Dcnn Based Technique to Analyze the Data of Cloudy and Snowy Season

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Abstract

Image Quality Analysis (IQA) is most significant concepts that is gaining attention among the researchers. Most images are considerably influenced by ambient lights. HumanVisual System perceives theimages quality in day and night time that causes the deprivation of luminance and features. In this article, we put forward an adaptive fuzzy-based DCNN technique that estimates the loss and enhancement of the images during seasonal changes. The natural scenery images are collected and preprocessed using Gaussian filter method that removes the unwanted noises. The preprocessed image is then guided with a guided filter method that helps to segment the seasonal changes of an image. The statistical features are extracted from the Adaptive Fuzzy-based Gamma Correction method that specifically leverages the gamma parameters using fuzzy-based decisional approach. Further on, the Deep Convolutional Neural Networks (DCNN) is running to classify the seasonal changes on images based on the computed image quality score. Investigational result have proven the accuracy of suggested technique in concerning of accuracy, precision and recall.

Keywords: *Image Quality Assessment (IQA), Human Visual System, Seasonal changes, Deep Convolutional Neural Networks, Gamma Correction.*

1. Introduction

The advancement made in digital technologies introduced several benefits for real-time applications. The recognition of multiple objects from an image is a tedious task due to various intrinsic and extrinsic properties. Thus, the methodological point of research has to be addressed. An efficient mining system deals with the features related to storage, processing, extraction, indexing, retrieval and patterns [1]. On the basis of requirements, it is grouped into two kinds, namely, function-oriented and information-oriented. In recent times, function-oriented image analysis is widely studied by researchers. Classification and clustering of the images are done on the basis of specific criteria. It can be either supervised (or) unsupervised classification systems [2]. In the viewpoint of supervised classification, the unlabelled images are grouped by the previous labelled images, whereas, in the aspect of unsupervised classification, the unlabelled images are grouped into meaningful clusters based on the image content. The important cause supporting the developmental growth of image excavation is the ability to conclude knowledge from the data of image using intelligent techniques. In order to draw out the high-level objects and their association with the pictures, the concepts of image excavation can be efficiently used on the low-level images.

Ambient light frequently causes not only contrast distortions even also brightness depletion in HVS. Specifically, in the brightness depletion is more serious, strong ambient light which causes dark perception. Nevertheless, only luminance enhancement guide to detail loss by a non-linear transfer function (e.g. gamma function) which increases contrast and increases luminance in a low intensity range [5,6]. Consequently, ambient light affects details in displayed images.The development of rapid PC systems and the World Wide Web (WWW) investigated methods for new market, rational, diversion and social open doors such as electronic distribution and advertisement, rubbing, continuous data transmission, knowledge sharing, organized effort among PCs, exchange requests, digital stores and libraries, web papers and magazines, video and sound arrangements [8]. Regardless of the increase in creativity, the cost viability of selling virtual goods as computerized images and video arrangements via transmission over WWW has increased extraordinarily. We know that one of the biggest revolutionary occasions of the last two decades has been the penetration of computerized media into a whole range of normal everyday angles of life.Digital data can be skillfully and with an exceptionally high quality, and PCs can be easily managed using it as well. In addition, digital information [9] can be transmitted quickly and cost-effectively via information correspondence systems, without losing quality. Advanced media provides a few preferences in particular over basic media. Digital speech, pictures, and video signals are of a higher quality than their simple partners. Change is easy because one can get to the specific discrete places that should be modified. Duplicating is necessary without any loyalty misfortunes [10]. The stages of quality assessment can be done on images from the levels:

- Pixel level: It is the lowest level of an image mining system. It operates on the raw data of the images such as colours, texture and shape of an image pixel. It helps to retrieve the images based on the defined features.
- Object-level: It resolves the limitations of pixel levels. With the help of features, it retrieves the image with similar objects.
- Semantic level: Since the object level could not deal with the recognition of a set of regions, the concept of the semantic level is used. Here, the known objects are trained, so as to respond to the relevant queries.
- Pattern level: The training features are referred to as patterns. The unlabelled data arematched with pattern and thus, the class of the objects is done.

