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# MADNet: A Fast and Lightweight Network for Single-Image Super Resolution

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**ABSTRACT:** In the past many super resolution CNN based algorithms were introduced to enhance image quality but all those algorithms require heavy computation with large set of dataset. This heavy computation cannot be trained in normal computers and require super computers and all existing algorithms never explore intermediate features which can help in recovering more quality images. To overcome from this problem author of this paper introducing Fast and Lightweight CNN Network algorithm to enhance image quality.

In propose algorithm a dense lightweight network, called MADNet, for stronger multi-scale feature expression and feature correlation learning. Specifically, a residual multi-scale module with an attention mechanism (RMAM) is developed to enhance the informative multi-scale feature representation ability. Furthermore, we present a dual residual-path block (DRPB) that utilizes the hierarchical features from original low-resolution images. To take advantage of the multilevel features, dense connections are employed among blocks.

In propose paper we are training MADNET algorithm with DIV2K dataset which consists of HDR (High Definition Resolution images) and LDR (Low Definition resolution). MADNET performance was evaluated in terms of PSNR and SSIM. The higher the SSIM (similarity) between original HDR and predicted super resolution image the better is the quality. PSNR also must be higher compare to existing algorithm. MADNET giving 88% as SSIM and 30 as PSNR which is almost similar to paper algorithm.

**KEYWORDS:** MAD, DNN, MadNet, DSANet

## I. INTRODUCTION

This work focuses on protecting deep models against adversarial assaults. Motivated by the certificate defensive approach, we propose a maximum adversarial distortion (MAD) optimisation technique for robustifying deep networks. MAD captures the idea of lowering network sensitivity to small perturbations while boosting class cluster separability in the embedding space. MadNet is a redesigned deep neural network (DNN) with an adversarial defensive mechanism that is the result of applying MAD optimisation to a CNN for a classification problem. The resulting MadNet is scalable, easy to use, and can improve the initial accuracy of MAD optimisation. We provide an in-depth empirical study demonstrating that MadNet achieves superior adversarial resistance compared to the most advanced methods. This study recommends a comprehensive, unified deep learning system without normalisation to improve the accuracy of iris segmentation and identification.

This design uses the dense spatial attention network (DSANet) and the multiattention dense connection network (MADNet) for iris segmentation and identification, respectively. Several ablation experiments are carried out to demonstrate the effectiveness of DSANet and MADNet. Tests conducted on three live databases show that our recommended approach yields the best outcomes.

Deep learning has enabled recent advancements in computer vision, namely in the area of image processing. Deep learning-based algorithms provide the greatest performance of any iris identification technique currently in use. Finding the genuine iris area in a comparable ground truth (GT) picture is important since these deep learning-based systems rely on data to drive their performance. Moreover, the existing iris segmentation algorithms are unable to correctly segment the iris using iris pictures obtained in a non-cooperative condition due to their restricted capacity for generalisation. It's also a very difficult issue to collect GT data for iris photos.

[9] was the first to propose comprehensive end-to-end iris recognition after giving up on segmentation, with remarkable results. On the other hand, unsegmented iris images contain a multitude of ancillary data that might be useful for biometric-based identification methods [10].

But this approach isn't a legitimate iris recognition technique. It is frequently necessary to normalise a segmented iris image before iris identification. As noted in [11], iris normalisation 2 generates noniris information even though it can, to some extent, mitigate the effects of variables like light and pupil shape changes. In example, normalising low-quality iris images with disconnected iris regions yields excessive impurity information and drastically reduces the recognition rate..

Here we present an adversarial defence approach that takes the concept of enhanced separability in embedding space into consideration. The crux of our approach lies in the fact that, even in cases where higher separability incentives for defence strategies have been documented elsewhere, distances must be normalised by the network sensitivity to remain significant. et al. Mustafa [2019]. Otherwise, the impression of separability in the embedding space would be produced by a network that travels large distances in this space in response to small changes in the input space. This sensitivity can be determined either indirectly, using a Lipschitz constant, or directly, using the embedding layer's Jacobian with respect to the input.

