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Advanced Denoising Model for QR Code Images Using Hough Transformation and Convolutional Neural Networks

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ABSTRACT

Quick Response (QR) code, a trademark for a two-dimensional code, has gained significant popularity in various sectors due to its innovative automatic identification and data detection capabilities in images. This research aims to enhance QR code identification rates by employing an effective pre-processing and detection method to mitigate noise levels in images with complicated backgrounds or uneven illumination. High-speed transformations on image blocks are utilized to improve recognition in these challenging conditions. A Convolutional Neural Network (CNN), a specialized network architecture for deep learning algorithms, is employed for QR image recognition and other pixel-based processing tasks. CNNs simplify the visuals without sacrificing essential information required for accurate predictions. In this paper, we propose an efficient Noise Removal in Quick Response Code Images using Hough Transformation (NRQRCI-HT) combined with CNN for noise reduction and accurate data identification. This method is benchmarked against traditional techniques, demonstrating superior performance levels in both noise removal and data identification accuracy.

1. INTRODUCTION

2D barcodes are well-known for using QR codes, which stand for Quick Response Code. With its excellent accuracy and reading speed, this code is highly effective. As an alternative means for users to ask people to join their contact list, Blackberry has included QR code capabilities into their handsets [1]. In addition to encryption, QR codes allow for decryption as well. Other users can scan and decode unique Blackberry pins by converting them into QR codes. Users who have been decoded can be added to contact lists [2]. As 2D international standard barcodes, QR codes are well-known for their high efficiency and outstanding qualities. The QR code can now carry up to 7,089 numbers, recognitions to its expanded ability to retain additional data is considered. In addition to letters and numbers, data can be stored in a variety of formats, such as Kanji characters, symbols, binary codes, and control codes [3].

The QR array might produce visual distortion during the decoding process. When images are scratched or damaged after the encoding process, they are subjected to distortions. There is also a level of error correction in QR codes [4]. Up to 30 percent of the original value can be corrected using this method. In some cases, distortions cannot be addressed. In the decoding process, black and white are the only colours that are considered to be important. Damage only occurs in the matrix's dark sections [5]. This problem was the impetus for this study. For example, HSV (colour segmentation), stem and binary image processing [6], and median filters were used to eliminate scratches from the QR code for noise reduction [7].

Using QR codes in real life is becoming more common as the digital information age progresses [8]. This dramatically improves the quality of life for people. Two-dimensional code image recognition has also gained much interest due to its quick progress. Decoding by conventional applications is a major difficulty for any embedding solution. Because picture pixels are embedded into a code, they alter its brightness, resulting in a higher chance of an error in binary coding [9]. The second barrier is the difficulty of incorporating the complete QR code into the embedded image or logo for noise removal [10]. Since the number of modules that may be replaced is inversely related to the code's rectification capability, this cannot be accomplished by simply swapping out existing information modules with the required image [11].

To retain the original image's visual fidelity while reducing the amount of corrupted modules, a good embedding approach should utilize as little space as possible. Hough transformations are used to pick a collection of changed pixels in the suggested approach. A visual distortion metric is minimized while keeping the chance of inaccuracy in check by optimizing the density of pixels and their matching luminance [12]. The decoding procedure is complete once the image has been acquired and its brightness has been calculated from the RGB components. Figure 1 shows the basic building blocks of QR code recognition, which include various signs and markers.

2D barcodes, like the QR Code, are popular because of their high storage capacity and speed of processing. Advertising and training are the two areas where this application's value is most apparent. Using a barcode to represent data that conveys its meaning, structure, and whole operation. In the first stage noise is used to encrypt QR codes, and in the second, filters are used to decode the noise [13]. Noise reduction is a crucial part of picture processing. There are a variety of methods for removing background noise from a photograph. The best Denoising model for QR images is one that is able to entirely remove noise as far as feasible while preserving the edges [14].

Each linear model and filter type has a particular use case. The most suited filter for reducing grain noise from a QR code is an averaging filter [15] since each pixel must be adjusted to the mean of the pixels in its vicinity and eliminate local differences caused by pixels [16]. This filter is sometimes known as the "average filter" because of its performance. For the removal of background noise, the median filter is an effective nonlinear digital filtering technique. For example, edge detection on a digital image can be improved by correcting noise in the pre-processing stages [17]. The median filter has a major benefit over linear filters in that it is able to remove the effect of input noise values that are exceedingly large. Figure 2 represents the clean QR code and noisy image and then de noised QR code.

