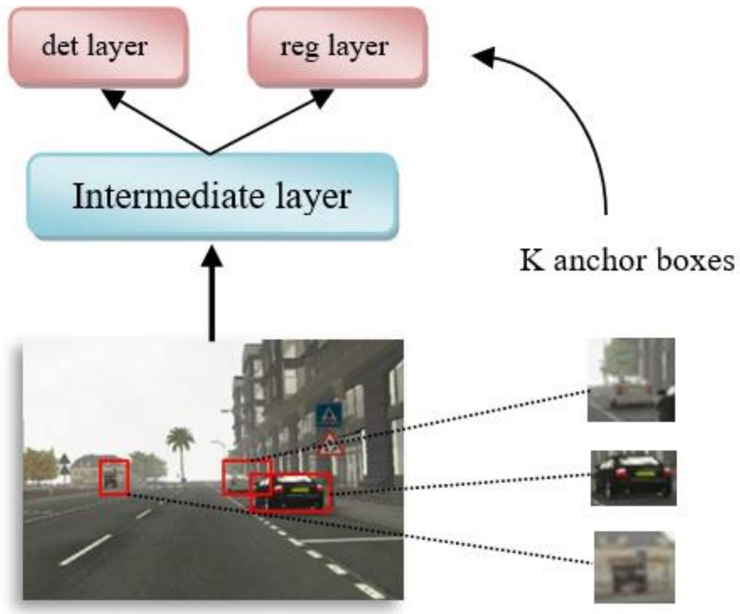


Figure 4. Region Proposal Network (RPN)

The Faster RCNN is integrated with CNN and RPN detector. Equation 6 describes the overall multi-task loss function as bounding box classification loss, and regression loss, with L_{cls} and L_{reg} functions defined in Equations (7) and (8).

$$L_{cls}(q_j, q_j^*) = -q_j^* \log(q_j) - (1-q_i^*)\log(1-q_j) \quad (6)$$

$$L_{reg}(t^v, u) = \sum_{y \epsilon y,z,w,h} L_1^{smooth}(t_j^v - u) \quad (7)$$

$$L_1^{smooth}(p) = \begin{cases} 0.5p,^2 & if\,|p| < 1 \\ |p| - 0.5, & otherwise \end{cases} \quad (8)$$

The gait images are detected using the Fast RCNN technique. To speed up the training process, Fast R-CNN was used to instead the conventional network to detecting regions. The regions are generated by moving a small window across the full convolution feature map of the output layer. The detection and regression layers are inextricably linked, as seen in Figure 3.

$$M = [\frac{q-q^a}{W^a}, \frac{r-r_a}{H_a}, \frac{logW}{W_a}, \frac{logH}{H_a}] \quad (9)$$

$$M^* = [\frac{q^*-q^a}{W^a}, \frac{r^*-r_a}{H_a}, \frac{logW^*}{W_a}, \frac{logH^*}{H_a}] \quad (10)$$

Where, W^*,H^* represents width, and height, $H_{a,}$ $represents\ the$ anchor's height , W_a represents the anchor's width. The partial derivative of the loss function is calculated with respect to a_j.

$$\frac{\partial l}{\partial a_i} = \sum_q \sum_r [j = j^*(q,r)] \frac{\partial l}{\partial b_{qr}} \quad (11)$$

Where q represents the image tensor input, the partial derivative $\frac{\partial l}{\partial b_{qr}}$ is gathered each ROI. The convolutional technique can be stated as follows:

$$r\ m^{k+1}, n^{k+1}, f = \sum_{m=0}^{128} \sum_{n=0}^{128} \sum_{f=0}^{N} F_{m,n,f} \times r^k_{m^{k+1}+m, n^{k+1}+m,n} \quad (12)$$

Where F represents the filter bank, f represents the filter number, N represents the number of filters, k represents the layer number, r represents the convolution output, and m and n represent the spatial coordinates.