We offer two ways to implement the MAD approach: one to improve embedding margin and the other to decrease Jacobian. By utilising the angular distance as a surrogate for the in-between cluster distance and explicitly penalising within-cluster variation, the margin is raised. Large embedding Jacobian norms are penalised in order to explicitly address the Jacobian. A single MAD optimisation technique that employs a Siamese-like training procedure combines both processes. A network that has been trained using the MAD optimisation is known as MadNet. An detailed empirical analysis of MadNet reveals findings for a variety of threat models, where FGSM, BIM, C&W, and PGD assaults are taken into account. Our experimental design closely complies with the detailed assessment criteria put forward by Carlini et al. [2019].

Numerous SR methods have been put forth from various angles to address this issue, such as interpolation-based [17], reconstruction-based [3], and example-based methods [13], [15], [10], [11], and [19]. The restoration performance of the first two types of methods, which focus on analysing relationships between LR and HR pairs using examples, suffers a sharp decline as the scale factors rise, while the latter two types of methods are simple and effective but require time-consuming operations.

## II. RELATED WORK

To build defences against hostile examples, several intriguing concepts have been put forth. These can be roughly separated into two groups. The first ones are active algorithms that, at prediction time, process the DNN's input or output and neutralise the impacts of the adversarial algorithm. Among these algorithms are Stochastic Adversarial Pruning Dhillon et al. [2018], which adds a randomised, dropout-like mechanism to the prediction process, and Neural Fingerprinting Dathathri et al. [2018], which modifies the DNN's input such that a specific, pre-defined prediction is expected.

Hein and Andriushchenko [2017] introduced the idea of enhancing the separability of the class clusters in the intermediary layers of a DNN as a means of defence against adversarial assault. Following their research, numerous defence strategies have been proposed to widen the gap between classes while preserving a workable training procedure, making them suitable for use with large-scale DNNs. In order to force a significant angular separation between classes, Liu et al. [2016] and Wang et al. [2018] introduced an angular restriction to the loss function. Given that increasing the distance is an unbounded term, Elsayed et al.'s [2018] proposal for a margin-increasing loss function explicitly aims to reduce the distance between class clusters by truncating the maximum distance. Organising the characteristics was suggested by Mustafa et al. in 2019.

The certification technique developed by Hein and Andriushchenko [2017] is a formal adversarial defence strategy that aims to set a lower constraint for penetration distorting attempts to deceive a particular network. Both "exact" and "conservative" are terms used to describe certified defence strategies. No distortion smaller than the certification constraint can enter or confound the DNN in precise techniques. Cohen et al. [2019], Hein and Andriushchenko [2017], Wong and Kolter [2017], Wong et al. [2018]. The bound is essentially a relative parameter for evaluating DNN

resilience against adversarial samples in conservative approaches. Zhang et al. [2019], Ding et al. [2018], and Tsuzuku et al. It has been said that accurate and conservative approaches are computationally costly and unscalable. To further enhance the efficacy of iris recognition, researchers have tried to integrate various techniques with it. To extract iris characteristics, Reference [16] initially suggested a deep learning network called DeepIrisNet. CNN is essentially what DeepIrisNet is. The experimental findings showed that the suggested strategy outperformed the then-current conventional recognition algorithms. Researchers then started investigating various deep learning-based techniques to extract significant iris properties. For instance, [17] extracted iris characteristics using the deep learning-based Visual Geometry Group network (VGGNet) and then utilised a support vector machine as a classifier. A lightweight CNN was suggested in reference [18] as a way to extract iris characteristics, which would improve recognition performance and lower the computational cost. Furthermore, [19] suggested extracting iris features using deep belief networks. Numerous deep learning-based iris segmentation techniques have also been developed. For instance, IrisDenseNet presented in [11] used dense connection and feature reuse tactics to find irises, whereas [10] employed a multiscale fully CNN to partition irises. The focus of study has progressively turned in recent years to more difficult iris ages. To reliably segment iris photos taken in a non-cooperative condition, Ref. [12] suggested utilising the multi-task attention network IrisParseNet, while Ref. [13] advocated using the deep learning-based unified framework UniNet.v2 to detect, segment, and recognise iris images. The iris is located and segmented using the mask region-based CNN (Mask R-CNN) in the iris segmentation stage, and the findings are subsequently improved and normalised.