2. *Literature Review*

This section includes study of various existing research techniques on image enhancement methods and the effect of seasonal changes on the image quality. The study of associated work includes the performance enhancement of display images and application of machine learning and deep learning-based algorithms for estimating the losses and enhancement of image data during seasonal changes. The objective-based Image Quality Assessment (IQA) has been developed rapidly on hand-crafted based features and the deep neural network-based features. The image quality score of the hand-crafted features is obtained from empirical observations. In [11], the authors have extracted the features using NSS technique,wherein the feature vectors are collected from discrete cosine coefficients. Finally, the Bayesian inference method was used to forecast the picture quality score. The authors in [12] have presented empirical distribution models to learn the features using spatial NSS models. The gradient data of an image was forecasted to determine the quality score. Similar to this, No Reference (NR)- IQA model [13] was designed to quality score calculation that was used for gradient magnitude map and the laplacian of gaussian response. The joint statistics of the two models were jointly performed to calculate the quality score before and after improvements. In continuation to it, gradient statistical information using gradient magnitude and gradient orientation [14] was studied to process the images. Further, AdaBoosting back-propagation neural network was also employed to classify images based on the quality score. It was explored in the analysis of perceptual qualities of stereoscopic images. It was mainly designed for the applications dealing with the characteristics of binocular vision, such as binocular fusion, binocular suppression and binocular energy response (BER). Henceforth, the concept of binocular visual characteristics of NR-SIQA models was designed.

The author in [15] explored the quality assessment process over the cyclopean images. The quality of the fused images were explored during the image fusion process. In [16], the NR-SIQA algorithm was designed to explore the superpixel images using the transmutation process of binocular perception models. However, the accuracy of the superpixel images are not remarkable. In [17], the authors have discussed the NR-SIQA technique which involved the concept of local patterns of BER and binocular rivalry response. The model has improved the precision of the BER than BRR. In [18], a self-similarity of BRR and BER in 3D images wasstudied. The image quality score was determined by the SVR. Moreover, the hand-crafted feature vectors that reduced the robustness. This was explored on the deep neural networks. In [19], multi-level representation models using VGGnet models explored the efficiency of the image quality. The hidden layers have introduced the levels of the image quality. This was extended to attention-based pooling networks [20] was studied to enhance the pooling issues. The automation of the local weight estimation was done to increase the local quality. This has not improved deep layers, however, quality of image at different stages was not ensured.

Author in [21] presented an improved Convolutional Neural Networks (CNN) on the NR-IQA algorithm. This was to eliminate the overlapping of pixels during the binding process of homogeneous. The network training on different metrics that were introduced for quality estimation. In [22], the authors have presented the quality of the images using structural semantics and spatial semantics. This was introduced to remove the quality of images by efficient noise removals. It was further explored on a feature-segmentation strategy to train CNN models without any pre-processing. Generative Adversarial Network (GANs) [23] was designed to explore new metrics for the quality assessment. The highly complicated neurons were not properly analyzed during the image quality assessment. Thus, it was not suitable for SIQA. the characteristics of the stereoscopic images in the deep neural network on NR-SIQA algorithms. However, the scalability of the designed network is not assured. In [24], the author has utilized segmented stacked autoencoders to simulate the complex structure of the visual cortex based on the visual perception route from eyes to the frontal lobe. In [25], the author presented a two-step network structure-based NRSIQA algorithm. In the first step, they utilized the structure similarity (SSIM) to provide a ground-truth for each image patch to train local prediction models.

3. *Proposed Methodology*

This section includes the framework of the proposed adaptive fuzzy-based DCNN technique used for the design of an enhanced technique for estimating the losses and enhancing the image data irrespective of seasonal changes using contour. The proposed phases in this study are:

3.1 Data Collection: Data collection is the first phase of this study. The natural scenery images are collected from the public repository.

3.2 Data Preprocessing: It is the second phase that discusses the cleaning of the data such as reducing noise, enhancing the visual quality of an image i.e contrast and brightness. A Gaussian filter is employed to remove the irrelevant noise presented in an image. Gaussian filters are generally used for detach the noise and smoothing. This Filter comprises of 2 parameters:

i. standard deviation σ and

ii. window dimensions.