$$Average\ Precision = 1/11 \sum_{recall-n} P(recall_n) \quad (13)$$

Where recall-n = [0, 0.1, 0.2, ……, 1.0]

$$Loss(\{u_j\},\{v_j\}) = \frac{1}{N_c} \sum j\, L_c(u_j, u_j^*) + \lambda \frac{1}{N_r} \sum_j q_j^*\ L_r(v_j, v_j^*) \quad (14)$$

$$L_c(q_j, q_j^*) = q_j^* log q_j - (1 - q_j^*) \log(1 - q_j) \quad (15)$$

Where, N_C, N_r are the weights by the normalized weighting parameter and the balancing parameter for the r and c layers, the v_j vector containing the four local coordinates of the predicted bounding box, and the anchor probabilities, I anchor-index with minibatch, L_c classification loss, v_j^* are ground truth boxes with + ve anchors. The logarithmic loss arising from the +ve anchor only activates the u_j^* L_r regression loss.

4. RESULT AND DISCUSSION

In this section, the Deep-APT has been proposed to effectively restore fog-free images and prevent accidents using FasterRCNN network in foggy weather condition. Here to analyse the per different scenario are gathered from the DAWN dataset. Furthermore, the proposed Faster RCNN Network was compared to various classic networks and cutting-edge models.

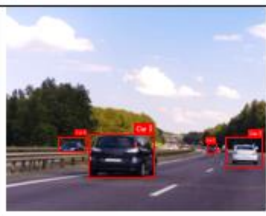
Input	Fog image	Defog image	Detection	Notify
Image 1				Car1→0.3m, Car2→5m, Car3→1m distance from user car.
Image 2				Bike1→7m distance from user car.
Image 3				Car1→10 m distance from user car.
Image 4				Car1→11m, Car2→ 12m, Truck1→13m distance from user car.
Image 5				Car1→12.2m, Truck1→11.6m distance from user car.
Image 6				Car1→ 4m, Car2→ 6m, Car3→ 8m, Car4→11m, distance from user car.
Image 7				Car1→5m, Car2→ 9m, Car3→19m, Car4→7m, distance from user car.

Figure 5. The experimental results of the proposed method using DAWN dataset

Figure 5 shows an experimental analysis of the Deep-APT model using the DAWN dataset. The input fog image is converted to a fog-free image and Faster R-CNN is used to recognize the vehicle. A car in front of the user's vehicle determines how far apart the user's vehicle is from the other vehicles.

4.1 Performance Analysis

In this paper, the performance analysis is measured based on PSNR, MSE and SSIM are used to explain the efficiency of the procedure as a result of the data analysis.

PSNR measures the quality of an image, the closer the image, and higher the value is to a usual fog-free image. It is considered as follows:

$$PSNR = 10.log_{10}(\frac{MAX_J^2}{MSE}) \quad (16)$$

where J is the innovative fogged image, and MAX is used to set 265 regarding an image with a bit depth of 9.

MSE is the sum of the squared errors between the compressed and original images, whether or not they are in variants. The better the decryption, the lower the MSE between two images; it is defined as:

$$\text{MSE } (u_1, u_2)= \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (u_1\ (x, y) - u_2\ (x, y))^2 \quad (17)$$

Where $u_1\ (x, y)$ and $u_2\ (x, y)$ indicate the original and decrypted images, respectively.

SSIM is also a fully referenced metric for evaluating the quality of images. The contrast module consists of three components: brightness, structure, and contrast. The distinction between the image that has been defogged and the genuine image without fog. A greater score denotes less distortion when measuring an image's distortion using the [0, 1] value range. As a result, it is calculated as follows:

$$SSIM\ (y, z) = \frac{(2\mu_y\mu_z+a_1)(\sigma_{yz}+a_2)}{(\mu_y^2+\mu_z^2+a_1)(\sigma_y^2+\sigma_z^2+a_2)} \quad (18)$$

where $\mu_y\mu_z$ are the means of images y and z, and σ_y^2, σ_z^2 are the average deviations of images y and z. σ_{yz} is the y and z covariances of the images, a_1 and a_2 are constants.

