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STEEL SURFACE DEFECT RECONSTRUCTION & IDENTIFICATION USING GAN FOR LOW-QUALITY IMAGES

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ABSTRACT

Deep learning is the focus of research on vision-based fault recognition (DL). Poor-quality photos usually lose crucial features, which hinders the performance of DL techniques. We employed the GAN Model to transform low-quality photos into high-quality images to solve this problem. Defects in reconstructed images are identified using the vgg16 model. The results of the studies show that the suggested strategy is more accurate and performs well even with noisy photos. To determine whether defect reconstruction for low-quality flaws is effective. Four indicators are utilized to evaluate the performances: PSNR, SSIM, cosine, and mutual information. These indications are very helpful for defect analysis.

Keywords: Deep learning, Generative adversarial Network, VGG16, Low-quality photos.

1. INTRODUCTION

Surface defect identification is a hot topic in industrial manufacturing since even slight flaws can mar a product's look. The most common methods for doing this rely on the work of skilled engineers [1]. They require a lot of time, and money, and are expensive to make mistakes. Deep learning (DL)-based approaches are now one of the most popular study fields due to their exceptional achievements and the rapid advancement of computer vision technology in recent years, vision-based inspection techniques have increasingly become essential in the identification of surface defects. On steel strips during manufacture, there could be blemishes like scars, scratches, inclusions, bright prints, burrs, black burn, iron scales, and other faults. The steel strip's interior is also compromised by these faults [2]. Finding surface faults in the steel strip is essential for improving the production quality of steel strips.

Low-resolution photos are those that have fewer pixels, more compression, or both when compared to a high-resolution image [3]. For lesser file sizes, the image quality is sacrificed. Rasterized pictures with low resolution, like photographs, may appear hazy or fuzzy. To train our models using high-quality images for simple resolution and to improve the recognition results, first reconstruct a high-quality image from a low-quality image. It can be done by utilizing GAN and VGG16.

GAN is a machine learning framework. A game pits two neural networks against one another (in the form of a zero-sum game). Using the same statistics as the training set, this approach learns to produce fresh data [4]. Its main concept is based on "indirect" training using the discriminator, which essentially implies that the generator is taught to not only minimize the distance to a certain image but also to trick the discriminator. It allows for the resolution of non-linear and underdetermined issues as well as the prevention of over-fitting brought on by direct input. Data labeling is a costly process. Since GANs are unsupervised, they don't need labeled data to be trained. Right now, GANs provide the sharpest images [5]. Backpropagation is the only method that can be used to train both GAN networks.

A pre-trained VGG 16 and CNN are utilized as a classifier and a feature extractor, respectively, and the feature maps are used as a feature extractor to find faults [6]. It attempts to employ this model in the absence of data since it performs more precisely and successfully than the traditional methods. The basis network utilized in transfer learning for feature extraction is Kera's VGG16 Standard Model volume base [7]. Meanwhile, Transfer Learning considerably cuts down on the number of training parameters required as well as the time required for parameter training.

2. LITERATURE SURVEY

2.1Ambiguous Surface Defect Image Classification of AMOLED Displays in Smartphones

A categorization method was put forth by Y. Park and Kweon for ambiguously shaped faults discovered on the surface of a display panel module common in the field of mobile displays. Due to the variety and familiarity of these surface flaws, it can be challenging to tell them apart. A novel filtering technique was developed to address the issue of ambiguous surface defect classification [8]. The filtering technique successfully distinguishes the foreground defective regions from the background, which has structured patterns, local illumination variation, and various lighting conditions for each of the inspection system's multiple cameras.

2.2 Steel Surface Defect Classification Using Deep Residual Neural Network

Three classes of surface flaws rolled in the metal may now be identified and categorized automatically, allowing defectoscopy to be carried out within a predetermined time and efficiency limits [9]. The ResNet50 neural network-based classifier was used as the foundation. Based on test data, the model is capable of identifying pictures of flat surfaces with damage into one of three categories with an overall accuracy of 96.91 percent.

2.3 Wafer Defect Pattern Recognition and Analysis Based on Convolutional Neural Network

This paper develops a method for analyzing wafer defect patterns using convolutional neural networks (CNN). They developed an 8-layer CNN model to analyze wafer map faults, and a 13-layer model to classify defect patterns. To investigate the problems, first, extract features from the classification network [10]. Dimensionality reduction and similarity ranking were then performed using PCA. Lastly, using the wafer maps that were returned, determine the underlying reasons for the examined samples.

