

SUPER RESOLUTION IMAGE ENHANCEMENT USING CNN

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ABSTRACT: In this paper, we describe the CNN based image enhancement technique. CNN equalization analyses on the based of super resolution further more calculate the metrics parameter of CNN technique. Image enhancement is a procedure of changing or adjusting image in order to make it more suitable for certain application. Convolution a neural network is considering one of the practical solutions to realize the super resolution. A selection of CNN based model with four convolution layer is Proposed each of which is named with the convolution parameter, and experimental result archives the best performance in super resolution reconstruction task.

General terms: Convolution Neural Network, Super Resolution Reconstruction, Fuzzy-C'Means Clustering, histogram Equalization

Key words: Adaptive Histogram Equalization, MN16T Filter shape, Convolutional Neural layer, Pooling layers, Digital image processing pixels

INTRODUCTION

The real international scenes have a totally huge variety of luminance ranges. But within the field of images, the regular cameras are not capable of taking pictures the genuine dynamic range of a natural scene. To beautify the dynamic range of the captured picture, a technique referred to as high Dynamic variety (HDR) imaging is typically used. HDR imaging is the method of capturing scenes with large intensity range than what conventional sensors can capture. It can faithfully seize the details in dark and bright part of the scene. If the intense and dark regions coexist within the identical scene, these regions have a tendency to be under- or over-saturated. in order to conquer the restrained dynamic range, excessive dynamic variety (HDR) imaging has been brought, and the functionality of taking photos in extremely HDR scenes has turn out to be essential for a current digital nevertheless digicam (DSC). because virtual imaging sensors, inclusive of price coupled gadgets, has decrease dynamic variety than analog poor movies, DSC notably is based on the auto exposure (AE) control feature to

determine the proper exposure cost for masking the maximum dynamic variety of the scene being taken. High Dynamic variety (HDR) imaging techniques have been applied in current years as an opportunity approach for virtual imaging. The predicament of virtual cameras in capturing actual scenes with huge lightness dynamic variety, a class of photograph acquisition and processing techniques, together named high Dynamic range imaging, won reputation. To accumulate HDR scenes, consecutive frames with one of a kind exposure are usually obtained and blended right into a HDR image this is viewable on regular shows and printers. Photo Enhancement is largely an only and appealing region of virtual photograph processing. Photograph enhancement is method used to decorate the general superiority of the corrupted snap shots can be attained via the usage of enhancement mechanisms. So that the human eye can certainly detect the important thing features of the images. It is used to put off. The irrelevant artifacts from the images like noise or brighten the photograph and it certainly to identify predominant features and then it appears advanced. Its miles an individual vicinity of virtual image processing. To create a photo show further beneficial to visualise and exam, it get better the image features which includes edges or barriers. It enlarges the dynamic variety of amassed features. It does no longer growth the built in content of facts. In this approach an image is captured thru a camera of different publicity and they're fused collectively to form a high Dynamic variety image [2], [3]. Shen et al [4] proposed a novel algorithm primarily based on extended Retinex version to fuse multi-publicity photographs. As opposed to composing the input photograph intensities, this approach decomposes them into the luminance and reflectance components which are composed independently before being merged together to supply the final end result. Gu et al [5] proposed an algorithm to fuse multi-publicity pix inside the gradient subject. Fused gradient field was derived from the structure tensor of inputs primarily based on multidimensional Riemannian geometry with a Euclidean metric. those proposals does not satisfy dynamic mode of image of

