

# Adaptive Deep Learning Detection Model for Multi-Foggy Images

Zainab Hussein Arif<sup>1,2</sup>, Moamin A. Mahmoud<sup>1</sup>, Karrar Hameed Abdulkareem<sup>3\*</sup>, Seifedine Kadry<sup>4,5,6</sup>, Mazin Abed Mohammed<sup>7,8</sup>, Mohammed Nasser Al-Mhiqani<sup>9</sup>, Alaa S. Al-Waisy<sup>2</sup>, Jan Nedoma<sup>8</sup>

<sup>1</sup> College of Computing and Informatics, Universiti Tenaga Nasional, 43000 Kajang, Selangor (Malaysia)

<sup>2</sup> Computer Technologies Engineering Department, Information Technology Collage, Imam Ja'afar Al-Sadiq University, Baghdad (Iraq)

<sup>3</sup> College of Agriculture, Al-Muthanna University, Samawah 66001 (Iraq)

<sup>4</sup> Department of Applied Data Science, Norrof University College, 4608 Kristiansand (Norway)

<sup>5</sup> Artificial Intelligence Research Center (AIRC), College of Engineering and Information Technology, Ajman University, Ajman, (United Arab Emirates)

<sup>6</sup> Department of Electrical and Computer Engineering, Lebanese American University, Byblos (Lebanon)

<sup>7</sup> College of Computer Science and Information Technology, University of Anbar, 11, Ramadi, Anbar (Iraq)

<sup>8</sup> Department of Telecommunications, VSB-Technical University of Ostrava, 70800 Ostrava (Czech Republic)

<sup>9</sup> School of Computer Science and Mathematics, Faculty of Natural Sciences Keele University (KU), Keele (United Kingdom)

Received 25 February 2021 | Accepted 3 February 2022 | Published 30 November 2022



## ABSTRACT

The fog has different features and effects within every single environment. Detection whether there is fog in the image is considered a challenge and giving the type of fog has a substantial enlightening effect on image defogging. Foggy scenes have different types such as scenes based on fog density level and scenes based on fog type. Machine learning techniques have a significant contribution to the detection of foggy scenes. However, most of the existing detection models are based on traditional machine learning models, and only a few studies have adopted deep learning models. Furthermore, most of the existing machines learning detection models are based on fog density-level scenes. However, to the best of our knowledge, there is no such detection model based on multi-fog type scenes have presented yet. Therefore, the main goal of our study is to propose an adaptive deep learning model for the detection of multi-fog types of images. Moreover, due to the lack of a publicly available dataset for inhomogeneous, homogenous, dark, and sky foggy scenes, a dataset for multi-fog scenes is presented in this study (<https://github.com/Karrar-H-Abdulkareem/Multi-Fog-Dataset>). Experiments were conducted in three stages. First, the data collection phase is based on eight resources to obtain the multi-fog scene dataset. Second, a classification experiment is conducted based on the ResNet-50 deep learning model to obtain detection results. Third, evaluation phase where the performance of the ResNet-50 detection model has been compared against three different models. Experimental results show that the proposed model has presented a stable classification performance for different foggy images with a 96% score for each of Classification Accuracy Rate (CAR), Recall, Precision, F1-Score which has specific theoretical and practical significance. Our proposed model is suitable as a pre-processing step and might be considered in different real-time applications.

## KEYWORDS

Deep Learning, Fog Detection, Foggy Image, Multi-Fog, Multi-Class Classification.

DOI: 10.9781/ijimai.2022.11.008

## I. INTRODUCTION

**F**OG recognition and detection of objects in foggy weather condition is important for many applications such as transportation systems, and autonomous driving [1]-[3]. Foggy conditions can cause a serious traffic safety problem if the autonomous car on-board smart sensors fail to detect other cars or pedestrians [4]-[5]. Therefore, development

of artificial intelligence methods and smart sensing technologies for fog recognition is important in machine vision.

As an atmospheric effect, fog creates a grey color over the scene, thereby degrading visibility in outdoor scene images [6]. Besides, the fog has been regarded as one of the main sources of accidents that occur in different environments like air, underwater, and over-land [7]. Fog is formed when the light which propagates through the atmosphere is scattered by particles like moisture and smoke; these particles are normally dispersed by air [8]. To eliminate the effects of the fog inside the obtained image, the art of dehazing is employed. The process of dehazing involves the elimination of the effects of fog

\* Corresponding author.

E-mail address: khak9784@mu.edu.iq

from outdoor images, as well as the restoration of fidelity details. Conceptually, the technique of dehazing image which is also referred to as “defogging” or “fog removal”, is an image enhancement that involves the elimination of undesirable visible effects from an image [9]. However, this technique is not the same as the conventional noise elimination technique and contrast enhancement techniques, since the degradation to image pixels that is induced by the presence of fog is dependent on the distance between the object and the acquisition device and the regional density of the fog [10]. The wide range of colors is overshadowed by the effect which the fog has on image pixels [11]. The presence of particles in the atmosphere, makes the execution of computer vision tasks in the presence of fog difficult and effective, thereby leading to the production of heavily degraded images [12]-[14]. Thus, it becomes crucial to subject the degraded images to process of defogging [15]-[17].

According to the popularity of the traditional machine learning techniques in vast application areas, such techniques have applied widely in the image defogging domain to tackle issues related to image denoising [18], image quality assessment [19], image segmentation [20], and image classification or detection [21]. Comparing with traditional techniques, deep learning-based methods have made remarkable progress in image dehazing problems, especially in image denoising [22] and image classification [23]. Most recently, several deep learning-based approaches have proposed that demonstrate more robustness as compared to the traditional non-learning-based methods [24]. With the presence of a deep learning model [25], complex networks can be created so that the problem of image classification can be solved. Such a problem is often solved using Convolutional neural networks (CNNs), where complex networks serve as a collection of feature extractors that are usually somewhat generic, and relatively free of any classification task [26]. Naturally, the performances of these algorithms are superior to those of conventional manually crafted priors-based techniques by a significantly large margin. This can be attributed to the fact that informative and useful features can be extracted by CNNs from large amounts of images with strong generalization capability [22]. More so, due to the automatic process of extracting features, human supervision is not required [23].

Determining the presence and magnitude of fog has a great enlightening effect on the process of image defogging. Since it is possible to perform subsequent processing selectively, images can be better understood [27]. The process of detecting fog in image can be thought as a classification problem [21], [28]. However, in this study we do not discriminate between classification and detection terms. Fog has a significant impact on the image and cause different types of noise such as contrast, color, and structure distortion [29]. Usually, the classification of foggy images is based on machine learning techniques. The machine learning models need to predict the image type according to relevant features with corresponding environment characteristics. Furthermore, foggy image features could be varied according to density of fog or foggy scene type. For example, in the inhomogeneous foggy scene, the distribution of the fog is not equal in whole image, while in the homogenous foggy scene the fog level almost the same in whole image. Thus, a significant challenge can be seen in terms of classification of image according to more complex foggy image features. Furthermore, a comprehensive platform that covers all characteristics of foggy images in the classification of foggy images should be developed.

Irrespective of the absence or presence of fog, the direct defogging algorithms are applied to images or videos. However, when real-world applications are involved, it is essential to determine if there is a need for the processing of the obtained image in the given environment by a defogging algorithm. This is because, without any judgment, the use of a defogging algorithm to restore an image may worsen the visibility

of the image as compared to the original image. Besides, a particular noise could be added to a picture that has no fog when the defogging algorithm is used in processing degraded images. This, in turn, distorts the image to a certain level. Other demerits of using a defogging algorithm include low efficiency of processing, un conducive for image recognition, and consumes much time. Thus, it is crucial to effectively determine the presence of fog in an image before it is subjected to the process of defogging. This implies that the classification and recognition of the acquired image before processing is practically significant and valuable for application; this must be considered before improving the efficiency of image processing [23],[29],[30].

Additionally, the extant technical theory is restricted to fog image processing, and as such, it is difficult to make a valid classification of the image as non-foggy or foggy. As a result, relying solely on subjective judgement will not be able to meet the demands of real-time and batch processing. Consequently, having a method for accurately determining the state of the image is critical [31]. Also, another problem associated with fog is the detection of context information that describes the condition of the environment such as snow, fog, or rain. This problem is well established in the extant literature [30].

This paper analyzes the suitability of four deep learning models (Xception, VGG-16, Inception-V3, ResNet-50) for fog detection. The methodology is evaluated based on the dataset of collected foggy images. The contribution of this study can be seen as follow:

- Based on seven public datasets, the first dataset that includes four foggy scenes (inhomogeneous, homogeneous, dark, and sky foggy scene) is presented to the research community and it is openly available from <https://github.com/Karrar-H-Abdulkareem/Multi-Fog-Dataset>.
- The first adaptive multi-class study is presented based on the classification of four foggy scenes which are inhomogeneous, homogeneous, dark, and sky foggy scenes. The adaptive term refers to capability of classification model to classify different foggy scenes.
- We adopted the ResNet-50 model for the classification of multi-class foggy images.