2.4 Strip Steel Defect Classification Using the Improved GAN and Efficient Net

The upgraded GAN and Efficient Net were used to develop a strip steel defect classification technique in this paper [11]. The label deconvolution network is built first, then conditional masks are then overlaid onto the generator and discriminator to create Mask CGAN. This is done via layer-by-layer deconvolution of the image labels to create conditional masks.

2.5 Steel Surface Defect Detection using Deep Learning

In this study, images from high-frequency and high-resolution cameras were used to generate deep learning CNN with Xception architecture to detect steel faults. The accuracy produced using the two procedures is 0.94 percent and 0.85 percent, respectively [12]. Throughout this instance, the Xception architecture exhibits optimal and consistent performance in the process and its outcomes.

3. PROPOSED METHOD

3.1 GAN

A recent area of study in computer vision called GAN has a potent capacity for data production. GAN could be able to recreate a high-quality image from a low-quality one. A GAN typically consists of a generator (G) and a discriminator (D)[13]. The discriminator must determine if the input is a fake reconstructed image or a high-quality image of the ground truth before the generator may rebuild a high-quality image from a low-quality one. A well-trained GAN can create false images and deceive the discriminator, making the entire GAN system comparable to a two-player minimax game. Let us consider **i** is a low-quality defect image and **j** is a ground truth high-quality image, the loss function can be defined as,

(1)

$$\text{Min max } L_{adv}(G, D) = E_{j\sim Pdata(h)}[\log(D(j))] + E_{i\sim pz(i)}[\log(D(1- D(G(z)))]$$

An artificial neural network called an autoencoder is used for unsupervised learning data encodings [14]. An autoencoder's goal is to learn a lower-dimensional representation (encoding) for a higher-dimensional dataset, generally for dimensionality reduction. An autoencoder is employed as the generator G, which consists of an encoder and a decoder, to fully learn the defect information. The encoder converts the low-quality faulty image into a latent space, and the decoder reconstructs a high-quality image taken from the latent space. Below Fig [1] is the GAN diagram.

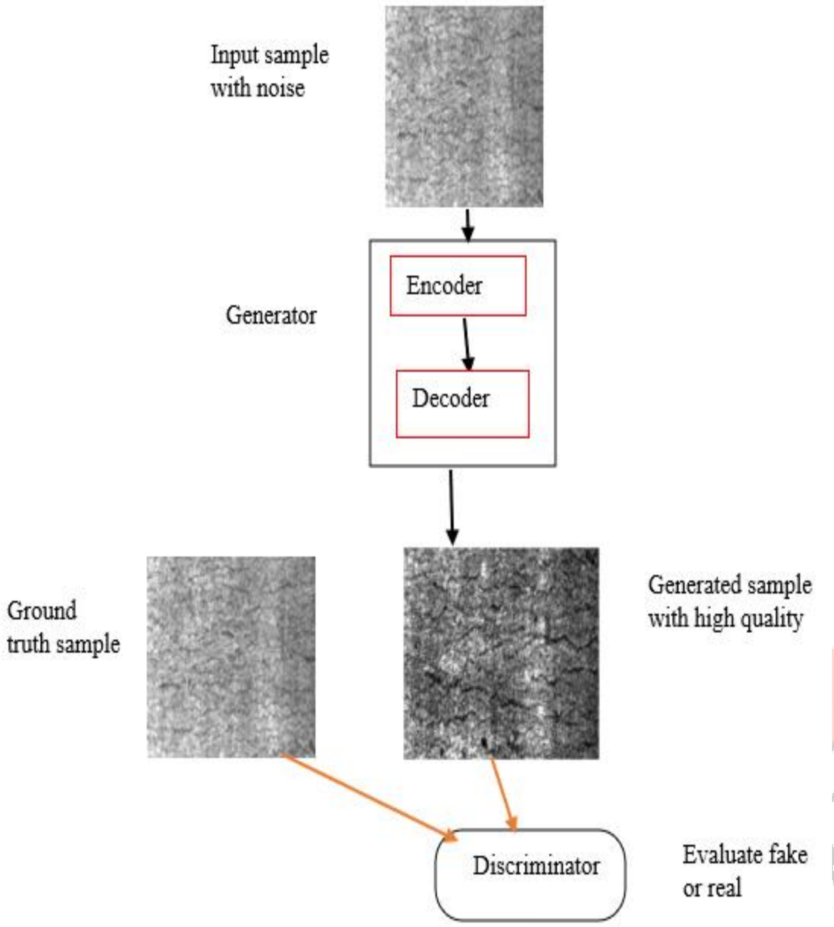

Figure 1: GAN Architecture

3.2 VGG16:

Conv Net is another name for a type of artificial neural network called a convolutional neural network, or CNN. several hidden layers in a convolutional neural network [15] in addition to the input and output layers. One of the top computer vision models to date is a form of CNN called VGG16 (Convolutional Neural Network). In our model, we used Five blocks to make up the VGG16 network. Two convolutional layers and one max-pooling layer are present in the first two blocks, while three convolutional layers and one max-pooling layer are present in the remaining three blocks. A global average pooling (GAP) layer is added for vectorization at the end of the previous block, and a classification layer is connected to the GAP. Figure [2] is the architecture of vgg16.