Table 1: The experimental result of various defogging methods on the DAWN dataset

Dataset	Estimation metrics	Reference [25]	Reference [17]	Reference [24]	Proposed
DAWN	PSNR	25.79	22.78	28.65	31.45
	MSE	12.45	16.12	19.03	9.13
	SSIM	0.70	0.76	0.88	0.65

Table 1 illustrate the experimental result of various defogging models based on the DAWN dataset. The proposed method gives the PSND, MSE and SSIM values that are lower than the other defogging methods. Using DAWN dataset, the MSE, SSIM and PSNR values for the Deep-APT method are 0.12, 0.65 and 0.12 respectively.

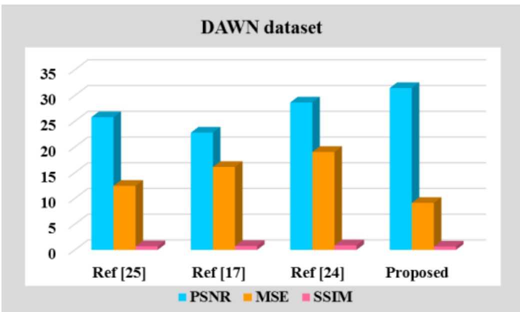


Figure 6. Comparison of MSE, PSNR, and SSIM with different methods using the DAWN dataset

Figure 6 illustrate, the comparison of MSE, SSIM, and PSNR with different methods using the DAWN dataset. In the proposed method PSNR value is 31.45, it is higher than the existing techniques, and the MSE and SSIM values are 9.13, and 0.65 which is better than existing techniques. The above experimental outcomes of the effectiveness of the proposed method in terms of the average running times of different methods. The proposed method running efficiency used the trained models on the DAWN datasets using to input the fog images into fog-free images. The proposed method suggests a faster running time than the current defogging methods and deep learning techniques. In terms of running speed or time, it is compared with other deep learning defogging methods.

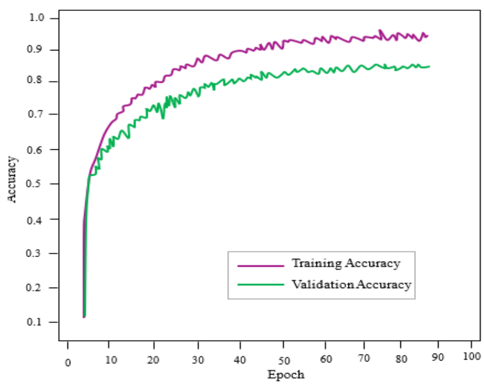


Figure 7. Accuracy graph of the Deep-APT model

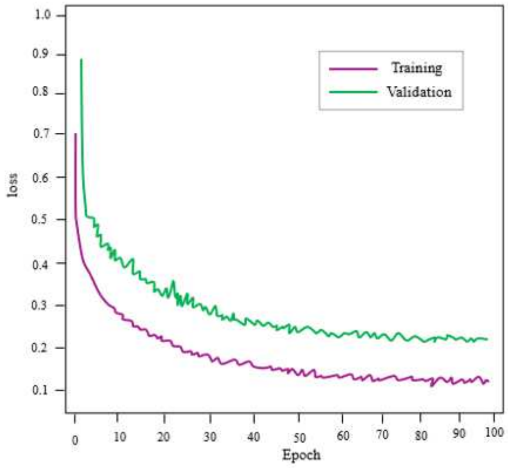


Figure 8. Loss graph of the Deep-APT model

The proposed Deep-APT model achieves maximum accuracy in both training accuracy and testing accuracy in both training and validation accuracy, as shown in Figure 7, and Figure 8. The performance based on accuracy, precision, recall and f1score and the accuracy achieved by the Deep-APT model is 99.89%. It clearly shows the to improve detection accuracy using Faster RCNN Network.