shifting scenes and suits handiest the static mode of scenes and various artifacts which includes ghosting cannot be prevented due to the sequential seize of in a different way exposed pics. There are numerous strategies wherein the digital camera and nearby movement are compensated to take away ghosting impact. Jacobs et al [6] proposed a ghost detection approach on entropy computation. In this method the local entropy is obtained and it's far brought to the distinction entropy values with that of the weighting component among the LDR photos. Khan et al presented an iterative ghost impact removal method. On this process through weighting the opportunity of pixels of a moving item we will obtain an HDR image. Zhang et al proposed to apply gradient route modifications the various one-of-a-kind pix for object motion detection. This technique is a disadvantage as it doesn't remember the nearby regions of a ghost photo and similarly this approach takes that the shifting place takes the small part of an image. Zhang et al proposed a new de-ghosting set of rules to overcome those shortcomings of the method offered by using Zhang et al through taking not best the temporal consistency but also spatial consistency. This approach generalizes the previous attempt however it fails to produce a perfect HDR pictures. Lee et al proposed to obtain a ghost-loose high dynamic range picture primarily based on a low-rank matrix of completion. In this method the low-matrix and sparse matrix technique is used represent the transferring objects. The ghost place detection is formulated because the low-rank matrix final touch hassle with more than one physical constraint at the houses of the ghost regions. But this approach is bear in mind as complexity for cell camera application

HISTOGRAM EQUILIZATION

Histogram equalization is an evaluation enhancement approach whereby pixel intensities are adjusted in an effort to achieve a new superior picture with expanded local assessment. For that reason, the intensities can be higher dispensed on the histogram. Several sorts of distinct non-adaptive and adaptive techniques. A sophisticated histogram-equalization set of rules for contrast enhancement are provided. Histogram equalization is the maximum famous set of rules for contrast enhancement because of its effectiveness and ease. It is able to be categorised into two branches consistent with the transformation feature used: global or local. Worldwide histogram equalization is

straightforward and speedy; however its comparison-enhancement power is extraordinarily low. Nearby histogram equalization, however, can enhance average assessment more successfully, but the complexity of computation required is very high due to its completely overlapped sub-blocks. In this paper, a low-bypass filter out-kind masks is used to get a no overlapped sub-block histogram-equalization feature to provide the high assessment associated with local histogram equalization however with the simplicity of world histogram equalization. This mask also eliminates the blockading impact of no overlapped sub-block histogram-equalization. The low-bypass filter out-kind mask is found out by means of partially overlapped sub-block histogram-equalization (POSHE). With the proposed method, for the reason that sub-blocks are an awful lot much less overlapped, the computation overhead is reduced by way of an issue of approximately a hundred as compared to that of local histogram equalization while nonetheless reaching excessive comparison. The proposed algorithm may be used for industrial functions where excessive efficiency is needed, along with camcorders, closed-circuit cameras, etc.

PROPOSED SYSTEM

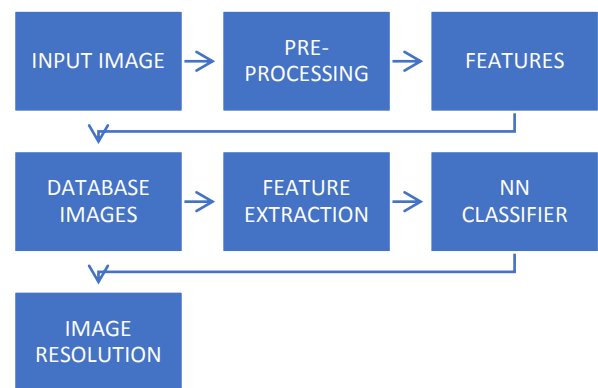


Fig.1.Block Diagram of image enhancement

CNNs, like neural networks, are made up of neurons with learnable weights and biases. Each neuron receives several inputs, takes a weighted sum over them, pass it through an activation function and responds with an output. The whole network has a loss function and all the tips and tricks that we developed for neural networks still apply on CNNs

POOLING LAYERS

Its function is to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network. Pooling layer operates on each feature map independently.

TYPICAL ARCHITECTURE OF A CNN

We have already discussed about convolution layers (denoted by CONV) and pooling layers (denoted by POOL). RELU is just a non-linearity which is applied similar to neural networks. The FC is the fully connected layer of neurons at the end of CNN. Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks and work in a similar way. CNNs are especially tricky to train, as they add even more hyper-parameters than a standard MLP. While the usual rules of thumb for learning rates and regularization constants still apply, the following should be kept in mind when optimizing CNNs.