The remaining parts of the paper present an overview of the related works (Section II), present the methodology (Section III), present and discusses the results (Section IV), discuss the application scenarios and the limitations of our approach (Section V), and state the conclusions (Section VI).

## II. RELATED WORKS

In general, the foggy scene is divided into two types, a scene based on fog level density and scenes based on fog type where different characteristics are recognized such as time, light source, and so on. Scenes based on fog type have different categories. First, an inhomogeneous foggy scene which is referred to an image that usually contains an uneven amount of fog that is distributed in the entire image [32]. Second, a homogenous foggy scene is assumed that amount of fog is equally distributed in the entire image [7]. Third, the dark foggy scene is common, including visible lights (artificial lights) sources with varying colors besides the presence of fog. The light sources also often introduce noticeable amounts of glow that are not present in daytime fog [33]. Fourth, sky foggy scenes where the color of the sky is usually very similar to the atmospheric light in a fog image [34], so the pixel with the highest intensity might correspond to a bright object rather than to the airlight [35].

Most of the current classification models in the image defogging area are based on two insights. First, classification models are based on binary classification, where the main target of these models is to

distinguish between two types of images, i.e., foggy and non-foggy, respectively [28]. Second, classification is based on multi-class models which is the main purpose of these models to classify images based on fog density [21]. Many studies have addressed the problem of foggy image classification, as illustrated in Table I.

Many techniques have been used to tackle the problem of foggy image classification. Most classification techniques belong to traditional machine learning approaches rather than deep learning. Even with new trends of transfer learning, many investigated studies prefer to use hand-crafted features, especially in terms of color and gradient features. Furthermore, the process of feature extraction quite complex in some studies. The SVM technique is widely used as a classification model to characterize foggy images since the high accuracy can be obtained [27]. All binary classification studies focused on the general foggy images classified as foggy and non-foggy images. Furthermore, the binary classification has generalized to the more specific foggy scene such as non-sky and foggy sky images. On the other hand, multi-class classification also has been used to classify the images based on fog levels such as light, medium, and heavy foggy scenes. Only one study [28] has combined each of binary and multi-class classification. However, many studies have success to classify the daytime while minimum proposed algorithms have ability to work in the night-time foggy images.

Kaiming et al. [39] have presented a residual learning framework where the layers learn residual functions with respect to the inputs received instead of learning unreferenced functions. This model allows the training of profound networks up to more than 1000 layers [39]. It is a well-established fact that the performance of a network is determined by its depth. In the area of computer vision, use of deeper networks is employed. Nevertheless, the training of a deeper network is difficult because of the problem of gradient vanishing, which is difficult to combat. Therefore, for this problem to be addressed, the use of ResNet can be employed [39] because it offers a training framework that can simplify the training of networks that are reasonably deeper than the previously used ones [40]. The motivation for this is the findings of scientific experiments that have shown that the level of training error increases as more layers are added. Conceptually, an increase in the number of layers should lead to increased modeling efficiency of Neural Networks, thereby preventing the occurrence of higher training error. This is attributed to the fact that after the propagation of gradients in many layers, they (gradients) vanish. Rather than enabling the uninterrupted flow of a portion of earlier information to later layers via Highway Networks through the addition of parameterized gating functions [41], the authors in [40] suggested that shortcut connections with identity should be simply added to the networks. Moreover, ResNet-50 has never been used before for the classification of foggy images, furthermore, according to the mentioned advantages, ResNet-50 has been employed for the classification target of four foggy image classes in this study.

Finally, the findings of the examined research have shown three major difficulties. First, most of the proposed models have lack of evaluation based on the benchmarked dataset and prefer to use the private dataset that is based on the authors' own experiment, which raises a question about the possibility of existed studies if can be generalized for more challenging scenarios in real-time applications. Furthermore, to the best of our knowledge, there is no such available public dataset that has been covered each inhomogeneous, homogeneous, dark, and sky foggy scene. Second, all mentioned studies have ignored the multi-class classification of foggy images based on the different scene types such as the inhomogeneous, homogeneous, dark, and sky foggy scene. Third, according to [23] the authors have shown the advantages of using deep learning models, especially in the matter of accuracy comparing with traditional

machine learning models in the binary classification of foggy images. However, to our knowledge, no study has applied a deep learning model for classification each of inhomogeneous, homogeneous, dark, and sky foggy image as multi-class classification task in the image defogging domain, which we consider to be a theoretical gap.

### III. METHODOLOGY

This section presents the full details for the proposed model into different phases as follows:

#### A. Data Collection Phase

As mentioned in the previous section, the lack of a public dataset based on four foggy scenes as well as all classification studies have been conducted based on private datasets which raise a significant challenge in this study. The main aim of this phase is to collect foggy images belong to four foggy scenes; namely, homogenous, inhomogeneous, dark, and sky foggy scene (see Fig.1). The baseline for collected images is the definition for each foggy scene that is already mentioned in section two, where each image scene has different characteristics. Furthermore, the source of collected images is based on seven datasets that can be identified as follows:

- Dehazing using color-lines dataset [42]: This dataset contains eleven foggy images; these images belong to indoor and outdoor foggy scenes. Furthermore, all images with PNG format, but with different dimensions, for instance, 1024, 1200, and so on.
- I-Haze dataset [43]: a dataset, in which 35 pairs of foggy and corresponding haze-free (ground-truth) indoor images are contained therein. Unlike the majority of the available dehazing databases, the real haze has been used in generating foggy images; the use of a professional haze machine was employed in generating the images. A MacBeth color checker was included in all the scenes so that color calibration can be eased while the evaluation of the dehazing algorithm can be improved. Besides, since the capturing of images is done within a controlled environment, both foggy and haze-free images are captured under the same lighting conditions. All images obtained have the JPG format with  $4675 \times 2833$  px dimensions.
- Kede dataset [44]: this dataset contains a total number of 225 images, out of which 200 are defogged, and 25 are foggy. The 225 images were divided into 9 image sets with 25 images each. These images are provided to cover diverse outdoor scenes and different



Fig. 1. Foggy scenes are based on different fog types.

TABLE I. EXISTING STUDIES ON CLASSIFICATION FOR FOGGY IMAGES.

Ref	Model	Features	Advantage	Classification type	Disadvantage	Scene type
[31]	SVM (linear kernel)	Hand-crafted features	New indicators to distinguish between foggy and non-foggy images	Binary	No comparative scenario provided	Foggy and non-foggy
[36]	SVM (linear kernel)	Hand-crafted features Scattering Model	Simple implementation	Multi-class	Features aren't good enough to describe the whole information of images	Clear, light foggy, medium foggy, and heavy foggy
[30]	SVM	Hand-crafted features	Sample size has a very small effect on speed	Binary	Lack of comprehensive evaluation scenario	Foggy and non-foggy
[21]	SVM (RBF)	Hand-crafted features	Hight potential for fog detection on daytime images	Multi-class	Doubtable to efficiently works in dark foggy scene	Excluded, No Fog, Low Fog, Fog and Dense Fog
[22]	AlexNet	Deep features	Process of feature extraction is automatic and needs no supervision	Binary	Number of hyper tuning parameters quite high	Foggy and non-foggy
[28]	SVM (LDA)	Hand-crafted features	Works well for day-time scenes	Binary	Limited only to grayscale images	Foggy and clear images in daytime
[28]	SVM (LDA)	Hand-crafted features	Works well in night-time scenes	Binary	Limited only to grayscale images	foggy and clear images in night-time
[23]	Deep learning	Hand-crafted features	Process of feature extraction is automatic and needs no supervision	Binary	Number of hyper tuning parameters quite high	Clear and foggy image
[27]	SVM (RBF)	hand-crafted features	Efficient for fog density classification	Multi-class	Complex features extraction	Fog-free, thin fog and dense fog image
[36]	19 classification techniques	Hand-crafted features	Comprehensive evaluation	Binary	Too many features extracted	Foggy and non-foggy
[37]	SVM	Hand-crafted features	Efficient to work for large sky foggy classification	Binary	Lack of evaluation scenario	Sky and non-sky foggy image
[38]	Two SVM (RBF) classifiers	Hand-crafted features	Better performance both on the detection rate and the misclassification	Binary	Performing poorly for night scenes	Sky and non-sky foggy image

degrees of haze thickness. These include humans, animals, plants, architecture, landscapes, statics, traffics, and night scenes. Many images were captured in the real world, but the simulation of the three hazy and static objects was done uniformly. All the images are provided in JPG with 4675 x 2833 dimensions. The evaluation of the image involved the participation of 24 naïve observers, out of which 12 were female and 12 males between the age of 22 and 28.