4.2 Comparative Analysis

The proposed Deep-APT was contrasted with a variety of other methods in order to show how effective it is. In a comparative study, the Deep-APT is compared with three existing approaches. Table 2 compares the overall effectiveness of DL with the existing techniques. the Faster R-CNN network is compared to DL methods like CNN, U-Net, and Alex Net. Performance evaluation was based on precision, recall, F1 score, and accuracy of the DL technique.

Table 2. Comparison between Deep learning networks

Networks	Accuracy (%)	Precision (%)	Specificity (%)	F1 Score (%)	Recall (%)
U-Net	95.43	92.29	94.32	89.12	90.68
Alex Net	97.61	94.56	93.75	93.95	91.88
CNN	96.76	92.05	95.98	86.58	89.34
Faster R-CNN	99.52	96.84	98.02	91.67	95.79

Figure 9, illustrate he Faster R-CNN network improves the overall accuracy of the U-Net, Alex Net, CNN and Fater R-CNN is 95.43%, 97.61%, 96.76%, and 99.52 % respectively. The overall specificity of the U-Net, Alex Net, CNN and Faster R-CNN is 94.32%, 93.75%, 95.98% and 98.02%. The overall precision of the U-Net, Alex Net, CNN and Faster R-CNN is 92.29%, 94.56%, 92.05% and 96.84%. The overall recall of the U-Net, Alex Net, CNN and Faster R-CNN is 90.68%, 91.88%, 89.34% and 95.79%. The overall F1 score of the U-Net, Alex Net, CNN and Faster R-CNN is 89.12%, 93.95%, 86.58% and 91.67%.

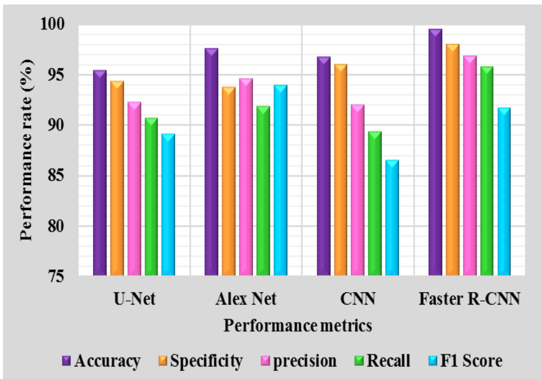


Figure 9. Comparison analysis of existing deep learning models

Table 3. Comparison of accuracy between suggested and Deep-APT

Authors	Methods	Accuracy
Ogunrinde, I.O. [16]	CR-YOLnet	84.09%
Pal, T., [18]	RDL	94.8%
Proposed	Deep-APT	99.52%

Table 3 illustrate that traditional network such as CR-YOLnet, and RDL are less accurate than the proposed method. The Deep-APT technique maintains excellent accuracy levels of 99.52%. The Proposed Deep-APT approach improves the overall accuracy of 15.43%, and 4.72% better than CR-YOLnet, and RDL respectively**.** According on the comparison above, the proposed Deep-APT model is more accurate than existing models.

5. CONCLUSION

In this paper, a novel Accident Prevention Technique (Deep-APT) has been proposed to effectively restore fog-free images and prevent accidents. Initially, the video sequence is converted to frames. The frames are pre-processed using an Adaptive dual threshold Tetrolet transform. It preprocesses foggy images to fog-free images it is used to remove noise in the image. To detect objects and distance in front of the car use FasterRCNN technology. The Deep-APT has been simulated using MATLAB. In experimental analyse the performance 50 images per different scenario are collected from the DAWN dataset. The simulated result shows the Deep-APT yields an overall accuracy is 99.52%. As compared to existing techniques, the proposed FasterRCNN network shows better results in terms of precision, accuracy, F1 score, and recall. Using DAWN dataset, the MSE, SSIM and PSNR values for the proposed method are 0.12, 0.65 and 0.12. The Deep-APT network improves the overall accuracy of 15.43%, and 4.72% better than CR-YOLnet, and RDL respectively. In future, we plan to perform further experiment and test our approach with additional image sequences.

Statement:

Ethical approval: My research guide reviewed and ethically approved this manuscript for publishing in this Journal.

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Informed consent: I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

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