In the event that σ value is huge, the picture smoothing impact will be higher. Filters of Gaussian smoothing are effective for implementing viable LPFs from the point of view of both the frequencies and spatial domains, and can be utilized adequately by engineers in practical applications of vision. In the event that σ score is high, the image smoothing impact will be more. It is mathematically expressed as,

$$G(Image_{frame}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{i_2}{2\sigma^2}}$$

For a given image I, the gaussian noise is removed by estimating the weighted average of pixels in the adjacent positions with a weight descending from the center position i. It is represented as, For noise filtering inputs, we ensure that g and I are nonidentical; in other words, the Gaussian spatial kernel is exploited on filtering input I while the Gaussian range kernel describes the influence of pixels from low-pass guidance.

3.3 Image segmentation: The procedure of splitting a picture into group or regions communicate to the different portion or complete objects is called image segmentation. Guided filter is employed to ease the segmentation process. It modifies pixel scores using the spatial information of the input image with reference to guide image. It follows linear operation wherein the smoothening is achieved. Here, the guide image plays a significant role over the input image so as to get the output image. Let k-be the given pixel of an image I, and the guided filtered image be I_k, then the required output image is represented as I_k . The weighted average of pixels in the neighborhood is given as:

$$\tilde{I_k} = \sum_{j \in W_k} W_{kj}(I_{enhanced})I_k$$

Where,

$I_{enhanced}$represents the enhanced images.

$W_k$is a set that contains all the indexes of pixels in the neighborhood of k-th pixel.

3.4 Feature Extraction: Here, a Fuzzy adaptive gamma correction method is employed over the guided filtered image. Gamma correction is the technique employed to enhance the visual quality of the image by means of adjusting the contrast and brightness of the image. Literature states that the selection of gamma parameters is time-consuming and thus, it is resolved by Adaptive Gamma Correction (AGC). Here, the gamma value is defined from the fuzzy decision over statistical features values extracted from the images. Initially, the initial image is analyzed with color channel stretching using RGB space which is then converted into HSI color space for contrast enhancement. Then, a fuzzy based adaptive gamma correction is explored on the intensity channel of an image so as to improve the local and global image details. Atlast, the enhanced image is transmuted into the RGB format.

Let us assume input color images I(m,n) that contain RGB color space as, R(m,n); G(m,n) and B (m,n), where R for Red; G for Green; B for Blue and (m,n) denotes image width and height. The channel stretching process stretches the color of the input images into the different color channels. Then, the maximum range with different sets of color information are viewed.For an instance, the Red color channel is stretched as,

$$R(m,n) \leftarrow \frac{R(m,n) - min\{R(m,n)\}}{max\{R(m,n)\} - min\{R(m,n)\}}$$

Where,

min{.} and max{.} are the minimum and the maximum values obtained from image pixels.

Furthermore, the image enhancement is done to improve the contrast with the intention of preserving the maximum information using fuzzy based adaptive gamma correction. The transmuted pixel intensity is calculated as,

$$T\{I(m,n)\} = round$$

Here, the gamma parameter γ is calculated as,

$$\gamma = 1 - C_{fuzzy}(i)$$

Where, C_{fuzzy} is defined as,

Maximize γ

Subject to the constraints: $\gamma \leq \mu_k(Z_k)$

The HSI channel is calculated as,

$$[H(m,n), S(m,n), I(m,n)] = T_{RGB}^{HSI}[R(m,n), G(m,n), B(m,n)]$$

Where,

T_{RGB}^{HSI} is the color transformation process. Thus, by preserving the H and S channels, the intensity is also improved. Therefore, in HSI space, the channel intensity is calculated as,

$$I(m,n) = \frac{\{R(m,n)+G(m,n)+B(m,n)\}}{3}$$

Furthermore, the image enhancement is done to improve the contrast with the intention of preserving the maximum information using fuzzy based adaptive gamma correction. The transmuted pixel intensity is calculated as,

$$T\{I(m,n)\} = round$$

Here, the gamma parameter γ is calculated as,

$$\gamma = 1 - C_{fuzzy}(i)$$

Where, C_{fuzzy} is defined as,

Maximize γ

Subject to the constraints: $\gamma \leq \mu_k(Z_k)$

$$\sum_{j=1}^{n} R_{ij} \leq a_i i = 1,2.\ldots.m$$

$$\sum_{j=1}^{n} G_{ij} \leq a_i i = 1,2.\ldots.m$$

$$\sum_{j=1}^{n} B_{ij} \leq a_i i = 1,2.\ldots.m$$

The color based parameters are tuned in the adaptive fuzzy systems with the consequent parameters of the number of rules. Two steps of training are required to feed into the classification systems. Structure learning which allows one to determine the appropriate structure of a network, that is, the best partitioning of the input space (number of membership functions for each input, number of rules). And parametric learning is carried out to adjust the membership functions and consequent parameters. In most systems the structure is fixed a priori by experts. However, in our study, the learning modes are combined in a sequential process.