- LIVE Image Defogging Database: The LIVE Image Defogging Database proposed by [45], this dataset has been used widely in many evaluation scenarios in image dehazing domain such as [7], [11],[46]. A total of 1100 natural fog-free, foggy, and test images have been presented by this database. Here 100 colored images were selected to provide adequately diverse images, and fog density from newly recorded foggy images, well-established foggy test images, and corresponding defogged images. The images were of different sizes ranging from 425 × 274 to 1024 × 768 pixels. Besides, few foggy scenes like dark foggy scenes, homogenous scenes, and inhomogeneous foggy scenes were contained in the images. However, all provided images are in different formats and dimensions.
- O-haze dataset [44]: O-haze is a dataset composed of 45 kinds of outdoor scenes. It contains pairs of corresponding haze-free images and real foggy images. Practically, the capturing of the foggy images was done in real haze using professional haze machines. All the images in this dataset represent the same visual content recorded under foggy and haze-free conditions and the same lighting condition. The significance of O-HAZE has been proven by using it to make a comparison of a representative set of state-of-the-art dehazing methods. The comparison involved the use of conventional image quality metrics like SSIM, PSNR, and CIEDE2000. Through this comparison, the shortcomings of

the current techniques are uncovered, and some based on the uncovered shortcomings, some of their underpinning hypotheses are questioned. Nevertheless, all the images have been provided in varying dimensions and formats.

- RESIDE Database: this dataset has been proposed by [47]; it has also been widely used in many evaluation studies [48], [49] and [50]; it features a large-scale synthetic training set and two different sets of designed quality evaluations, respectively. RESIDE has diverse data sources and image contents. This dataset has indoor and outdoor images, clear and foggy images, with more than 12,000 real-world images. However, all provided images are in different formats and dimensions.
- Foggy Image dataset (FI): this dataset was proposed by [51] which contained 200 foggy images. The corresponding manual labeled ground truths have been provided in this dataset. This dataset was mainly used for object detection in foggy weather. However, all provided images are in the PNG format but with different dimensions.

Furthermore, the data collection process time depends on the volume of images in each dataset. The final set of collected images depend on the availability of four mentioned foggy scenes in each defined dataset. However, the number of collected images may present a negative effect on the classification task, especially with deep learning models, especially when the number of collected images for the training dataset is small. Thus, a recommended solution is needed to avoid such a challenge.

### B. Classification of Foggy Image Phase

This phase focuses on all processes relevant to the multi-class classification model such as pre-processing, classification model, and evaluation process (see Fig. 2).

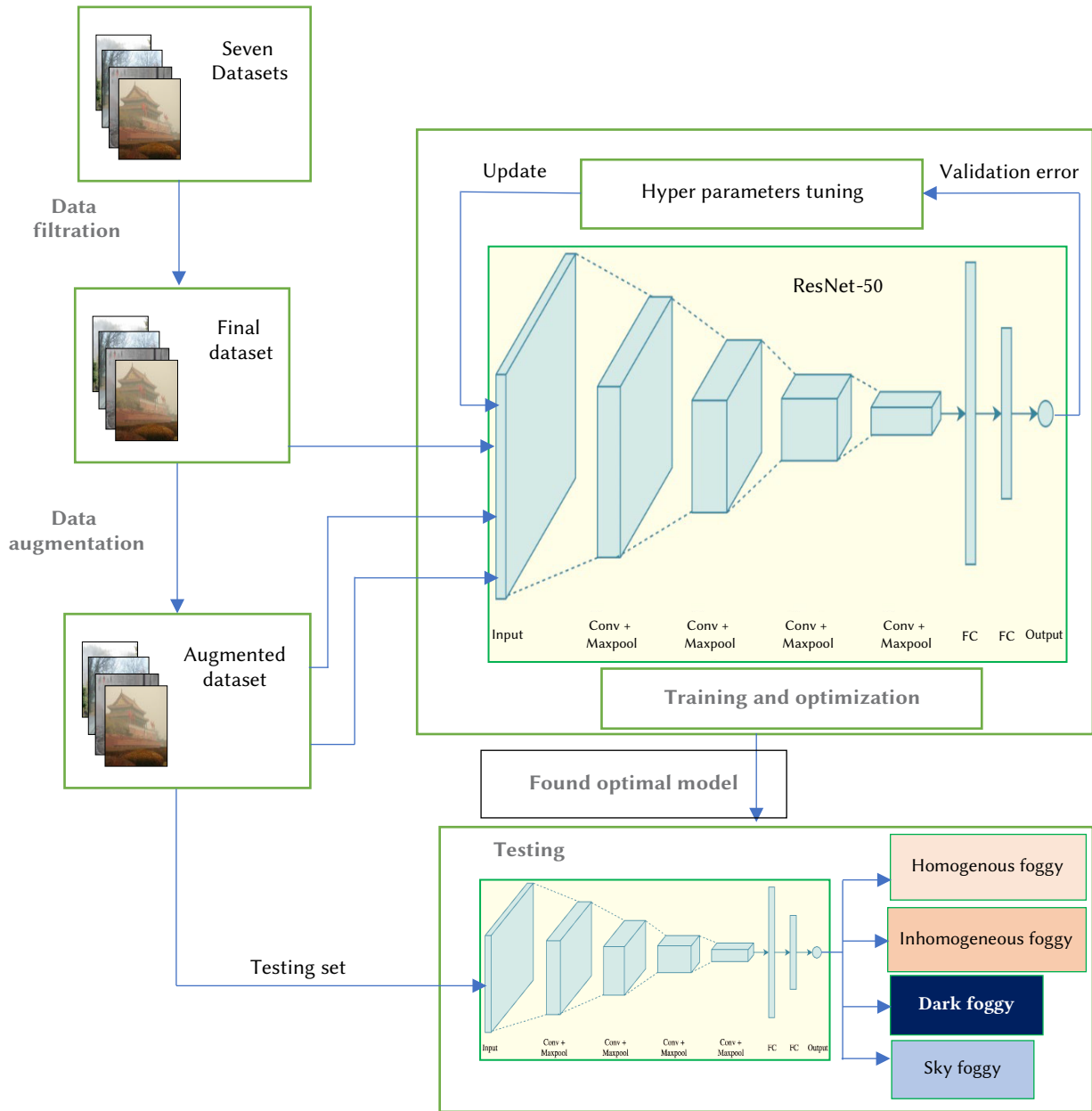


Fig. 2. New classification model for four multi-fog classes.

### C. Data Pre-Processing Stage

Before training the model, it is fundamental to apply pre-processing techniques to avoid distorted information. Thus, it allows a correct and more straightforward evaluation of data through the network. In this research, the images of the foggy scenes are collected from different sources. The images are captured by different types of equipment and contain different acquisition parameters. As a result, there exist considerable variations in the intensity of the images. However, the proposed CNN model implements several standard pre-processing procedures to ensure that the generalization of the CNN models is not negatively affected, as follows:

- **Resizing:** we need first to acquire a constant dimension because all images in this dataset vary in dimension and resolution (365×465 to 1125×859 pixels). Subsequently, all the images are scaled to specific pixels based on the corresponding CNN model (e.g., ResNet\_50 224×224 pixels).
- **Normalization:** In the normalization part, to set the scaling limit, we use a precalculated mean subtraction of the ImageNet database to normalize the intensity values [52]. Then we scale the intensity values from [0, 255] to the intensity range of [0, 1] using the min-max normalization formula.
- **Image data shuffling:** Random shuffling of data is a standard procedure in all machine learning pipelines, and image classification is not an exception; its purpose is to break possible biases during data preparation - e.g., putting all the sky foggy images first and then the homogenous ones in a foggy image classification dataset.
- Furthermore, make all input data in a similar image format where all foggy images will be set to PNG format.
- **Data augmentation:** A data augmentation procedure is suggested to avoid the overfitting problem during the learning process especially with a small dataset [53,-57] and increase the

generalization ability of the last trained model, we will perform a detailed offline augmentation over the collected foggy images in our dataset, the listed augmentation technics will apply to original images:

1. Rotation with range = 5 degrees.
2. Zoom With range=0.1.
3. Width Shifting with range=0.1.
4. Height Shifting with range=0.1.
5. Horizontal flip.

Zoom is a float value for the zoom\_range parameter that takes a lower limit and an upper limit. The shift technique helps in improving those images that are not properly positioned. The values specified are either specified in the form of percentage or integer (in our paper we use percentage). Random flip is a Boolean input that randomly flipping half of the images horizontally or vertically. We have excluded some of the augmentation techniques, for instance, brightness since the most defect in the foggy image is the low contrast, so applying such augmentation technique may affect the real characteristics of the images thus affects all other analysis processes.