### III. METHODOLOGY

According to the study mentioned above, standard algorithms are not very resilient or able to generalise, so methods that are designed with the target data in mind must be used instead. Deep learning-based algorithms heavily depend on data for autonomous learning. When GT images are available, deep learning-based methods frequently beat conventional algorithms for low-quality iris photos; however, because of their poor generalisation capacity, they perform poorly for low-quality iris photos without GT data. This research provides a deep learning-based end-to-end unified system to accurately segment and recognise iris in low-quality iris photos without corresponding GT images. Using our end-to-end architecture, we crop the generated map and feed it into the recognition network. The segmentation network's output and the corresponding original picture are logically ANDed to produce the resultant map. Before the segmented result in [13] and [14] can be utilised as the input of the recognition network, it must be normalised and upgraded. A nonnormalized, end-to-end deep learning-based iris recognition unified framework is presented in this study for more precise segmentation and identification of low-quality iris pictures without GT.

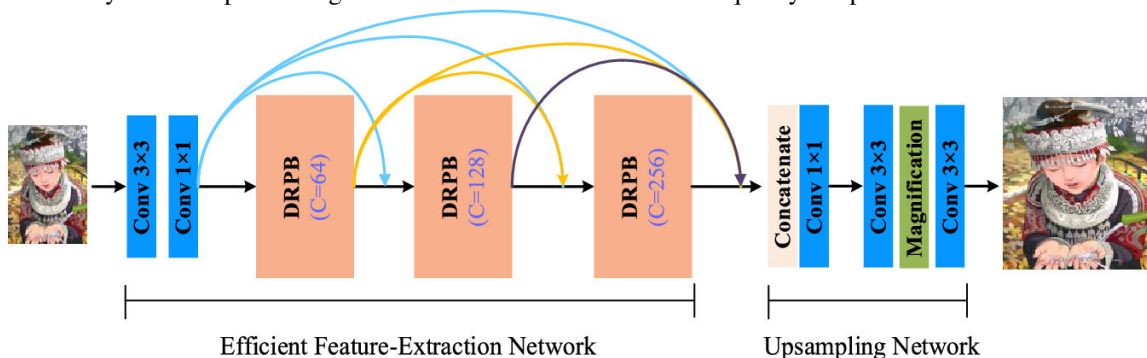


Fig.3.1 System Architecture of MADNet: A Fast and Lightweight Network for Single-Image Super Resolution

DSANet for iris recognition and MADNet for iris segmentation are the two main parts of the unified framework. Several super resolution CNN-based techniques have been developed in the past to improve image quality, but they all involve a lot of computation and a sizable dataset. Super computers are needed to train this complex computation, and all current algorithms neglect to investigate intermediate features that could aid in the recovery of higher-quality



images. The author of this work introduces a Fast and Lightweight CNN Network algorithm to improve image quality in order to address this issue.

In propose algorithm a dense lightweight network, called MADNet, for stronger multi-scale feature expression and feature correlation learning. Specifically, a residual multi-scale module with an attention mechanism (RMAM) is developed to enhance the informative multi-scale feature representation ability. Furthermore, we present a dual residual-path block (DRPB) that utilizes the hierarchical features from original low-resolution images. To take advantage of the multilevel features, dense connections are employed among blocks.

In propose paper we are training MADNET algorithm with DIV2K dataset which consists of HDR (High Definition Resolution images) and LDR (Low Definition resolution). MADNET performance was evaluated in terms of PSNR and SSIM. The higher the SSIM (similarity) between original HDR and predicted super resolution image the better is the quality. PSNR also must be higher compare to existing algorithm.