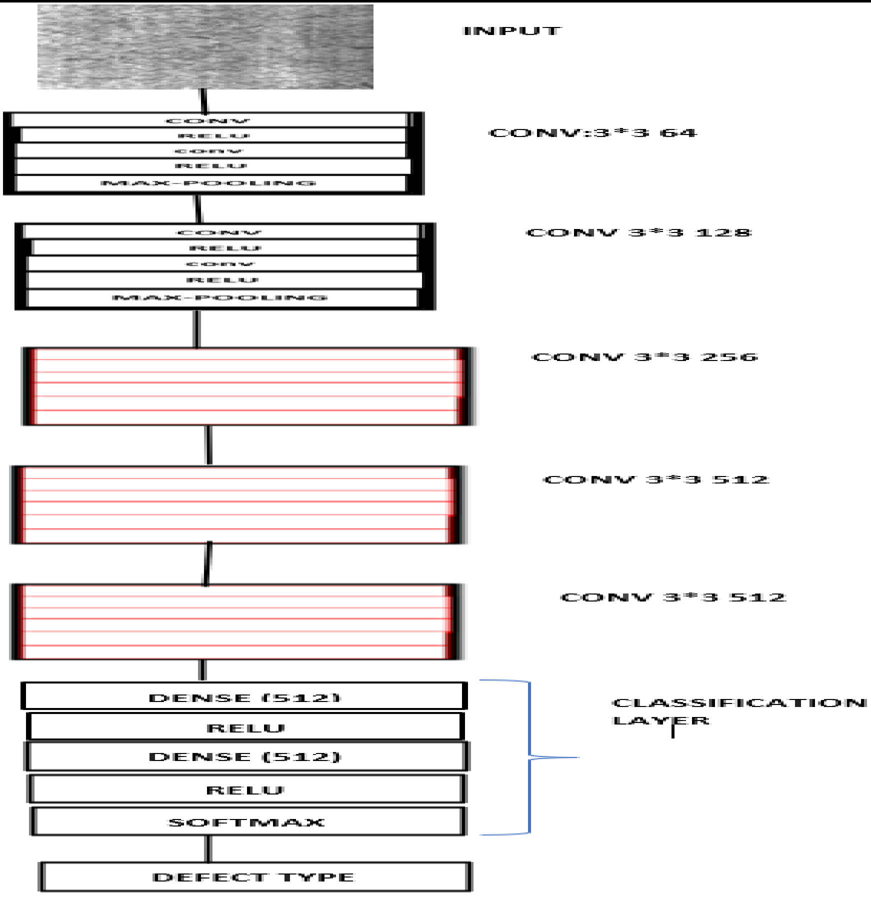

Figure 2: VGG16 architecture

Consider A the input defect picture, B to be the suggested vgg16's result, and C to be the ground truth label. Cross entropy is utilized as the vgg16's loss function, which is defined below.

$$L(B,C)=C \log B - (1-C) \log(1-B) \qquad (2)$$

A VGG16 that was pretrained by ImageNet is utilized. Before feeding the image into the VGG16, the image is also normalized into the [0,1] range with no additional data augmentation.

4. EXPERIMENTAL RESULTS

To evaluate the performances, the proposed method is tested on several indicators such as PSNR, SSIM, CS, and MI. we discussed this briefly below.

4.1 Dataset:

In our experiment, we used 2 datasets the NYU-V2 dataset and the NEU dataset. The GAN and VGG16 Models were trained by the NYU-V2 dataset and tested by the NEU dataset. A detailed description of the datasets is provided below.

4.1.1 NYU-Depth V2 data set:

The NYU-Depth V2 data collection consists of video clips taken by the RGB and Depth cameras of the Microsoft Kinect in a range of indoor settings [16]. 1449 pairs of aligned RGB and depth images that are highly labeled, 464 new scenes from three cities, and 407,024 new unidentified frames are included. Several elements make up the dataset: Labelled A portion of the video data that have extensive multi-class labeling. These data have also undergone preprocessing to fill in any holes in the depth labels. Raw: The accelerometer, depth, and RGB raw data from the Kinect.