#### D. Image Classification Based on ResNet50 Model

In this paper, ResNet-50 is applied for several reasons, including: (i) to reduce the training time required to obtain the last trained model, and low training error rate especially when the depth of network is increased, (ii) to increase the prediction accuracy of the proposed Multi-class foggy images classification model. To mention, the process of detection fog depends on different factors. First, scene type is the first indicator for detection for instance; image that taken at the night with presence of artificial light considered as dark foggy image. Second, image that contained fog in small portion or overall image also consider as foggy image.

Here, we employed an efficient pre-trained ResNet-50 model. Residual Network (ResNet) one of the most powerful deep CNNs. ResNet is similar to other CNNs, which have convolutional, pooling, activation maps, and fully connected layers stacked sequentially one over the other. The only main difference between ResNet and other CNNs is the identity connection, which is originating from the input layer to the end of the residual block (see Fig. 3-b).

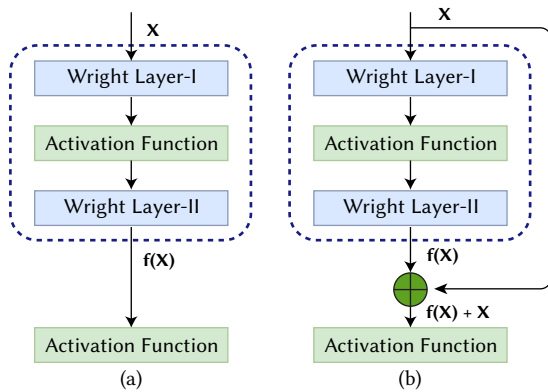


Fig. 3. Concept of ResNet-50 model.

We simply explain the theory of the ResNet-50 below. We explicitly make these layers fit a residual mapping, instead of each few stacked layers directly fit a desired underlying mapping  $H(x)$ . We let the stacked nonlinear layers fit another mapping of  $F(x) := H(x) - x$ . The original mapping is recast into  $F(x) + x$ . The formulation of  $F(x) + x$  can implement by feedforward neural networks with shortcut connections. The shortcut method uses the connection that skips one or more layers,

which simply performs identity mapping. Their outputs are added to the outputs of the stacked layers. Identity shortcut connections do not add any extra parameter or computational complexity. The network can be trained end-to-end by stochastic gradient descent (SGD) with backpropagation.

The main steps of the proposed training methodology can be summarized as follows:

1. Dividing the augmented database into three different sets: Training set, Validation set, and Test set.
2. Select initial values for a set of hyper-parameters (e.g., learning rate, momentum, weight decay, etc.).
3. Training the ResNet-50 using the training set and the hyper-parameters set in step 2.
4. Using the validation set to evaluate the performance of the ResNet-50 during the training process.
5. Repeating steps 3 through 4 for 20 epochs.
6. Selecting the best-trained model with minimal error rate on the validation set.

#### E. Evaluation Phase

Based on the testing set and the best-trained model, the evaluation process will be conducted. To evaluate the quantitative performance of the proposed model, such as evaluation metrics Classification Accuracy Rate (CAR), Precision, Recall, and F1 score are computed to validate the efficiency and reliability of the proposed system using the testing set. Furthermore, all mentioned metrics are calculated based on the weighted average value have chosen for the multi-class classification setup, which preferable if you suspect there might be a class imbalance (i.e., you may have many more examples of one class than of other classes). Weighted-avg is calculating metrics for each label, and find their average weighted by support (the number of true instances for each label). Each of weighted CAR, Precision, Recall, and F1 score is calculated according to equations [1]:

$$CAR = \frac{\sum_{i=1}^m \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}}{m} \quad (1)$$

$$Precision = \frac{\sum_{i=1}^m tp_i}{\sum_{i=1}^m (tp_i + fp_i)} \quad (2)$$

$$Recall = \frac{\sum_{i=1}^l tp_i}{\sum_{i=1}^l (tp_i + fn_i)} \quad (3)$$

$$F\_score = \frac{\sum_i^m |y_i| \frac{2tp_i}{2tp_i + fp_i + fn_i}}{\sum_i^m |y_i|} \quad (4)$$

If  $m$  is the total number of classes in the dataset, then  $i$  value from 1 to  $m$ . Furthermore, to compare the performance of the proposed detection model, the process of evaluation will be conducted within three deep learning models, namely, Xception, VGG-16, Inception-V3.

## IV. RESULTS

This section presents in detail the experimental results, analyses, and discussions towards the accomplishments of the proposed multi-class image defogging classification model based on multi-fog types. The remaining of this section consists of five broad sections and is organized as follows in line with the proposed methodology discussed in section 3. Subsection 4.1 discusses the results of data collection. Subsection 4.2 presents the foggy images of classification results.

#### A. Data Collection

The total images are 1166 used in this study based on the main foggy scene categories are homogeneous scene, inhomogeneous scene,

TABLE II. THE DISTRIBUTION OF FOGGY IMAGES BASED ON EIGHT DATA RESOURCES

Foggy Scene	Dehazing using Color-Lines	I-HAZE	IVCDehazing (Kede)	LIVE Image Defogging Database	O-HAZE	RESIDE	Saliency Detection Based (FI)	Internet	Total
Homogeneous scene	11	30	3	114	45	41	12	-	256
Inhomogeneous scene	-	-	-	37	-	31	-	105	175
Dark scene	-	-	3	13	-	257	2	-	274
Sky scene	-	-	2	62	-	384	15	-	463
Total	11	30	8	226	45	713	29	105	1166

dark scene, and sky scene. The details of the foggy scene categories are presented in Table II. We labeled the images manually according to the class definition.

Based on Table II, for every dataset, the main processes of the proposed methods are evaluated and analyzed. The foggy scene with a large dataset that is used in the experimental results is the sky scene with 463 images, followed by that dark scene with 274 images. Furthermore, homogeneous scene includes 256 images, and inhomogeneous scene contains 175 images with total cases are 1166 images. The homogeneous scene as having 114 images in LIVE Image Defogging Database from 256 as total, while IVCDehazing (Kede) contains 3 images only. The other distributed in the datasets for the homogeneous scene are Dehazing using Color-Lines 11 images, I-HAZE 30 images, O-HAZE 45 images, RESIDE 41 images, and Saliency Detection Based (FI) 12 samples.

The inhomogeneous scene has 105 images for internet source from 175 as total in this class, while LIVE Image Defogging Database contains 37 images only. The other distributed in the datasets for the inhomogeneous scene is RESIDE 31 images. For Dark scene have 257 images for RESIDE database from 274 as total in this class, while Saliency Detection Based (FI) Database contains 2 images only, LIVE Image Defogging Database contains 13 images, and IVCDehazing (Kede) database contains three samples. Finally, Sky scene has 384 images for RESIDE database from 463 as total in this foggy scene, but IVCDehazing (Kede) database contains 2 images only, LIVE Image Defogging Database involve 62 images, and Saliency Detection Based (FI) contains 15 images as shown in Table II. The most source that has contributed to our collected data is RESIDE dataset, while each of Dehazing using Color-Lines and IVCDehazing datasets have the lowest contribution.

However, the variation of samples or cases is affecting the training and testing process. It is observed that some datasets have good samples in the specific foggy scene, but others do not have enough samples for the training and testing process. Furthermore, the most type of foggy class that is prone to create an imbalanced dataset is the inhomogeneous foggy image class followed by each of the homogenous and dark foggy scene classes. Thus, the dataset with mentioned flaws will present a significant challenge when the real experiment is conducted, that is why an efficient solution is needed to adopt for tackling such issues.

### B. Foggy Images of Classification Results

In the domain of artificial intelligence, especially deep learning utilization, big data is the main fundamental to supporting the learning task of the features of objects in image processing and classification.

The network training demands big data to support the feature extraction process to get better features of the objects. Data augmentation and data equilibrium are used to avoid the problem of few image samples that are not enough for the training process. Data augmentation is important to transforming the training samples or images and generating new images by confirmed techniques. Using data augmentation, the original database can be enhanced and

increased. Also, notably in the training work, assist in preventing the overfitting issue. Thus, it is important to adopt mentioned processes for the detection and classification performance of the proposed model.

In the collected foggy images, most of these images are extracted from different datasets with different characteristics and numbers. This type of database cannot be applied directly to the training process, especially using deep learning methods. However, the scale of this database classified based on the original images is very small to qualify the sample number of images that can be used for the training process. Thus, the data augmentation must be performed on the databases to qualify the samples used and the need to ensure a useful feature extracted. To provide a more efficient training process with adequate deep learning results and avoid previously mentioned issues with the collected dataset, a data augmentation approach has been adopted in our study. Several data augmentation techniques have been applied, such as Rotation, Zoom, Width Shifting, Height Shifting, and Horizontal flip. The results of the data augmentation process are presented in Table III.