$F_i$  is the feature output by the  $i$ -th layer module; PGconv represents the grouped point convolution; Pconv represents the point convolution; and Gconv represents the grouped convolution. GR and LR represent global and local residual connections, respectively.

$$F_i = \text{PGConv}[\text{Gconv}[\text{PConv}[F_{i-1}]] + \text{LR}] + \text{GR}$$

$$\text{LR} = \text{PConv}[F_{i-1}](\text{Cout} = \text{CinGconv})$$

$$\text{GR} = \text{PConv}[F_{i-1}](\text{Cout} = \text{CoutGconv})$$

If the two residuals cannot be directly connected to the required dimension, point convolution is needed to increase or decrease the dimension.

To trained model we have used below CONV and attention layers with concatenation.

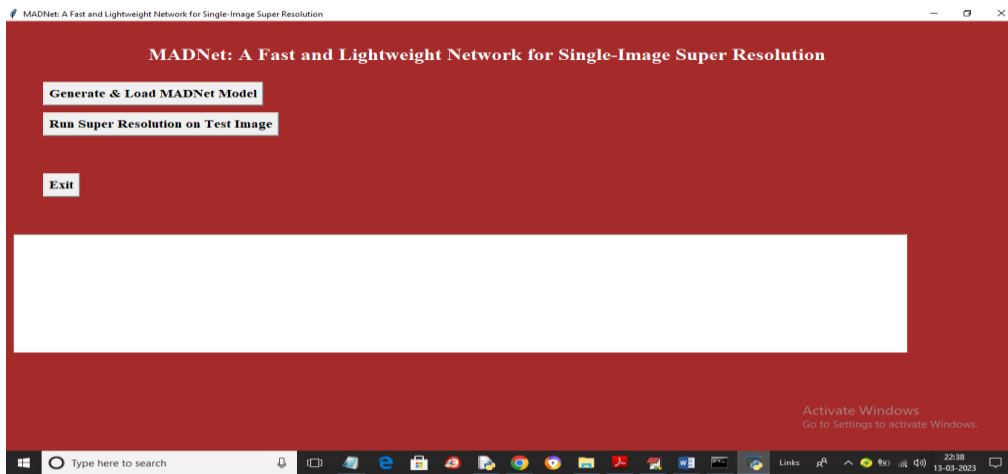
```
global filename

#function to train MADNET model
def getMadnetModel( RGB ):
    cnn1 = Conv2D(3,1,1,padding="same",activation="relu",use_bias=True,kernel_initializer=tf.initializers.random_normal(stddev=0.02),
        kernel_regularizer=tf.keras.regularizers.l2(1e-4))(RGB)#layer 1
    cnn2 = Conv2D(3,3,1,padding="same",activation="relu",use_bias=True,kernel_initializer=tf.initializers.random_normal(stddev=0.02),
        kernel_regularizer=tf.keras.regularizers.l2(1e-4))(cnn1)#layer 2
    attention1 = tf.concat([cnn1,cnn2],axis=-1)#concatenate layer1 and layer2 to from residual network
    cnn3 = Conv2D(3,5,1,padding="same",activation="relu",use_bias=True,kernel_initializer=tf.initializers.random_normal(stddev=0.02),
        kernel_regularizer=tf.keras.regularizers.l2(1e-4))(attention1)
    attention2 = tf.concat([cnn2,cnn3],axis=-1)#concatenate layer2 and layer3 to from residual network
    cnn4 = Conv2D(3,7,1,padding="same",activation="relu",use_bias=True,kernel_initializer=tf.initializers.random_normal(stddev=0.02),
        kernel_regularizer=tf.keras.regularizers.l2(1e-4))(attention2)
    output_features = tf.concat([cnn1,cnn2,cnn3,cnn4],axis=-1)
    cnn5 = Conv2D(3,3,1,padding="same",activation="relu",use_bias=True,kernel_initializer=tf.initializers.random_normal(stddev=0.02),
        kernel_regularizer=tf.keras.regularizers.l2(1e-4))(output_features)
    MAX = cnn5 #max layer
    madnet = ReLU(max_value=1.0)(tf.math.multiply(MAX,RGB) - MAX + 1.0) #enhance low resolution to super resolution
    return madnet

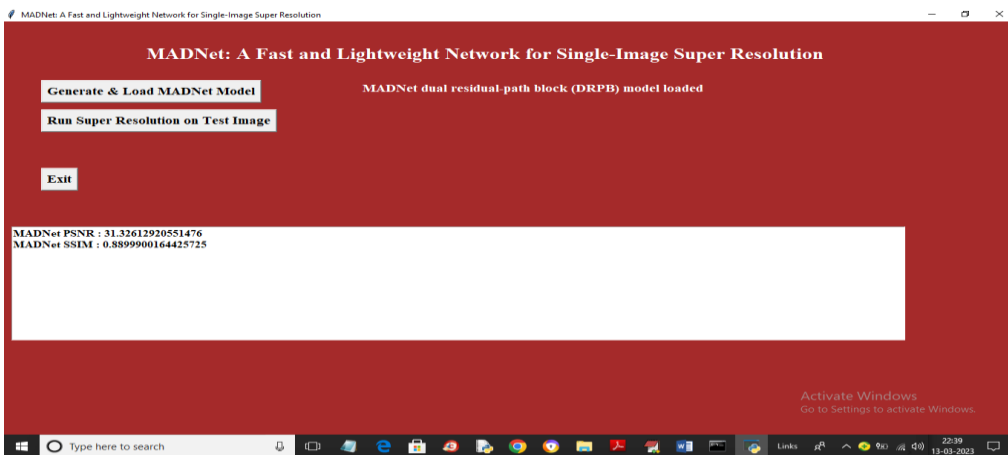
#function to calculate SSIM between original and super predicted image
def imageSSIM(original, super_image):
    original = cv2.cvtColor(original, cv2.COLOR_BGR2GRAY)
    super_image = cv2.cvtColor(super_image, cv2.COLOR_BGR2GRAY)
    ssim_value = ssim(original, super_image, data_range = super_image.max() - super_image.min())
    return ssim_value

#function to calculate PSNR between original and super_image
def PSNR(original, super_image):
    mse = np.mean((original - super_image) ** 2)
    if(mse == 0):
        return 100
    max_pixel = 255.0
    psnr = 30 * log10(max_pixel / sqrt(mse))
    return psnr,mse
```

