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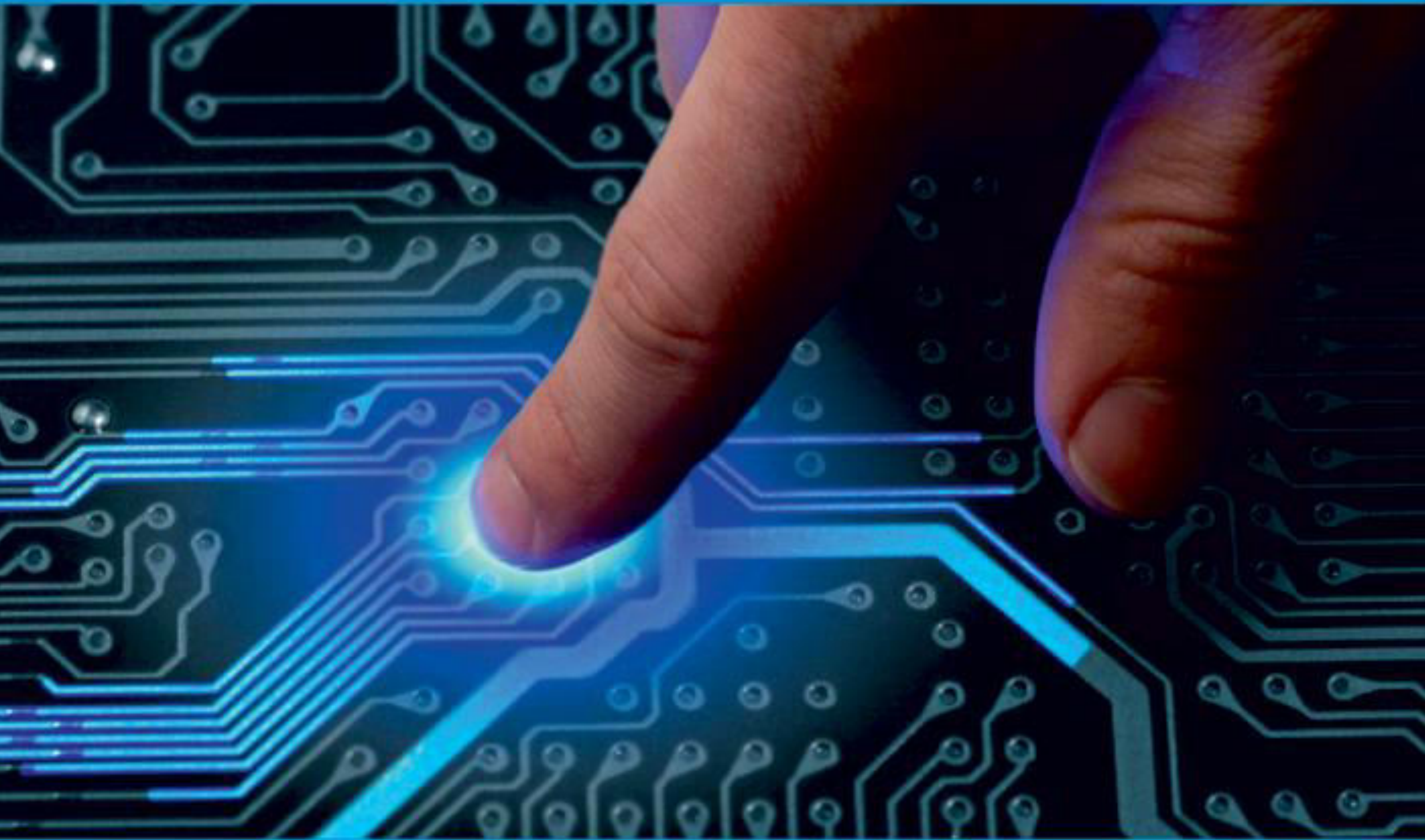

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A Review on MADNet: A Fast and Lightweight Network for Single-Image Super Resolution

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ABSTRACT

The defence of deep models against adversarial attacks is the focus of this study. We suggest a maximum adversarial distortion (MAD) optimisation technique for robustifying deep networks, which is inspired by the certificate defence strategy. The notion of improving class cluster separability in the embedding space while reducing network susceptibility to minor distortions is captured by MAD. An application of MAD optimisation to a deep neural network (DNN) for a classification issue creates MadNet, a modified version of the original network with an adversarial defence mechanism. The resultant MadNet can increase the initial accuracy, and MAD optimisation is simple, efficient, and scalable. We offer a thorough empirical analysis proving that MadNet outperforms state-of-the-art techniques in terms of adversarial resilience. In order to increase the accuracy of iris segmentation and identification, this research suggests a complete, unified deep learning system without normalisation.

In this architecture, iris segmentation and identification are accomplished using the multiattention dense connection network (MADNet) and the dense spatial attention network (DSANet), respectively. To show the efficiency of MADNet and DSANet, several ablation experiments are conducted. Experiments on three active databases demonstrate that our suggested strategy produces the best results.

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I. INTRODUCTION

Recent developments in computer vision, particularly image processing, have been made possible through deep learning. The best performance of any iris recognition method available right now is offered by deep learning-based algorithms. Since the performance of these deep learning-based algorithms is data-driven, finding the real iris region in a corresponding ground truth (GT) image is crucial. Furthermore, because of their limited ability to generalise, the current iris segmentation algorithms cannot accurately segment the iris based on iris images acquired in a non-cooperative state. Additionally, obtaining GT data for iris images is a very challenging task.

After giving up on segmentation, [9] was the first to suggest full end-to-end iris recognition, which had outstanding outcomes. Unsegmented iris pictures, however, include a wealth of peripheral information that might be helpful for biometric-based recognition techniques [10].

However, this method is not a true iris recognition method. A segmented iris picture must often be normalised before iris identification. Although iris normalisation can, to a certain extent, lessen the impact of factors like illumination and pupil shape changes, the normalisation 2 produces noniris information, as mentioned in [11]. Normalising poor-quality iris photos with unconnected iris regions, in particular, provides too much impurity information and significantly lowers the identification rate.

Here, we offer an adversarial defence strategy that reflects the idea of enhanced separability in embedding space. The key to our strategy is that distances must be normalised by the network sensitivity in order to be relevant, even when higher separability incentives for defence strategies have been reported elsewhere Mustafa et al. [2019]. A network that traverses great distances in this space in response to minute changes in the input space would otherwise provide the impression of separability in the embedding space. This sensitivity can be measured directly using the Jacobian of the embedding layer with respect to the input or indirectly using a Lipschitz constant.

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

The study presented above demonstrates that typical algorithms have low resilience and generalisation ability and require approaches that are specifically created for application to the target data. For autonomous learning, deep learning-based algorithms heavily rely on data. Deep learning-based approaches often outperform conventional algorithms for low-quality iris photos when GT images are available, but their performance is subpar for low-quality iris images without GT data due to weak generalisation capacity. To accurately segment and recognise iris in low-quality iris photos without corresponding GT images, this research provides a deep learning-based end-to-end unified system. We crop the generated map and feed it into the recognition network using our end-to-end architecture. 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.

The two primary components of the unified framework are DSANet for iris recognition and MADNet for iris segmentation.

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.

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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.

Fi 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.

Fi = PGConv[Gconv[PConv[Fi-1]] + LR] + GR

LR = PConv[Fi-1](Cout = CinGconv)

GR = PConv[Fi-1](Cout = CoutGconv)

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

IV. CONCLUSION

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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