TABLE III. AUGMENTED DATASETS AND FOGGY SCENE CATEGORIES

Foggy Scene	Total
Homogeneous scene	1536
Inhomogeneous scene	1050
Dark scene	1639
Sky scene	2766
<b>Total</b>	<b>6991</b>

As shown in Table III, the number of images within each foggy scene type has increased five times from the original set. For instance, the number of homogenous foggy images in the collected dataset was 256 while after applying data augmentation processes, the image number became 1536. Furthermore, other types of foggy images have increased from 175 to 1050 for inhomogeneous foggy images, from 274 to 1639 for dark foggy images, and from 463 to 2766 for foggy sky images. The dataset has increased from 1166 to 6991 foggy images. However, the difference between the original collected and augmented datasets with foggy Scene categories shows in Fig. 4.

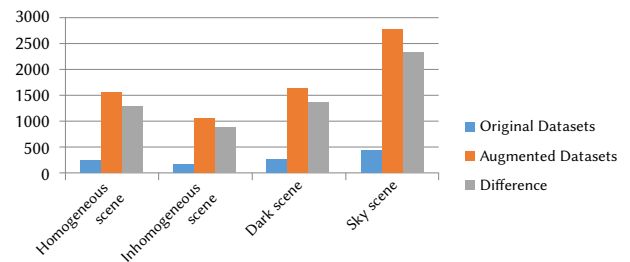


Fig. 4. The difference between original databases collected and augmented datasets with foggy scene categories.

TABLE IV. THE NUMBER OF IMAGES USED IN THE EXPERIMENT WITH EACH FOGGY SCENE CLASS

Class No.	Class Name	Training Set	Validation Set	Testing Set	Total
1	Homogeneous foggy	1108	120	308	1,536
2	Inhomogeneous foggy	760	80	210	1,050
3	Sky foggy	2011	200	555	2,766
4	Dark foggy	1181	130	328	1,639
-	All	5,060	530	1401	6,991

The numbers of images related to each foggy scene category are listed in Table IV. To train and test our network on a multi-fog type dataset, we selected 70% (5060) of sample images evenly from each scene category for training and 10% (530) for validation, and 20% (1401) as the test set. Adam optimizer was used to fine-tune the parameters while using hyper-parameters with the number of epochs set to 20, batch size = 10, learning rate = 0.0001, momentum = 0.9, and weight decay = 0.0002. AS shown in Table V. To mention, all hyper-parameters have applied for proposed model and state-of-art methods.

TABLE V. HYPER PARAMETERS AND THEIR VALUES

Hyper-Parameters	Values
Optimization Method	Adam
Momentum	0.9
Weight-Decay	0.0002
Batch Size	10
Activation Function	ReLU
Learning Rate	0.0001
Total No. of Epochs	20
Dropout ration	0.5
# Nodes in the softmax layer	4

The most critical configuration setting in the deep learning model is the learning rate and the number of epochs. To mention, the base for setting the learning rate as 0.0001 is that during experiment configuration, we found that our network with learning rate more than 0.0001 we got only 70% as CAR. When we set the learning rate to 0.0001, the CAR increased to 96%. The same CAR rate (96%) was obtained when we decreased the learning rate to 0.00001. The more surprising results that at a threshold of more than 0.0001, we found our network cannot detect inhomogeneous foggy scenes instead detect all inhomogeneous foggy images as homogenous, dark, and sky foggy scenes respectively. Thus, a scenario of misleading results has been presented by our network when the learning rate more than 0.0001. The base for selecting the number of epochs as 20 is that during the experiment we found when setting the number of epochs to 5, we got a model with 92 accuracies. Then at 10 and 15 epochs, we found that CAR is the same where have increased to 95%. After that we have increased the number of epochs to 20, we found there is less increase in the CAR rate with a score of 96%. However, to this limit, we found no point in increasing the number of epochs since we achieved a good CAR rate besides the level of CAR has increased with a small rate.

In this work, the performance of four different deep learning models (e.g., ResNet-50, VGG-19, Inception-V3, and Xception) were assessed using the testing set in the foggy dataset. Each model was trained using Adam optimizer using a learning rate policy where the learning rate decreases when learning does not advance for some time. The hyperparameters displayed in Table VI used for training purposes. We use a batch re-balancing strategy for better distribution of each foggy class at a batch level. The proposed foggy classification system

was built using the Keras deep learning library with a TensorFlow backend. Based on equations (1, 2,3, and 4) the overall evaluation results for ResNet-50 with other deep learning models are presented in Table VI, where each of CAR, Recall, Precision, and F1-Score are used as indicators for comparison scenario. In the multiclass problems, the calculation is performed as the average of each per-class metric [58]. The best performance has been presented by each of ResNet-50 and VGG-16 models. However, as one can see that comparing with the other three deep learning models, the best performance was achieved using the ResNet-50 model with CAR of 96 %, Recall of 96%, Precision of 96%, and F1-Score of 96%. This was followed by the VGG-16 model that achieved a higher result than Inception-V3 and Xception models in terms of all evaluation metrics values. Each of Inception-V3 and Xception got the poorest performance values among the four deep learning models. Where the minimum values of evaluation metrics have scored by these models, for instance, the CAR value has not exceeded more than 66% for Xception, and 62% for the Inception-V3 model. Xception is better than Inception-V3, especially in terms of F1-Score value. The ResNet-50 model has adequate results as it is the most massive deep learning structure among other pre-trained models (VGG-16, Inception-V3, and Xception). Since the ResNet-50 model allows the information flow through the network with residual connections, that is, the gradient value does not diminish through backpropagation, and the deepest structures have the best classification performance.

TABLE VI. THE PERFORMANCE COMPARISON OF THE ADOPTED FOUR DEEP LEARNING MODELS

Quantitative Measures	Xception	VGG-16	Inception-V3	ResNet-50
<b>CAR</b>	0.66	0.92	0.62	0.96
<b>Recall</b>	0.66	0.92	0.62	0.96
<b>Precision</b>	0.71	0.92	0.67	0.96
<b>F1-Score</b>	0.67	0.91	0.58	0.96

Multi-class classification is prone to imbalance issue which could present compromised performance; therefore, we must highlight the CAR for each class to measure the performance of our model per each foggy scene class. Four confusion matrices with normalized values are presented in Fig. 5.

The ResNet-50 model has the highest classification result per each foggy scene class. This model managed to correctly detect 310 (95% detection rate) out 328 as dark foggy images, 287 (94%) as homogenous foggy images, 193 (91%) as inhomogeneous foggy images, and 536 (99%) as sky foggy images. On the other hand, the VGG-16 model has succeeded to detect 292 (91%) as dark, 274 (84%) as homogenous, 186 (90%) as inhomogeneous, and 529 (97%) as sky foggy images.

The Xception model has a lower rate of detection than the previous two models in all foggy classes, where only 202 (62%) detected as dark, 200 (65%) as homogenous, 134 (64%) as inhomogeneous, and 385 (69%) as sky foggy images. Finally, the lowest detection rate has scored by Inception-V3 in all foggy image classes except for sky foggy class, where this model has presented a significant performance with a detection rate equal to 97% (536 out of 555 foggy sky images); also this model has the same results when comparing with VGG-16 based on detection for sky foggy images. Furthermore, this model has only detected 166 (51%) as dark, 141 (46%) as homogenous, and 25 (12%) as inhomogeneous foggy images. However, based on the results of four deep learning models, overall, the maximum misclassification (low detection) rate has been scored by Inception-V3 in terms of inhomogeneous foggy images where 88% of images are classified incorrectly. On the other hand, the lowest misclassification (highest detection) rate can be seen in the ResNet-50 wherein the foggy sky class only 1% of images