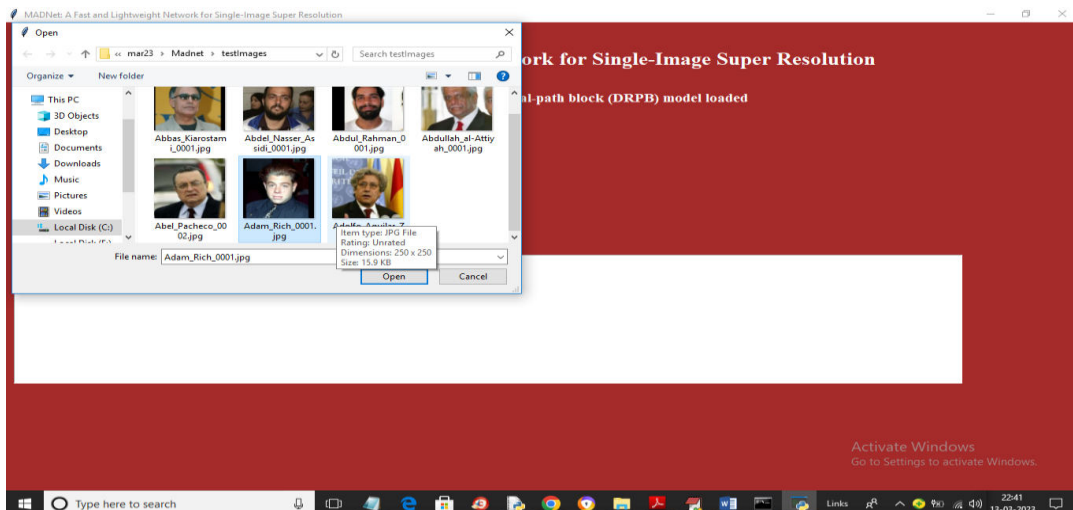
In above screen we are creating code for MADNET algorithm.