In order to classify the seasonal images, the formation of proper rules are incorporated into the input layer of the DCNN. In the first step, the training dataset consists of features obtained from the seasonal images fed into the fuzzy memberships that discertinates the data processing into the data with specific intervals. In the second step, the generated fuzzy rules are given into the fuzzy classifier. In the test datasets, the input is fuzzified and then the fuzzified input is matched with the fuzzy rules defined from the base of rules. Atlast, the fuzzy score is formulated from the defuzzification process in order to classify the seasonal images into snowy and cloudy. The features like entropy, colourfulness and the contrast are estimated. The fuzzy membership function definition and fuzzy rule base are the two important steps in fuzzy rule classifier. Fuzzy Membership function is designed by choosing the proper membership function. In our case, a triangular membership function is used to convert the input data into the fuzzified value.

***3.5 Image quality enhancement*:** The quality of the enhanced images are assessed by four metrics, namely,

a) Entropy: It defines the volume of information content available in an image. It is calculated as:

$$Entropy: -\sum_{i} p(i)log\big(p(i)\big)$$

b) Contrast: It is the measure of image quality that explores the local measurements used to quantize the image for better contrast. It is calculated as:

$$Contrast = \frac{1}{N}\sum_{m=1}^{M}\sum_{n=1}^{N} I^2 e^{(m,n)} - \left(\frac{1}{N}\sum_{m=1}^{M}\sum_{n=1}^{N} (I_e(m,n))\right)^2$$

c) Colorfulness: It represents the ironic color contents of an image. The larger value of colorfulness represents the highest color. It is calculated as:

$$Colorfulness = \sigma_{rgyb} + \left(0.3 \times \mu_{rgyb}\right)$$

3.6 Image Classification: Depending on the enhanced images as input, the image quality is classified using Convolutional Neural Networks (CNN). CNN is fundamentally utilized in convolving an image along with kernels to obtain feature maps. The weights within the kernels help to connect every unit of the feature map to prior layers. These kernel weights are used at the time of dataset training to enhance the input characteristics. The weights that require training within the convolutional layers are lesser than that for layers that are fully connected since the kernels are typical to each unit of the specific feature map. Depending on the enhanced images as input, the image quality is classified using Convolutional Neural Networks (CNN).

Feature vectors of each enhanced image will be fed to CNN and hence the training will be carried out. The functionality of CNN can be bifurcated into four key areas.

- The feature vectors of the enhanced image will be fed to the input layer.
- The convolutional layer decides the number of hidden neurons that are associated with the input local regions via the computation of scalar product among the regions associated with the volume of the input and the weights of the neurons.
- The fully connected layer generates scores for the quality classes with the help of activation functions that are utilized for the process of classification.
- Finally, the output neurons consist of classes of image quality such as low, medium and high.