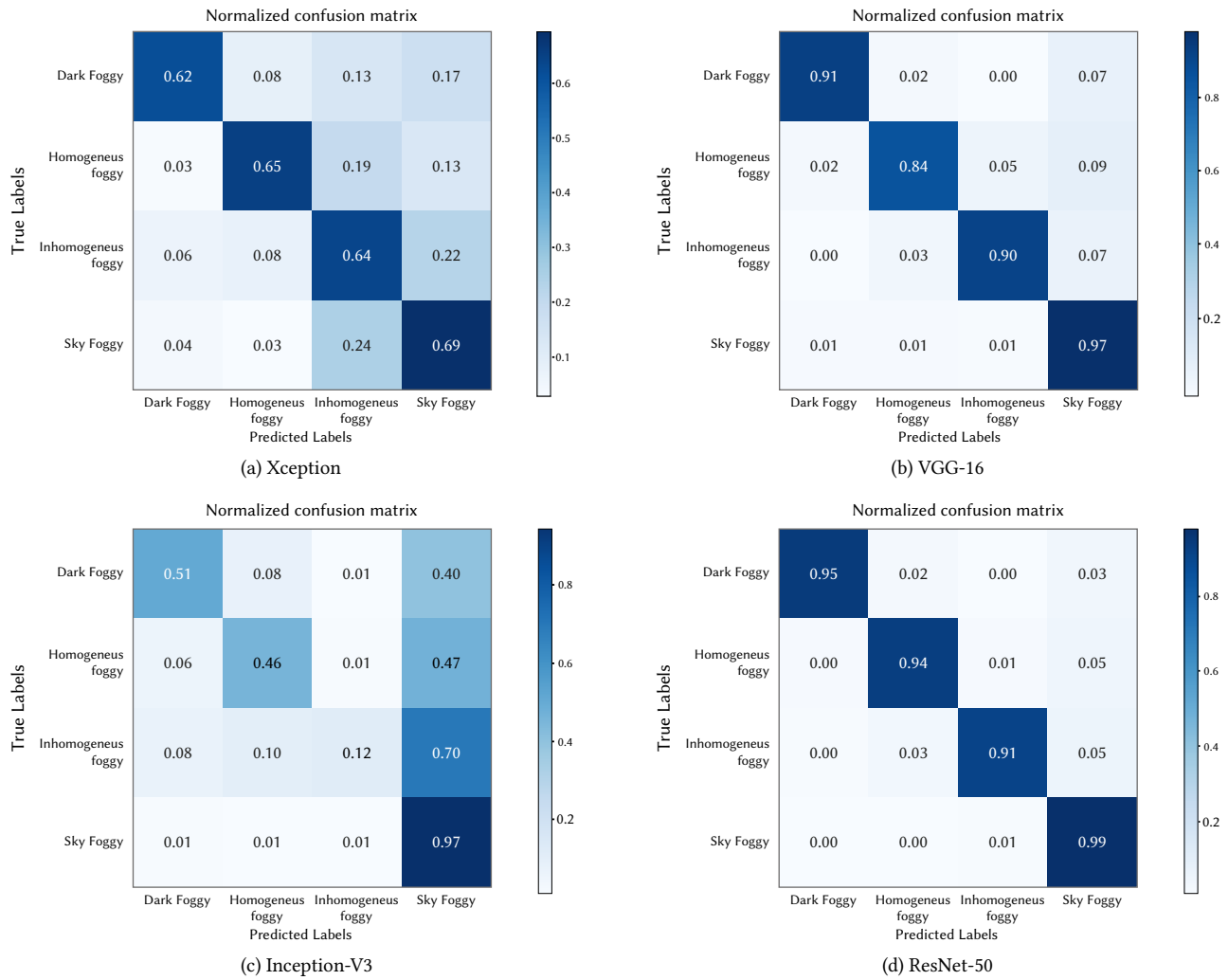


Fig. 5. Confusion matrices: (a) Xception (b), VGG-19, (c) Inception-V3, and (d) ResNet-50.

have classified incorrectly. To end, the classification performance is balanced overall classes and in almost all models except Inception-V3 which presented high imbalance classification performance.

## V. DISCUSSION

### A. Application Scenario

Our foggy image detection model can perform in real-time applications and is suitable as a pre-processing step, for many real-world applications such as basic image defogging, traffic surveillance systems, and driving assistance applications (3-D scene reconstruction in foggy weather, object detection, and recognition, etc.). Our detection model can serve in the driver assistant system as adaptive approach from multi perspectives, first, in the driver assistant system where the car is considered as a non-fixed object that can move through different fog environments, day, night, city, and mountains. For instance, when the car moves on the road in the daytime with fixed fog density in the air, thus the most suitable to detect the foggy scene is the detection algorithm based on the homogenous foggy scene. Second, when the car move inside the city at nighttime and more artificial lights are presented with fog. In this scenario, the most dominant detection algorithm is that based on detecting the dark foggy image. Third, when the car moves on the top of the mountain where the scene is including two aspects. The captured image may contain a wide area of sky in the image. Most of the fog in the mountain area is unevenly distributed;

thus, the inhomogeneous foggy scene is presented. Therefore, an adaptive detection algorithm is needed to detect the sky foggy scene besides detecting the inhomogeneous foggy scene whenever presented. To end, our detection model can fulfill the conditions of detection in each one of the previously mentioned cases. Moreover, even if all scenarios are presented together or individually, our algorithm can tackle the issues of detection in different foggy environments; thus, the primary goal of our proposed model is achieved. Furthermore, to provide users with a cost-efficient solution for contrast restoration in driving scenarios, the possibility of our algorithm if can be ported on mobile devices still questionable where more lightweight deep learning architecture is needed for such applications.

### 1. Comparison With State-Of-The-Art Methods

Since our study classified foggy images based and deep learning model and deep features, these two aspects have used as criteria for selecting the benchmark study.

According to the related works section, we found that the most relevant study to our work was study [22]. However, this study has tested only binary classification where the model classified images as foggy and non-foggy type. For this reason, we implemented the same model based on our dataset where the model classifies images to inhomogeneous, homogeneous, dark, and sky foggy image. Table VII show the comparison with state-of-the-art method based on well know evaluation metrics.

TABLE VII. COMPARISON WITH STATE-OF-THE-ART METHODS

Quantitative Measures	Study [22]	Proposed model
CAR	0.67	0.96
Recall	0.67	0.96
Precision	0.71	0.96
F1-Score	0.64	0.96

Table VII showed that proposed model outperformed the benchmark study in all quantitative measures. Thus, the proposed study has presented very efficient performance compared with benchmarked study.

## 2. Limitations

- Some images are confused with other images such as sky images with homogenous and inhomogeneous where some of these images may contain sky area but with different ranges so maybe the model misclassified images (create overlapping scenario), in other words, classify homogeneous and inhomogeneous images as sky ones. So, with image segmentation technique could solve such issue and define the region of interests in the homogenous and inhomogeneous foggy scene.
- When we configured our model with 0.001 learning rate, we found that our model cannot detect homogenous foggy images at all and have misleading results. Where 194 out of 308 homogenous foggy images were classified as sky foggy images, 78 images classified as dark foggy, and 36 images as inhomogeneous foggy. Besides the same learning rate, the CAR rate has been achieved was only 70%. While less than 0.001 we have achieved good CAR beside there are no misleading results.
- More real datasets based on four foggy scenes (inhomogeneous, homogenous, sky, and dark) are needed to build rather than only depend on the image augmentation techniques because even with advantages of this techniques it provides geometrical transformations for the images but unfortunately this does not reflect different fog characteristics in the foggy images which are the base for the scene complexity.

## VI. CONCLUSIONS

The main contributions of this paper lie in two folds. First, the development of a new detection model for multi-fog scenes based on a deep learning approach. Second, a collected dataset of multi-fog images based on publicly available datasets is presented. A total of 1166 different foggy images are collected from different resources. To provide an efficient training process by tackle overfitting and imbalanced dataset issues, the same set has increased to 6991 foggy images by using data augmentation techniques. More pre-processing procedures have been applied to the datasets. The 6991 images are the basis for the training, validation, and testing of the proposed model.

Our proposed method has successfully detected the foggy images with different fog types, including inhomogeneous, homogeneous, dark, and sky foggy scene. The processes and steps of the proposed detection model were described. The development of the proposed deep learning detection model was formed based on ResNet-50 architecture. To verify the efficiency of the proposed model, an evaluation experiment has been conducted based on different measurements as well as within different deep learning models. The results confirm that:

(1) Comparing with the other three deep learning models; the best performance was achieved using the ResNet-50 model with CAR of 96 %, Recall of 96%, Precision of 96%, and F1-Score of 96%. This was followed by VGG-16 model that achieved a higher result than the Inception-V3 and Xception models in terms of all evaluation metrics values.

(2) The ResNet-50 model has the highest classification result per each foggy scene class. This model managed to correctly detect 310 (95% detection rate) out 328 as dark foggy images, 287 (94%) as homogenous foggy images, 193 (91%) as inhomogeneous foggy images, and 536 (99%) as sky foggy images.

(3) Based on the results of four deep learning models, overall, the maximum misclassification (low detection) rate has been scored by Inception-V3 in terms of inhomogeneous foggy images where 88% of images are classified incorrectly. On the other hand, the lowest misclassification rate can be seen in the ResNet-50 wherein the foggy sky class only 1% of images have classified incorrectly. This is followed by 5% as a misclassification rate for dark, 6% for homogenous, and 8% for inhomogeneous.

## ACKNOWLEDGMENT

This work is funded by the projects SP2022/18 and SP2022/34, assigned to VSB-Technical University of Ostrava, the Ministry of Education, Youth and Sports in the Czech Republic.