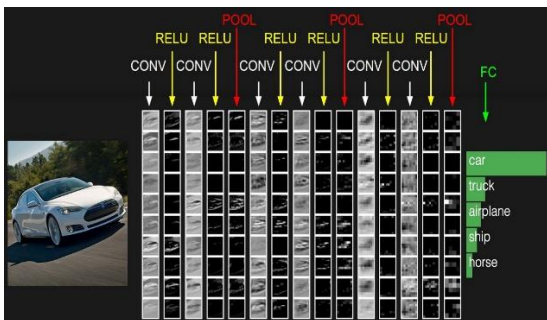


Fig 2. Architecture of a CNN

CLASSIFICATION OF IMAGES

BINARY IMAGE

A binary image is a digital image that has only two possible values for each pixel. Typically the two colors used for a binary image are black and white though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color.

Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit (0 or 1). This name black and white, monochrome or monochromatic are often used for this concept, but may also designate any images that have only one sample per pixel, such as grayscale images

Binary images often arise in digital image processing as masks or as the result of certain

operations such as segmentation, thresholding, and dithering. Some input/output devices, such as laser printers, fax machines, and bi-level computer displays, can only handle bi-level images

GRAY SCALE IMAGE

A grayscale image is a digital image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray (0-255), varying from black (0) at the weakest intensity to white (255) at the strongest.

Grayscale images are distinct from one-bit black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called bi-level or binary images). Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the absence of any chromatic variation.

Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured. But also they can be synthesized from a full color image; see the section about converting to grayscale.

COLOUR IMAGE

A (digital) color image is a digital image that includes color information for each pixel. Each pixel has a particular value which determines its appearing color. This value is qualified by three numbers giving the decomposition of the color in the three primary colors Red, Green and Blue. Any color visible to human eye can be represented this way. The decomposition of a color in the three primary colors is quantified by a number between 0 and 255. For example, white will be coded as $R = 255, G = 255, B = 255$; black will be known as $(R,G,B) = (0,0,0)$; and say, bright pink will be: $(255,0,255)$. In other words, an image is an enormous two-dimensional array of color values, pixels, each of them coded on 3 bytes, representing the three primary colours. This allows the image to contain a total of $256 \times 256 \times 256 = 16.8$ million different colours. This technique is also known as RGB encoding, and is specifically adapted to human vision

It is observable that our behaviour and social interaction are greatly influenced by emotions of people whom we intend to interact with. Hence a successful emotion recognition system could have great impact in improving human computer interaction systems in such a way as to make them be more user-friendly and acting more human-like.

Moreover, there are a number of applications where emotion recognition can play an important role including biometric authentication, high-technology surveillance and security systems, image retrieval, and passive demographical data collections.

It is unarguable that face is one the most important feature that characterises human beings. By only looking ones' faces, we are not only able to tell who they are but also perceive a lot of information such as their emotions, ages and genders.

This is why emotion recognition by face has received much interest in computer vision research community over past two decades.

DIGITAL IMAGE PROCESSING

The identification of objects in an image would probably start with image processing techniques such as noise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures.

The clever bit is to interpret collections of these shapes as single objects, e.g. cars on a road, boxes on a conveyor belt or cancerous cells on a microscope slide. One reason this is an AI problem is that an object can appear very different when viewed from different angles or under different lighting. Another problem is deciding what features belong to what object and which are background or shadows etc. The human visual system performs these tasks mostly unconsciously but a computer requires skilful programming and lots of processing power to approach human performance. Manipulating data in the form of an image through several possible techniques. An image is usually interpreted as a two-dimensional array of brightness values, and is most familiarly represented by such patterns as those of a photographic print, slide, television screen, or movie screen. An image can be processed optically or digitally with a computer.

To digitally process an image, it is first necessary to reduce the image to a series of numbers that can be manipulated by the computer. Each number representing the brightness value of the image at a particular location is called a picture element, or pixel. A typical digitized image may have 512×512 or roughly 250,000 pixels, although much larger images are becoming common. Once the image has been digitized, there are three basic operations that can be performed on it in the computer. For a point operation, a pixel value in the output image depends on a single pixel value in the input image. For local operations, several neighbouring pixels in the input image determine the value of an output image pixel. In a global operation, all of the input image pixels contribute to an output image pixel value.