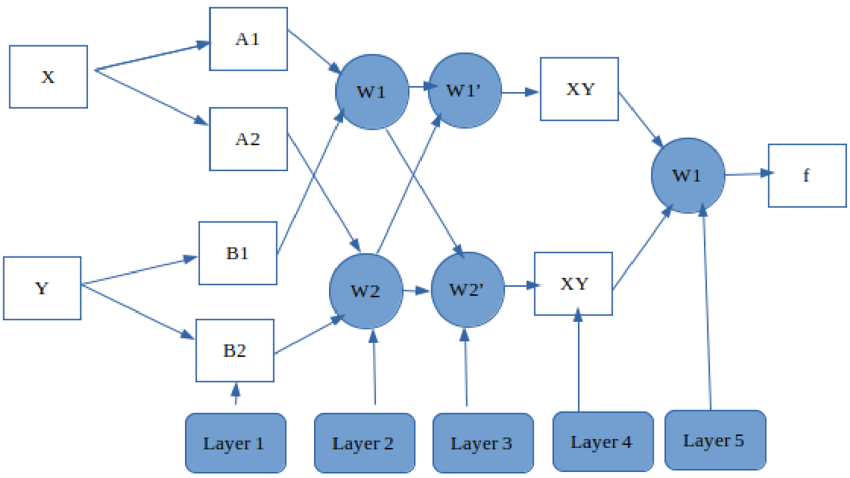


Fig.1. DCNN- Weight initialization with the adaptive fuzzy system

The fig.1 presents the weight initialization with the base of adaptive fuzzy systems. Each fuzzy layer combines with the Deep-CNN so as to convolute with the pooling and convolutions layer of the neural networks. The pooling layers in the CNNs perform on the neighboring sets of neurons of similar kernel maps. The segmented regions are sorted with the nearby pooling units. Each pooling will have the spaced pixels separately and thus, a review of region of size x* x is in the center position of the pooling unit. Generally, the network has 8 layers by weights wherein 5 layers are used as convolutional layers, two layers are fully-connected and the final layer is the flatten layer. The outcome of the flatten layers is to find out the quality of an image. The kernels of the 2-5 conv layers are attached only for individual's kernel maps in the earlier layer that reside on the similar GPU. The kernels of the third convolutional layer are inserted into the maps of the second layer. Likewise, the neurons of the fully-connected layer are mapped with the previous convoluted layer. The 2nd convolutional layers make use of the response normalization process. The mapped RN and the fifth convolutional layers are performed in max pooling layer. Similar to it, the ReLu unit has the convolutional layer with the fully connected layer. The first convolutional layer obtains the information through the strides of pixels. By combining the different versions of convolutional layers, the neurons rely on extracting the other neurons.

4. Results and Discussions:

It is a fact that MATLAB is employed for numerical computing as well as symbolic computing. Additionally, it combines with the intelligent program to represent the information in numerical form. This programming capability has extended the developmental tools for all fields of science and engineering. The tool box comprises an exhaustive arrangement of standard calculations, functions, application and representations. To organize and analyze the images, different image processing tools are available that sorts out the determination of pixels. The image is imported into matrix from as, w * h * c where, w and h are the width and height images and c is the count of channels within the images. The proposed fuzzy based CNN is compared with the existing LO gradient minimization method for different seasonal changes.

Case 1: Cloudy

Fig. 1. Input images- Cloudy

Fig. 2. Performing Gaussian filter frames

Fig. 3. IRR frames

Fig. 4. Enhanced images

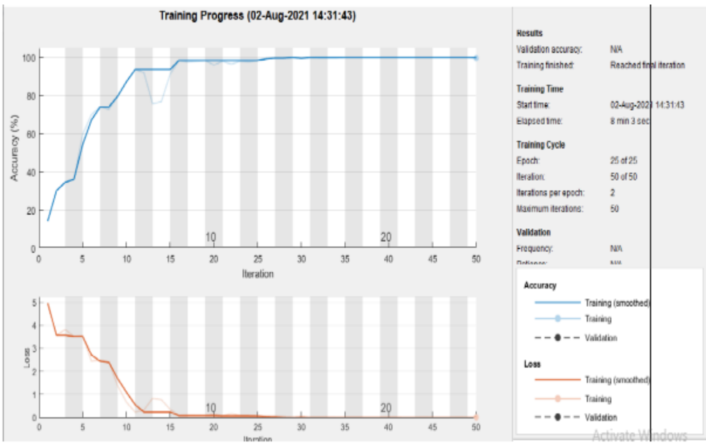
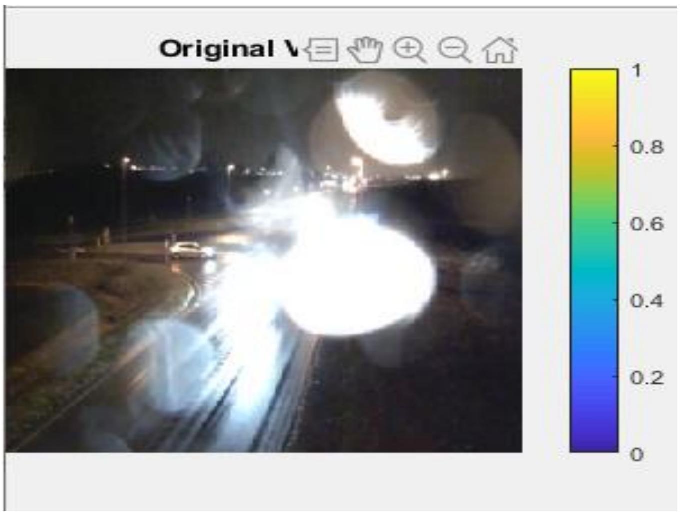