## REFERENCES

- [1] O. Iparraguirre, A. Amundarain, A. Brazalez, and D. Borro, "Sensors on the move: Onboard camera-based real-time traffic alerts paving the way for cooperative roads," *Sensors*, vol. 21, no. 4, p. 1254, 2021, doi:10.3390/s21041254.
- [2] A. Ronen, E. Agassi, and O. Yaron, "Sensing with polarized lidar in degraded visibility conditions due to fog and low clouds," *Sensors*, vol. 21, no. 7, p. 2510, 2021, doi:10.3390/s21072510
- [3] Z. Liu, Y. He, C. Wang, R. Song, "Analysis of the Influence of Foggy Weather Environment on the Detection Effect of Machine Vision Obstacles," *Sensors*, vol. 20, no. 2, p. 349, 2020, doi: 10.3390/s20020349
- [4] G. Broughton, F. Majer, T. Rouček, Y. Ruichek, Z. Yan, and T. Krajník, "Learning to see through the haze: Multi-sensor learning-fusion system for vulnerable traffic participant detection in fog," *Robotics and Autonomous Systems*, vol. 136, p. 103687, 2021 doi:10.1016/j.robot.2020.103687
- [5] D. Nair and P. Sankaran, "Color image dehazing using surround filter and dark channel prior," *Journal of Visual Communication and Image Representation*, vol. 50, pp. 9-15, 2018.
- [6] Y. Xu, J. Wen, L. Fei, and Z. Zhang, "Review of Video and Image Defogging Algorithms and Related Studies on Image Restoration and Enhancement," *IEEE Access*, vol. 4, pp. 165-188, 2016.
- [7] S. G. Narasimhan and S. K. Nayar, "Vision and the atmosphere," *International Journal of Computer Vision*, vol. 48, no. 3, pp. 233-254, 2002.
- [8] K. H. Abdulkareem, et al., "A Novel Multi-Perspective Benchmarking Framework for Selecting Image Dehazing Intelligent Algorithms Based on BWM and Group VIKOR Techniques," *International Journal of Information Technology & Decision Making*, Vol. 19, no. 3, pp. 909-957, 2020.
- [9] K. H. Abdulkareem et al., "A new standardisation and selection framework for real-time image dehazing algorithms from multi-foggy scenes based on fuzzy Delphi and hybrid multi-criteria decision analysis methods," *Neural Computing and Applications*, Vol. 33, no. 4, pp. 1029-1054, 2021.
- [10] W. Wang and X. Yuan, "Recent advances in image dehazing," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 3, pp. 410-436, 2017.
- [11] C. Qu, D.-Y. Bi, P. Sui, A.-N. Chao, and Y.-F. Wang, "Robust Dehaze Algorithm for Degraded Image of CMOS Image Sensors," *Sensors*, vol. 17, no. 10, p. 2175, 2017.
- [12] J.-M. Guo, J.-y. Syue, V. R. Radzicki, and H. Lee, "An efficient fusion-based defogging," *IEEE Transactions on Image Processing*, vol. 26, no. 9, pp. 4217-4228, 2017.
- [13] N. Baig, M. M. Riaz, A. Ghafoor, and A. M. Siddiqui, "Image dehazing using quadtree decomposition and entropy-based contextual regularization," *IEEE Signal Processing Letters*, vol. 23, no. 6, pp. 853-857, 2016.
- [14] K. Kim, S. Kim, and K.-S. Kim, "Effective image enhancement techniques for fog-affected indoor and outdoor images," *IET Image Processing*, vol. 12, no. 4, pp. 465-471, 2017.

- [15] Y. Wang and P. Yuen, "Image dehazing based on partitioning reconstruction and entropy-based alternating fast-weighted guided filters," *Optical Engineering*, vol. 56, no. 5, p. 053111, 2017.
- [16] A. Alajarmeh, R. A. Salam, K. Abdulrahim, M. F. Marhusin, A. A. Zaidan, and B. B. Zaidan, "Real-time framework for image dehazing based on linear transmission and constant-time airlight estimation," *Information Sciences*, vol. 436–437, pp. 108-130, 2018.
- [17] K. Tang, J. Yang, and J. Wang, "Investigating Haze-Relevant Features in a Learning Framework for Image Dehazing," in 2014 IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 2995-3002.
- [18] Y. Shi and X. Jiang, "Deep quality assessment toward defogged aerial images," *Signal Processing: Image Communication*, vol. 83, p. 115808, 2020.
- [19] C. Qing, Y. Hu, X. Xu, and W. Huang, "Image haze removal using depth-based cluster and self-adaptive parameters," in 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 2017, pp. 1070-1075: IEEE.
- [20] M. Pavlić, H. Belzner, G. Rigoll, and S. Ilić, "Image based fog detection in vehicles," in 2012 IEEE Intelligent Vehicles Symposium, 2012, pp. 1132-1137: IEEE.
- [21] Y. Liu, J. Pan, J. Ren, and Z. Su, "Learning deep priors for image dehazing," in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 2492-2500.
- [22] L. Guo et al., "Haze Image Classification Method Based on Alexnet Network Transfer Model," in *Journal of Physics: Conference Series*, 2019, vol. 1176, no. 3, p. 032011: IOP Publishing.
- [23] H. Zhang, V. Sindagi, and V. M. Patel, "Multi-scale single image dehazing using perceptual pyramid deep network," in Proceedings of the IEEE conference on computer vision and pattern recognition workshops, 2018, pp. 902-911.
- [24] C. Hernandez-Olivan, J. R. Beltran, and D. Diaz-Guerra, "Music Boundary Detection using Convolutional Neural Networks: A comparative analysis of combined input features," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 7, no. 2, pp. 78-88, 2021, <https://doi.org/10.9781/ijimai.2021.10.005>.
- [25] M.I. Khattak, et al., "Automated detection of COVID-19 using chest x-ray images and CT scans through multilayer-spatial convolutional neural networks," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 6, no. 6, pp. 15-24, 2021. <https://doi.org/10.9781/ijimai.2021.04.002>.
- [26] Y. Chen, J. Wang, S. Li, and W. Wang, "Multi-feature based Foggy Image Classification," in *IOP Conference Series: Earth and Environmental Science*, 2019, vol. 234, no. 1, p. 012089: IOP Publishing.
- [27] M. Pavlic, G. Rigoll, and S. Ilic, "Classification of images in fog and fog-free scenes for use in vehicles," in 2013 IEEE Intelligent Vehicles Symposium (IV), 2013, pp. 481-486: IEEE.
- [28] Y. Xu, J. Wen, L. K. Fei, and Z. Zhang, "Review of Video and Image Defogging Algorithms and Related Studies on Image Restoration and Enhancement," *IEEE Access*, vol. 4, pp. 165-188, 2016.
- [29] H. Shi, Q. Wang, and L. Xie, "A Method of Automatic Detection of Fog Image Based on SVM Classification," *Revista de la Facultad de Ingenieria*, vol. 31, no. 9, pp. 211-218, 2016.
- [30] X. Yu, C. Xiao, M. Deng, and L. Peng, "A classification algorithm to distinguish image as haze or non-haze," in 2011 Sixth International Conference on Image and Graphics, 2011, pp. 286-289: IEEE.
- [31] J.-P. Tarel, N. Hautiere, A. Cord, D. Gruyer, and H. Halmaoui, "Improved visibility of road scene images under heterogeneous fog," in 2010 IEEE Intelligent Vehicles Symposium, 2010, pp. 478-485: IEEE.
- [32] Y. Li, R. T. Tan, and M. S. Brown, "Nighttime haze removal with glow and multiple light colors," in Proceedings of the IEEE International Conference on Computer Vision, 2015, pp. 226-234.
- [33] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE transactions on pattern analysis and machine intelligence*, vol. 33, no. 12, pp. 2341-2353, 2011.
- [34] D. Berman, T. Treibitz, and S. Avidan, "Air-light estimation using haze-lines," in 2017 IEEE International Conference on Computational Photography (ICCP), 2017, pp. 1-9: IEEE.
- [35] Y. Zhang, G. Sun, Q. Ren, and D. Zhao, "Foggy images classification based on features extraction and SVM," in 2013 International Conference on Software Engineering and Computer Science, 2013: Atlantis Press.
- [36] S. Shrivastava, R. K. Thakur, and P. Tokas, "Classification of hazy and non-hazy images," in 2017 International Conference on Recent Innovations in Signal processing and Embedded Systems (RISE), 2017, pp. 148-152: IEEE.
- [37] Y. Liu, H. Li, and M. Wang, "Single image dehazing via large sky region segmentation and multiscale opening dark channel model," *IEEE Access*, vol. 5, pp. 8890-8903, 2017.
- [38] Y. Song, H. Luo, J. Ma, B. Hui, and Z. Chang, "Sky detection in hazy image," *Sensors*, vol. 18, no. 4, p. 1060, 2018.
- [39] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770-778.
- [40] Z. Chen, Z. Xie, W. Zhang, and X. Xu, "ResNet and Model Fusion for Automatic Spoofing Detection," in INTERSPEECH, 2017, pp. 102-106.
- [41] R. K. Srivastava, K. Greff, and J. Schmidhuber, "Highway networks," 2015. Arxiv:1505.00387
- [42] R. Fattal, "Dehazing using color-lines," *ACM transactions on graphics (TOG)*, vol. 34, no. 1, p. 13, 2014.
- [43] C. O. Ancuti, C. Ancuti, R. Timofte, and C. De Vleeschouwer, "O-haze: a dehazing benchmark with real hazy and haze-free outdoor images," in Proceedings of the IEEE conference on computer vision and pattern recognition workshops, 2018, pp. 754-762.
- [44] K. D. Ma, W. T. Liu, and Z. Wang, "Perceptual evaluation of single image dehazing algorithms," in 2015 IEEE International Conference on Image Processing, 2015, pp. 3600-3604.
- [45] L. K. Choi, J. You, and A. C. Bovik, "Referenceless prediction of perceptual fog density and perceptual image defogging," *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 3888-3901, 2015.
- [46] A. Galdran, J. Vazquez-Corral, D. Pardo, and M. Bertalmio, "Fusion-based variational image dehazing," *IEEE Signal Processing Letters*, vol. 24, no. 2, pp. 151-155, 2016.
- [47] B. Li et al., "Benchmarking Single-Image Dehazing and Beyond," *IEEE Transactions on Image Processing*, vol. 28, no. 1, pp. 492-505, 2019.
- [48] J. Li, G. Li, and H. Fan, "Image dehazing using residual-based deep CNN," *IEEE Access*, vol. 6, pp. 26831-26842, 2018.
- [49] Y. Qu, Y. Chen, J. Huang, and Y. Xie, "Enhanced pix2pix dehazing network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 8160-8168.
- [50] J. Zhang and D. Tao, "FAMED-Net: a fast and accurate multi-scale end-to-end dehazing network," *IEEE Transactions on Image Processing*, vol. 29, pp. 72-84, 2019.
- [51] X. Zhu, X. Xu, and N. Mu, "Saliency Detection Based on the Combination of High-Level Knowledge and Low-Level Cues in Foggy Images," *Entropy*, vol. 21, no. 4, p. 374, 2019.
- [52] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097-1105.
- [53] Abayomi-Alli, O. O., Damasevicius, R., Maskeliunas, R., & Abayomi-Alli, A. (2020). "BiLSTM with data augmentation using interpolation methods to improve early detection of parkinson disease," *Proceedings of the 2020 Federated Conference on Computer Science and Information Systems, FedCSIS 2020*, 371-380. doi:10.15439/2020F188
- [54] Abayomi-Alli, O. O., Damaševičius, R., Wiczorek, M., & Woźniak, M. (2020). "Data augmentation using principal component resampling for image recognition by deep learning," In *Artificial Intelligence and Soft Computing* (pp. 39–48). Springer International Publishing. doi:10.1007/978-3-030-61534-5\_4
- [55] Arif, Zainab Hussein, et al. "Comprehensive Review of machine Learning (ML) in Image Defogging: Taxonomy of Concepts, Scenes, Feature Extraction, and Classification techniques," *IET Image Processing* (2021)
- [56] K. H. Abdulkareem, et al., "Mapping and Deep Analysis of Image Dehazing: Coherent Taxonomy, Datasets, Open Challenges, Motivations, and Recommendations," *International Journal of Interactive Multimedia and Artificial Intelligence*, Vol. 7, no. 2, pp. 172-198, 2021.
- [57] Al-Mhiqani, Mohammed Nasser, et al. "New insider threat detection method based on recurrent neural networks," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 17, no. 3, pp. 1474-1479, 2020.
- [58] M. Hossin, and D. M. Sulaiman, "A review on evaluation metrics for data classification evaluations," *International Journal of Data Mining & Knowledge Management Process*, vol. 5, no. 2, pp. 1-11, 2015.