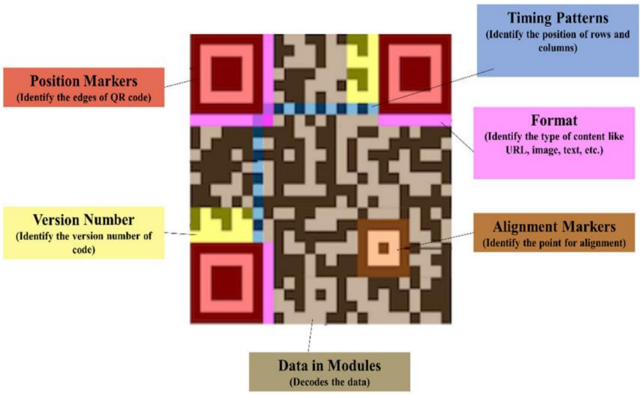

Figure 1. Components of QR code recognition

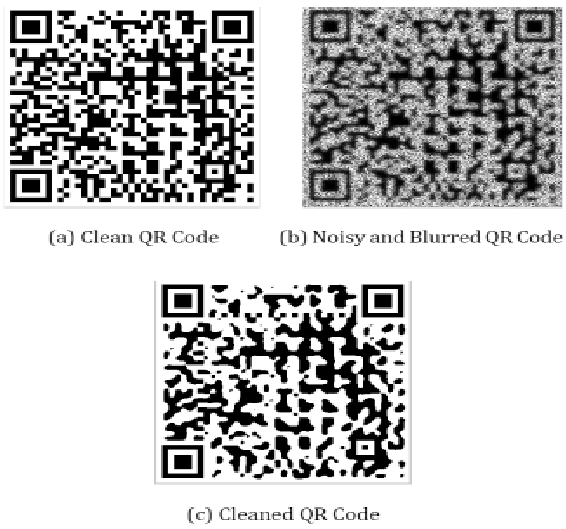

Figure 2. QR image, Noisy QR image and Cleaned QR image

This study helps to address many issues of recognising QR code through the proposal of an an efficient Noise Removal in Quick Response Code Images using Hough Transformation model. The Hough transform model offers an efficient solution that can fit the distorted QR picture into the geometrical pattern of distortion [18]. Due to their great accuracy, CNNs are utilized for picture classification and recognition of QR images. The CNN is a structured representation that first constructs a network in a funnel form, and then generates a fully linked layer. It is composed of all the neurons connecting to each other and yielding the final result. Whether it comes to processing visual, spoken, or audio signals, CNN outperforms conventional neural networks. The basic architecture of CNN is shown in Figure 3.

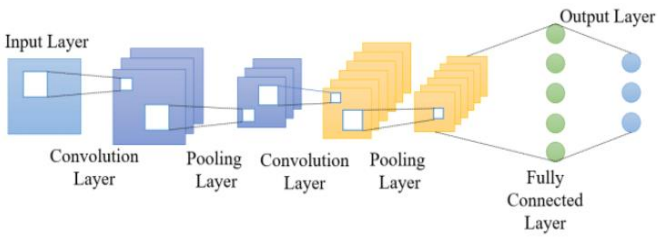

Figure 3. CNN architecture

The first layer of a convolutional network is the convolutional layer. Further convolutional layers or pooling layers can be introduced after the initial convolutional layer, but the fully connected layer always comes last. The CNN gets smarter as it progresses through the layers, eventually being able to recognize entire scenes. Basic elements like colours and borders are prioritised in the first layer. After the visual data has been processed by several layers of a convolutional neural network (CNN), it begins to detect larger sections or features of the item, and may then identify the target object. The proposed research makes use of automatic model using CNN layers for accurate denoising of QR images. This study addresses an essential research topic of QR code distortion and noise removal model, which in the current software systems was a severe research issue that need to be handled.

2. LITERATURE SURVEY

The selection of a grey threshold is critical to the success of binarization. Jiang et al. [1] presented an improved strategy to correcting photos with uneven illumination based on the estimation of the background grey levels. The author has done extensive research into the two-dimensional code's technique of binarization and positioning and recommended enhancements.

Vera et al. [2] improved the QR code encoding and decoding techniques. In order to save data, this architecture included a two-dimensional QR code recognition. For the purpose of removing the QR code's edge and decreasing resolution, Karrach et al. [3] used the maximum inter-class variance approach to binarilyze the image. After that, they applied gradient sharpening directly on the binary image. QR code processing is improved by this method, however it does not work in complex environments or with varying lighting.