Fig. 5. Performance of CNN classifier

Case 2: Snowy



Fg. 6. Input images- Snowy

Fig. 7. Gaussian filter frames

Fig. 8. Enhanced image

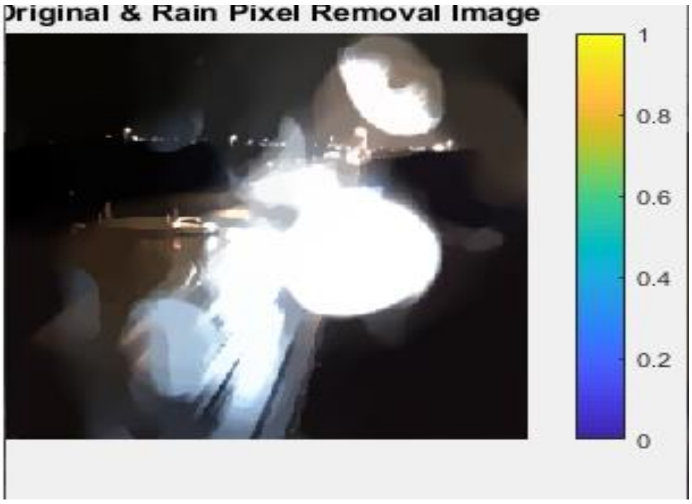


Fig. 9.Snowy pixel removal image

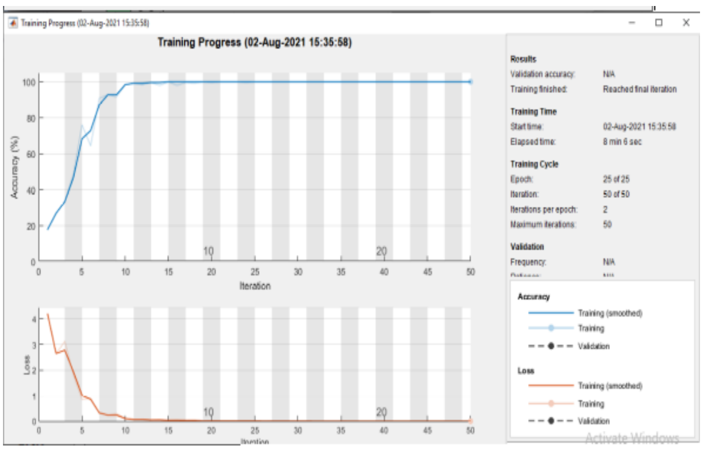


Fig. 10. Performance of CNN classifier

Table 1: Performance metric analysis of all seasonal changes

	Cloudy	Snowy
Accuracy	83.09 %	83.09 %
Sensitivity	87.50%	87.50%
Specificity	71%	71%

Table 2: Comparative analysis between existing and proposed method

	Cloudy		Snowy	
	PSNR	SNR	PSNR	SNR
Existing method	22.7011	6.569	6.0522	0.0309
Proposed method	29.2554	0.0146	33.9715	27.9502

It is inferred from the above table results that the proposed method has the highest PSNR and SNR value than the existing method. The concept of fuzzy decision for gamma value has significantly improved the HVS's performance.

5. *Conclusion*:

In this paper, we propose an adaptive fuzzy-based DCNN technique that estimates the loss and enhancement of the images during seasonal changes. The natural scenery images are collected and preprocessed using Gaussian filter method that removes the unwanted noises. The preprocessed image is then guided with a guided filter method that helps to segment the seasonal changes of an image. The statistical features are extracted from the Adaptive Fuzzy-based Gamma Correction method that specifically leverages the gamma parameters using fuzzy-based decisional approach. Further on, the Deep Convolutional Neural Networks (DCNN) is employed to classify the seasonal changes on images based on the computed image quality score. Experimental results have proven the efficiency of the proposed technique in terms of accuracy, precision and recall.

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