These operations, taken singly or in combination, are the means by which the image is enhanced, restored, or compressed. An image is enhanced when it is modified so that the information it contains is more clearly evident, but enhancement can also include making the image more visually appealing.

An example is noise smoothing. To smooth a noisy image, median filtering can be applied with a 3×3 pixel window. This means that the value of every pixel in the noisy image is recorded, along with the values of its nearest eight neighbours. These nine numbers are then ordered according to size, and the median is selected as the value for the pixel in the new image. As the 3×3 window is moved one pixel at a time across the noisy image, the filtered image is formed.

Another example of enhancement is contrast manipulation, where each pixel's value in the new image depends solely on that pixel's value in the old image; in other words, this is a point operation. Contrast manipulation is commonly performed by adjusting the brightness and contrast controls on a television set, or by controlling the exposure and development time in printmaking. Another point operation is that of pseudo colouring a black-and-white image, by assigning arbitrary colours to the gray levels. This technique is popular in thermograph (the imaging of heat), where hotter objects (with high pixel values) are assigned one color (for example, red), and cool objects (with low pixel values) are assigned another color (for example, blue), with other colours assigned to intermediate values.

Recognizing object classes in real-world images is a long standing goal in Computer vision. Conceptually, this is challenging due to large appearance variations of object instances belonging to the same class. Additionally, distortions from background clutter, scale, and viewpoint variations can render appearances of even the same object instance to be vastly different. Further challenges arise from interclass similarity in which instances from different classes can appear very similar. Consequently, models for object classes must be flexible enough to accommodate class variability, yet discriminative enough to sieve out true object instances in cluttered images. These seemingly paradoxical requirements of an object class model make recognition difficult. This paper addresses two goals of recognition are image classification and object detection. The task of image classification is to determine if an object class is present in an image, while object detection localizes all instances of that class from an image. Toward these goals, the main contribution in this paper is an approach for object class recognition that employs edge information only. The novelty of our approach is that we represent contours by very simple and generic shape primitives of line segments and ellipses, coupled with a flexible method to learn discriminative primitive combinations. These primitives are complementary in nature, where line segment models straight contour and ellipse models curved contour. We choose an ellipse as it is one of the simplest circular shapes, yet is sufficiently flexible to model curved shapes. These shape primitives possess several attractive properties. First, unlike edge-based descriptors they support abstract and perceptually meaningful reasoning like parallelism and adjacency. Also, unlike contour fragment features, storage demands by these primitives are independent of object size and are efficiently represented with four parameters for a line and five parameters for an ellipse.

Additionally, matching between primitives can be efficiently computed (e.g., with geometric properties), unlike contour fragments, which require comparisons between individual edge pixels. Finally, as geometric properties are easily scale normalized, they simplify matching across scales. In contrast, contour fragments are not scale invariant, and one is forced either to rescale fragments, which introduces aliasing effects (e.g., when edge pixels are pulled apart), or to resize an image before extracting fragments, which degrades image resolution.

In recent studies it is shown that the generic nature of line segments and ellipses affords them an innate ability to represent complex shapes and structures. While individually less distinctive, by combining a number of these primitives, we empower a combination to be sufficiently discriminative. Here, each combination is a two-layer abstraction of primitives: pairs of primitives (termed shape tokens) at the first layer, and a learned number of shape tokens at the second layer. We do not constrain a combination to have a fixed number of shape-tokens, but allow it to automatically and flexibly adapt to an object class. This number influences a combination's ability to represent shapes, where simple shapes favour fewer shape-tokens than complex ones. Consequently, discriminative combinations of varying complexity can be exploited to represent an object class. We learn this combination by exploiting distinguishing shape, geometric, and structural constraints of an object class. Shape constraints describe the visual aspect of shape tokens, while geometric constraints describe its spatial layout (configurations). Structural constraints enforce possible poses/structures of an object by the relationships (e.g., XOR relationship) between shape-tokens.