Zainab Hussein Arif

Zainab Hussein Arif received the B.Sc. degree in computer science and information technology, in 2016 from University of Qadisiyah. She obtained master degree Universiti Tenaga Nasional (Uniten) in 2021 in computer science and information technology. Her research interests include data science and biomedical computing. Link: <https://scholar.google.com/citations?user=ecBErWQAAAAJ&hl=en&authuser=1>



Moamin A. Mahmoud

Moamin A. Mahmoud received the bachelor's degree in mathematics from the College of Mathematics and Computer Science, University of Mosul, Iraq, in 2007, the Master of Information Technology degree from the College of Graduate Studies, Universiti Tenaga Nasional (UNITEN), Malaysia, in 2010, and the Ph.D. degree in information and communication technology from UNITEN, in 2013. Since 2014, he has been with the Department of Software Engineering, Universiti Tenaga Nasional, as a Senior Lecturer. His current research interests include artificial intelligence, distributed and autonomous systems, complex adaptive systems, and the IoT-based smart systems.



Karrar Hameed Abdulk

Karrar Hameed Abdulkareem received the B.S. degree in computer science (Artificial Intelligence) from the University of Technology, Iraq, in 2007, and the M.S. degree in computer science (Internetworking Technology) from the Universiti Teknikal Malaysia Melaka (UTeM), Malaysia, in 2016. He Obtained Ph.D. degree in Computer Science and Information Technology from Universiti Tun

Hussein Onn Malaysia (UTHM), Malaysia. He has produced more than 55 articles into different ISI Web of Science journals, such as IEEE internet of things, Journal of King Saud University - Computer and Information Sciences, Computer methods and programs in biomedicine (Elsevier), Neural Computing and Applications (Springer), IEEE Access, Journal of infection and public health (Elsevier), International Journal of Information Technology & Decision Making (World Scientific), Computers, Materials & Continua (Tech Science Press), Soft Computing (Springer), and Sensors (MDPI). He has a total number of citations over 1666 (Google Scholar H-Index = 23). He has collaborated with many researchers over international countries. He has served as a reviewer for more than 28 international journals. His research area includes Multi-Criteria Decision Making, Artificial Intelligence, Data Science, and Fog Computing.



Seifedine Kadry

Seifedine Kadry (Senior Member, IEEE) received the bachelor's degree from Lebanese University, in 1999, the dual M.S. degree from Reims University, France, in 2002, and EPFL, Lausanne, the Ph.D. degree from Blaise Pascal University, France, in 2007, and the H.D.R. degree from Rouen University, in 2017. His current research interests include data science, education using technology, system

prognostics, stochastic systems, and probability and reliability analysis. He is an ABET Program Evaluator of computing and an ABET Program Evaluator of Engineering Tech.



Mazin Abed Mohammed

Mazin Abed Mohammed received the B.Sc. degree in computer science from the University of Anbar, Iraq, in 2008, the M.Sc. degree in information technology from UNITEN, Malaysia, in 2011, and the Ph.D. degree in information technology from UTeM, Malaysia, in 2019. He is currently a Lecturer with the College of Computer Science and Information Technology, University of Anbar,

Iraq. His research interests include artificial intelligence, biomedical computing, and optimization.



Mohammed N. Al-Mhiqani

Mohammed N. Al-Mhiqani received his BSc in Computer Science (Computer Networking) in 2014, his MSc in Computer Science (Internetworking Technology) from Universiti Teknikal Malaysia Melaka (UTeM) in 2015, and his PhD in cybersecurity and artificial intelligence from UTeM in 2022. He joined the School of Computing and Mathematics at Keele University in 2022 as a postdoctoral research associate. His research interests include cybersecurity, cyber physical systems security, insider threats, artificial intelligence, and health informatics.



Alaa S. Al-Wais

Alaa S. Al-WaisY is a doctor of philosophy in computer science. He received his BSc in 2009 and MSc in 2011 in computer science from Al-Anbar University. In 2018, he received PhD in digital imaging and visualization from the University of Bradford. His research interests include pattern recognition, image processing, computer vision, medical imaging, designing and implementing unimodal and multimodal biometric systems.



Jan Nedoma

Jan Nedoma (Senior Member, IEEE) is currently an Associate Professor and the Head of the Optoelectronics Laboratory with the Department of Telecommunications, Faculty of Electrical Engineering and Computer Science, Technical University of Ostrava. He is a member of the scientific council, a member of doctoral, habilitation, and professors' committees, and a Guarantor of bachelor's study programs at Faculty of Electrical Engineering and Computer Science, Technical University of Ostrava. During his scientific career, he was the Leader or a co-investigator of more than 25 projects and has more than 175 journal articles and conference papers in his research areas. He holds ten valid Czech patents. His research interests include optical communications, optical atmospheric communications, optoelectronics, optical measurements, measurements in telecommunication technology, signal processing, fiber-optic sensors, and biomedical engineering.