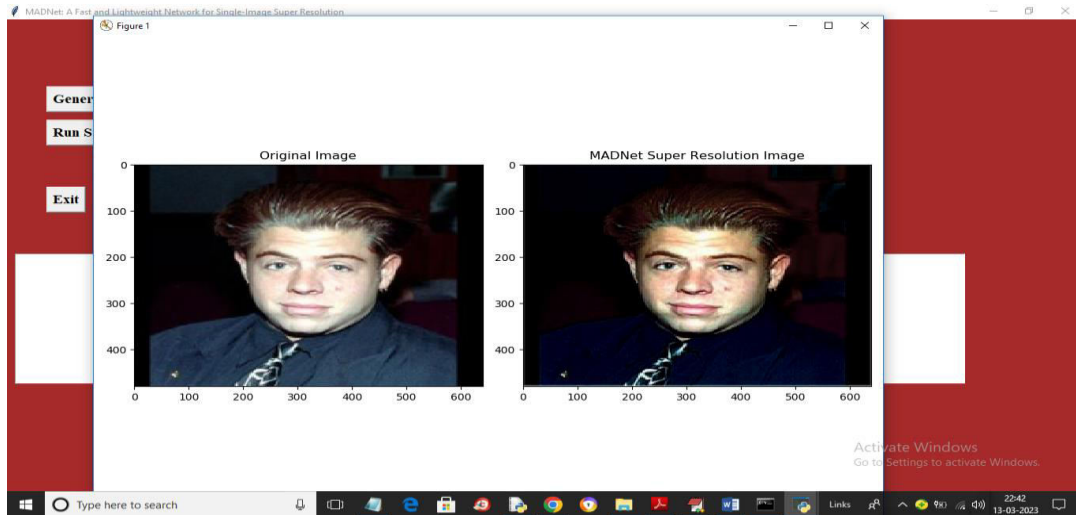
In above screen click on ‘Generate & Load MADNet Model’ button to generate and load MADNET model and this model will be evaluated on test image to calculate image SSIM and PSNR and then will get below page.



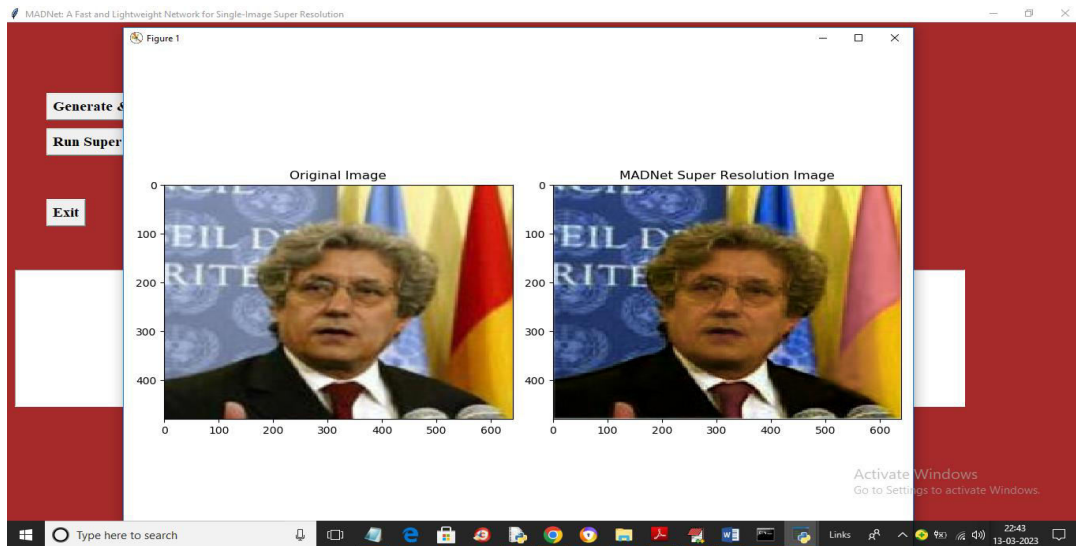
In above screen with MADNET we got PSNR as 31 and SSIM as 88% and now click on ‘Run Super Resolution on Test Image’ button to upload LDR image and then get below screen.