4.1.2 NEU Dataset:

Roll-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In), and scratches are six types of common surface flaws of hot-rolled steel strip (Sc) [17]. 1,800 grayscale pictures are present in the database: 300. Approximately six distinct types of faults were in this dataset, but training all of those photos would take hours, so I only used two, such as inclusion and crazing.

The two models used in the suggested methodology are GAN and VGG16. For image reconstruction, the GAN model is employed, and for recognition, the vgg16 model is used. We incorporated shoddy steel strip photos into our model. Defect identification is a challenging task when working with low-quality photos since they are compressed (fewer pixels) and contain some unreliable information. For converting low-quality photographs into high-quality images, we proposed the GAN model. By converting high-quality images, the faults existing in images can be easily spotted since images are in high expansion and have more pixels. The primary goal of employing GAN is to be able to reconstruct images from noisy and masked photos and recover lost information by converting high-quality images [18].

We can shorten the training period by using pre-trained models like the GAN and Vgg16 models. The NYU-V2 dataset was used to train the GAN model. It was possible to train the GAN model using exceptional pictures. It also includes noisy and masking images. The technical constraints of the picture capture sensor or unfavorable environmental factors frequently result in noise [19]. Typically, noise is defined as an unpredictably changing brightness or color. Since these difficulties are frequently inevitable in real-world scenarios, image noise is a widespread issue. To encode input images from the NEU dataset before storing them in a latent space, we used an autoencoder in GAN. Following that, the decoder tried to piece together the high-quality image from the latent space. Between the reconstructed image and the ground truth image, we may calculate the reconstruction loss. To calculate reconstruction loss,

$$L_{rec}=\|a1-G1(Z)\|_2^2 \qquad (3)$$

The discriminator separates the high-quality ground truth image from the reconstruction. To trick the discriminator. The high-quality pictures were then loaded into the vgg16 model. The high-quality image helps the vgg16 model identify the flaw. High-quality photographs contain all the information, while low-quality images are typically compressed and lose some crucial information. The model can quickly spot faults by turning low-quality photos into high-quality ones. The vgg16 model also computed the reconstruction loss. Two components make up the experiments. The evaluation of the performance of low-quality defect reconstruction is the initial step. The performance is assessed using four metrics such as PSNR, SSIM, MI, and CS, assuming that a reconstructed picture G1(z) and a ground truth high-quality image a1 are available.

4.2 PSNR: The peak signal-to-noise ratio between two pictures, measured in decibels, is computed by the PSNR block. This ratio is used to compare the original and compressed image quality. The quality of the compressed or rebuilt image improves with increasing PSNR. Image compression quality is compared using the peak signal-to-noise ratio (PSNR) and mean-square error (MSE) [20]. The PSNR represents a measure of the peak error, whereas the MSE represents the cumulative squared error between the original and compressed image. The formulae for calculating PSNR are below.

$$\text{PSNR}=10log_{10}\left(\frac{(2^n-1)^2}{MSE}\right) \qquad (4)$$

4.3 SSIM: A tool for calculating how similar two images are is called the Structural Similarity (SSIM) index. With the assumption that the other image is thought to be of ideal quality [21], the SSIM index can be used to assess the quality of a being compared.

$$\text{SSIM}=\frac{(2\mu_{G1(z)}\mu_{a1}+D1)(2\sigma_{G1(z)a1}+D2)}{(\mu_{G1(Z)}^2+\mu_{a1}^2+D1)(\sigma_{G1(z)}^2+\sigma_{a1}^2+D2)} \qquad (5)$$

4.4 MI: Mutual information, which is calculated between two variables, gauges how much uncertainty there is in one variable when the other's value is known [22].

(6)

$$MI \quad = \sum_{G1(Z),a1} p(G1(Z), a1) log \frac{p(G1(Z),a1)}{p(G1(Z))p(a1)}$$

4.5 Cosine similarity: Regardless of the size of the documents [23] cosine similarity is a statistic used to determine how similar they are

$$\boldsymbol{CS} = \frac{\boldsymbol{G1(Z).a1}}{||\boldsymbol{G1(Z)}||\ ||\boldsymbol{a1}||} \qquad (7)$$

The following are the result windows,Figure[3] describes starting of the window when we run the defect module it will be appeared,Figure[4] describes first we have load the GAN and VGG16 pre-trained model. Figure[5] describes uploading test images from the NEU dataset. Figure[6] shows a high-quality image with defect recognition, and Figure[7] shows the performance factors and type of image.