Fuzzy based fusion

A fuzzy concept is a idea of which the bounds of software can vary significantly in step with context or conditions, instead of being constant as soon as and for all.[1] this indicates the idea is indistinct in some way, missing a set, specific meaning, without however being uncertain or meaningless altogether.[2] It has a precise which means, which may be made greater precise most effective through similarly elaboration and specification, which include a closer definition of the context in which the concept is used.

A fuzzy idea is understood through scientists as an idea that's "to an extent applicable" in a scenario, and it therefore implies gradations of importance. The exceptional acknowledged instance of a fuzzy concept around the sector is an amber visitors mild, and indeed fuzzy principles are widely used in traffic manipulate systems.[3] nowadays engineers, statisticians and programmers often represent fuzzy ideas mathematically the usage of fuzzy variables, fuzzy sets and fuzzy values.[4] because the 1970s, the use of fuzzy ideas has risen gigantically in all walks of life

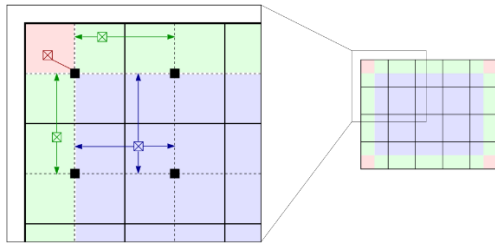


Fig 3. Fuzzy based fusion

The redistribution will push a few boxes over the clip limit all over again (vicinity shaded green inside the discern), resulting in an effective clip limit that is huge than the prescribed restriction and the suitable fee of which depends on the photo. If that is undesirable, the redistribution manner may be repeated recursively till the extra is negligible.

Adaptive histogram equalization in its sincere form provided above, each with and without evaluation limiting, requires the computation of a particular neighbourhood histogram and transformation characteristic for every pixel in the picture. This makes the method very pricey computationally.

Interpolation allows a considerable development in efficiency without compromising the extraordinary of the end result.[3] The photograph is partitioned into further sized rectangular tiles as proven in the right part of the parent underneath. (Sixty 4 tiles in eight columns and eight rows is a common choice.[4]) A histogram, CDF and transformation feature is then computed for every of the tiles. The transformation competencies are appropriate for the tile center pixels, black squares in the left part of the determinant. All different pixels are converted with as much as 4 transformation abilities of the tiles with center pixels closest to them, and are assigned interpolated values. Pixels in the bulk of the image (shaded blue) are bilinearly interpolated, pixels close to the boundary (shaded inexperienced) are linearly interpolated, and pixels close to corners (shaded purple) are transformed with the transformation feature of the corner tile. The interpolation coefficients mirror the vicinity of pixels some of the nearest tile center pixels, in order that the end result is continuous because the pixel processes tile middle.

WORKING

Image is basically presented as 2-D array of brightness value. The pre processing stage includes process such as noise reduction, low level features extraction,

identification of edges and texture identification. The image that will be representing will be stored as a 2-D Array of brightness value. Feature extraction is mainly by edge detection. The features extraction will be one of the throughout part of the process (Basically by the brighter value)

The database that is used to train the model is a pre trained model. The neural networks classifiers will use set of independent filter. That is used set the parameters. Here in our model we use a 4 filter at the output and 2 at the input. The filter is MNIST filter. In order to make the process, less incentives we will be pooling layers to reduce the size so it can fit the filter shape and size. The image information that is to be upscaled mostly lies in the edges. Edges are nothing but sudden changes or discontinuity. The edges are detected by applying mock to the input images. The mock type can be horizontal, vertical or diagonal mock.

GLCM FEATUES

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j . By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i, j) in the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. Because the processing required to calculate a GLCM for the full dynamic range of an image is prohibitive, graycomatrix scales the input image. By default, graycomatrix uses scaling to reduce the number of intensity values in gray scale image from 256 to eight. The number of gray levels determines the size of the GLCM. To control the number of gray levels in the GLCM and the scaling of intensity values, using the Num Levels and the Gray Limits parameters of the graycomatrix function.