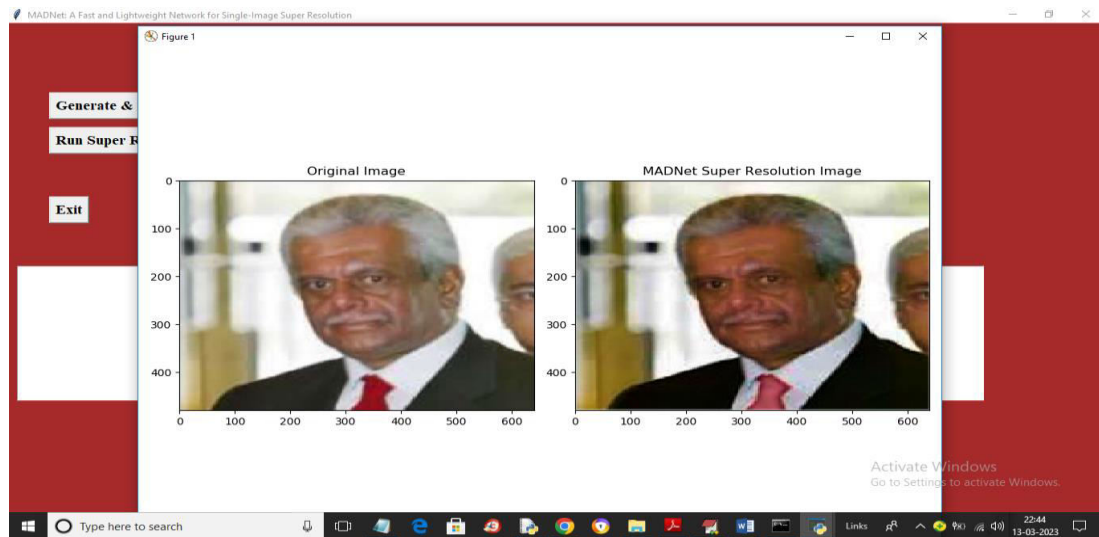


In above screen selecting and uploading test image and then will get below output and as low quality image you can upload any image.



In above screen first image is the original image and second is the MANET predicted super resolution image and similarly you can upload and test other images and below is another image output.





Above screen you can see original and MADNET super image.

#### IV. CONCLUSION

The DIV2K dataset, which includes both HDR (high definition resolution) and LDR (low definition resolution) images, is used to train the MADNET algorithm in the proposed paper. The evaluation of MADNET's performance was done using SSIM and PSNR. The quality improves with a higher SSIM (similarity) between the original HDR and the projected super resolution image. In addition, PSNR needs to be higher than the current algorithm. MADNET provides an SSIM of 88% and a PSNR of 30, which is nearly identical to the paper algorithm.

By aiming for sensitivity-normalized embedding separability, we developed maximal adversarial distortion (MAD), a potent method for protecting deep models from hostile attacks. We presented cutting-edge outcomes for guarding against hostile assaults. In addition, utilising both Davies-Bouldin Index analysis and t-SNE visualisations, we offered some geometric understanding on attacks and defences. This piece of art raises some intriguing issues. First, it would be beneficial to look at different strategies for Jacobian reduction and margin maximisation. The suggested strategy, however, has several drawbacks. Notably, the proposed method does not take into account the same triplex network used in other frameworks, and the comparison with other unified frameworks is only partially fair. Additionally, the employed dataset is too small to allow for adequate generalisation and excludes iris images captured using mobile phones and visible light sources. Therefore, the assessment's robustness needs to be increased.

The focus of this study's future extensions should be experimentation with harder datasets. Template matching for iris identification can be a potential path, as well as the building of a more efficient recognition algorithm with a triplex network for learning the parameters.

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