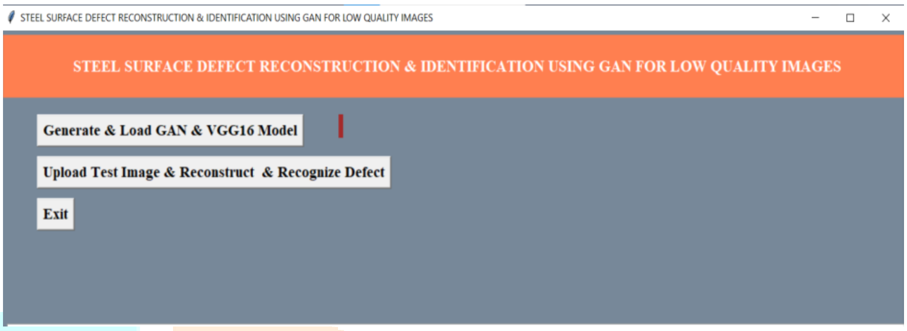

Figure3: starting window

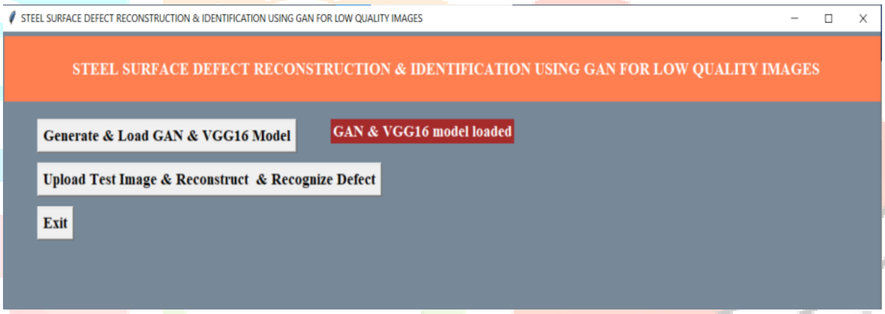

Figure4: loading GAN and VGG16 model

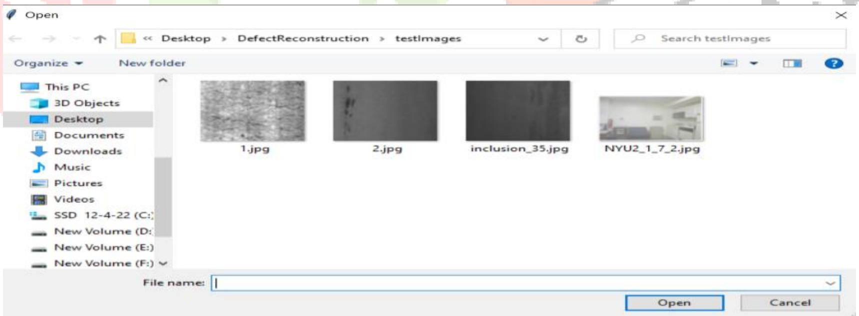

Figure 5: selecting the test image from the NEU dataset

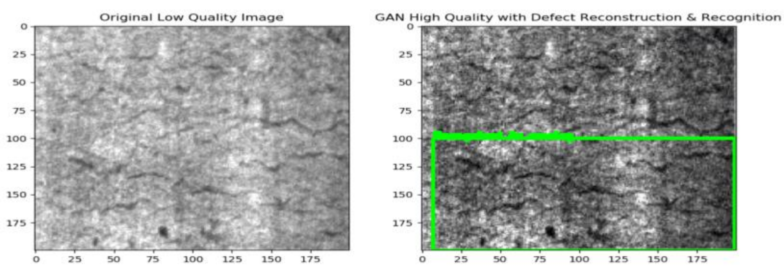

Figure 6: high- quality image with defect recognition

Figure:7 calculated performance indicators and type of image recognition.

5. CONCLUSION AND FUTURE WORK

In vision-based defect recognition, DL is a center for research. However, most contemporary DL approaches are image quality sensitive, and a low-quality image may lead the models to perform poorly. This study presents a GAN-based DL technique for low-quality defect recognition, to address this issue. The proposed technique is better suited for textural defects, such as those found in steel, where the GAN may learn meaningful information from the context. Furthermore, having enough training examples ensures better reconstruction and recognition. GAN is a time-consuming model for training and it requires a high configuration of the system. In the future, we will work on developing a lightweight model. It can be able to identify the new defects in the images.

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