The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. To illustrate, the following figure shows

how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. GLCM(1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. graycomatrix continues processing the input image, scanning the image for other pixel pairs (i,j) and recording the sums in the corresponding elements of the GLCM.

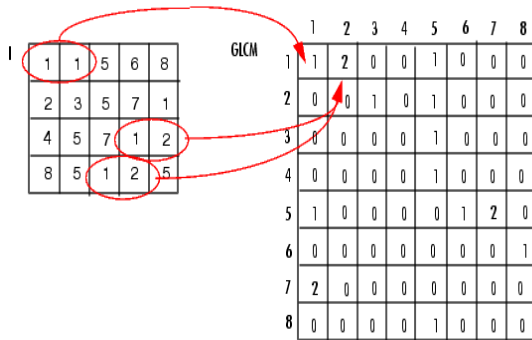


Fig 4. GLCM Features

To create multiple GLCMs, specify an array of offsets to the graycomatrix function. These offsets define pixel relationships of varying direction and distance. For example, you can define an array of offsets that specify four directions (horizontal, vertical, and two diagonals) and four distances. In this case, the input image is represented by 16 GLCMs. When you calculate statistics from these GLCMs, you can take the average.

You specify these offsets as a p-by-2 array of integers. Each row in the array is a two-element vector, [row_offset, col_offset], that specifies one offset. Row_offset is the number of rows between the pixel of interest and its neighbour. Col_offset is the number of columns between the pixel of interest and its neighbour. This example creates an offset that specifies four directions and 4 distances for each direction. After you create the GLCMs, you can derive several statistics from them using the graycoprops function. These statistics provide information about the texture of an image. Statistic such as Contrasts, Correlation, Energy, Homogeneity gives information about image.

HOW NN WORKS

Although the implementation is very different, neural networks are conceptually similar to K-Nearest Neighbor (k-NN) models. The basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables. Consider this figure:

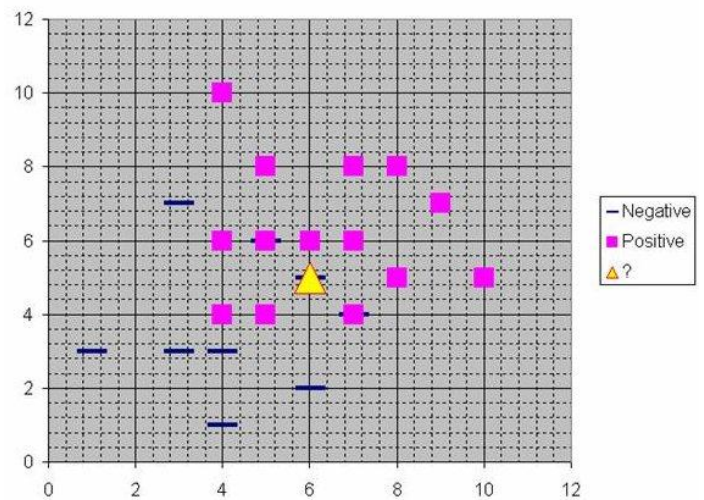


Fig 5. Graphical representation of Neural Networks

Assume that each case in the training set has two predictor variables, x and y. The cases are plotted using their x,y coordinates as shown in the figure. Also assume that the target variable has two categories, positive which is denoted by a square and negative which is denoted by a dash. Now, suppose we are trying to predict the value of a new case represented by the triangle with predictor values x=6, y=5.1. Should we predict the target as positive or negative? Notice that the triangle is position almost exactly on top of a dash representing a negative value. But that dash is in a fairly unusual position compared to the other dashes which are clustered below the squares and left of center. So it could be that the underlying negative value is an odd case.

The nearest neighbour classification performed for this example depends on how many neighboring points are considered. If 1-NN is used and only the closest point is considered, then clearly the new point should be classified as negative since it is on top of a known negative point. On the other hand, if 9-NN classification is used and the closest 9 points are considered, then the effect of the surrounding 8 positive points may overbalance the close negative point.

A neural network builds on this foundation and generalizes it to consider all of the other points. The distance is computed from the point being evaluated to each of the other points, and a radial basis function (RBF) (also called a kernel function) is applied to the distance to compute the weight (influence) for each point. The radial basis function is so named because the radius distance is the argument to the function.

Weight = RBF (distance)

The further some other point is from the new point, the less influence it has.

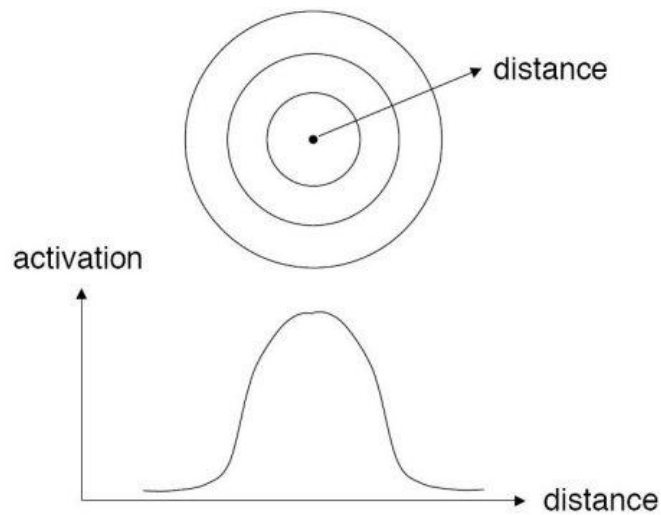


Fig 6. NN works in the unit area of the image (Activation is said by the image enhanced in the Y axis and distance covered by the image in X axis)

RESULT

These results I believe are impressive, the model must have developed a 'knowledge' of what a group of pixels must have been in the original subject of the photograph image. It knows that certain areas are blurred and knows to reconstruct a blurred background. The model couldn't do this if it hadn't performed well on the feature activations of the loss function. Effectively the model has reverse engineered what features would match those pixels to match the activations in the loss function.



Fig 7. Enhanced image

CONCLUSION

Data hiding is becoming one of the most rapidly advancing techniques the field of research especially with increase in technological advancements in internet and multimedia technology. With the technology advancing on one side, so has the rate of threat to hack, tamper or steal the data that is being transmitted over these medial also increased in leaps and bounds. This has necessitated an ever growing and systematic approach to ensure the security of transmitted and received content. On the other hand, the advent of tele based services have introduced medical image processing also to the data embedding arena especially for hospital management of patient records and subsequent follow up services and treatments. This maintenance of records also acts as data base for researchers all over to access any data as and when required.

FUTURE SCOPE

Data hiding has been an evergreen field since its inception in the late 1970's with the ever increasing need for security, speed and low cost as part of requirements of any transmission or reception system. Things need to be done at a very rapid rate without any compensation in loss of data or time. Data hiding has proved to be the ideal choice for such applications. It has grown in leaps and bounds with the advent of broadband and communication technologies which is capable of spanning the entire globe within a few minutes. It has played key roles in covert communication, image and video tagging, broadcast monitoring and copyright protection. With the ever existing introduction of new transforms which are improvements over their predecessors in some way or the other also could contribute to the growth of data hiding in an attempt to further bring about the optimality. Directionality features of new transforms like the Curvelet transforms,

Slantlet transforms could also be possibly investigated for its exploitation. As far as data hiding is concerned, there cannot be a point of saturation with the ever increasing threats and new hacking techniques in real world. With the advent of tele services, data hiding could cut costs and distance and travel miles and miles within a few minutes. It could also be an important tool in forensics for tracking criminal records and immediate identification of suspects. It could drastically reduce the effort of INTERPOL (International Police) and could bring about a better coordination globally. With the fast booming integrated circuit (IC) technology, data hiding concepts have been exposed to field programmable gate arrays (FPGA) using wavelet transforms, lifting based wavelet transforms. It could greatly aid in real time applications 129 with reduction in space, cost and time. This technology could be a great boon in preventing fake passports and forged identity cards especially in airline industries

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