In order to identify a QR Code Module edge and projection algorithm limitation, Belussi and Hirata [5] employed the Hough transform to turn the QR code horizontally. It's less effective if there are long lines with regular spacing between the QR code and the user. The DnCNN model was proposed by Zhang et al. [6], with the primary idea being to learn the image noise and then subtract the noise picture from the learned noise to create a noise-free image. A convex hull technique was presented by Tribak and Zaz [7] to the detection of boundaries of a dual QR code. QR image recognition, on the other hand, can only be used in the absence of background noise and so is not appropriate for large-scale detection.

In the literature, Mao et al. [8] presented the self-encoding structure RED-Net, which filters noise information while keeping information about the structure for the subsequent image reconstruction process, and gradually compresses the noisy picture information through convolutional layers. This article integrates the aforementioned network topologies on the basis of the image fragmentation theory, employing DnCNN to estimate the texture portion of the noisy image and RED-Net to evaluate the cartoon segment.

The window histogram method and Histogram Oriented Gradients (HOG) were used by Ciążyński and Fabijanska [9] to determine local features. There are two primary gradient directions in a QR code, and this yields the ratios between them. However, Szentandrási et al. [10] employed a checkerboard-like layout in the QR photos to estimate edge pixels. Using morphological detection techniques, Gaur and Tiwari [11] suggested an edge detection detector-based methodology.

In order to estimate the QR code's quadrilateral bounds, Suran [12] devised an approach that incorporates Harris' edge recognition with a convex hull algorithm. A new technique developed by Sun et al. [13] combines the identification of the Canny edge with the contour-filling technology by recognizing four corners of the QR code. A deep barcode technique to remove noise was presented by Hansen et al. [14]. In order to recognise 1D and 2D bar codes, Zharkov et al. [15] proposed a fast and reliable method of semi-segmented, deep learning. To recognize QR codes and assess patterns, Chou et al. [16] used neural architectures based on the neural network.

Kurniawan et al. [17] used a cascade of weak QR Code Finder pattern classifiers. In order to determine if three groups are spatially structured as three corners of a square region, the geometric relationships between the recognized patterns of the candidate finder are assessed. The first lateral and vertical scans had been carried out by Chen et al. [18] in order to find QR coding patterns accompanied by the PCA approach, which permits the deletion of false positives. Lin et al. [19] employed 7 invariants in Hu models as feature descriptors in the FP preliminary placement instead of PCA. The resultant functional vector is compared to the characteristic vectors of Euclidean samples.

Li et al. [20] developed a paradigm in which similar strategies are compressed in a row-length encoded binary image. Then the average FP ratios are searched row by row. Found FPs set a minimal contained area where a modified Knuth–Morris–Pratt quick-exploration approach has been used for the preliminary points for the ratios of 1:3:1 to calculate the FP co-ordinate center.

Denoising techniques that use deep learning train models from many pairings of clean and noisy images using convolutional neural networks (CNNs) without requiring the user to manually provide picture priors. In recent years, we have witnessed the rapid development of these techniques, greatly enhancing the denoising effect. When it comes to AWGN elimination, the well-known DnCNN [21] performs admirably. The denoising performance is further improved by RIDNet [22], which focuses on denoising models. Within the variational inference framework, VDN [23] derives a novel form of evidence lower bound observation (ELBO) as the training target by making assumptions about the distribution of clean images and noise. These CNN-based denoising techniques use network learning of low-level features to bring noise-free photos back to life.

3. PROPOSED MODEL

There are many advantages to 2D barcodes over linear barcodes, including the ability to store more information, as well as a lower mistake rate [19] because of encryption and the ability to scan in all directions [20]. As a result, 2D barcodes can now be used in a wider variety of industries. s. This isn't as dependent on scanner or printed material quality as other typical 2D codes, which are based on black and white [21]. The decoding of a QR code is based on the same protocols used to generate it. The most difficult part of creating a QR code is recognizing it with increased precision and speed [22]. When a QR code is used in the real world, there are three essential steps: localization, image pre-processing and decoding. The term "localization" refers to the process of identifying a QR code and determining its precise placement within an image. When a QR code has been spotted, its image is enhanced to remove blur, noise, angular perspective and other issues that may prevent effective decoding. In the final stage, the data is acquired and is based on the QR code's standard architecture. The proposed model makes of CNN for automatic denoising process of QR images. Using common QR image features, region-based segmentation techniques seek to separate or group regions. Some characteristics of an image include. values for brightness extracted from the original photos or calculated using some kind of image operator. Identifiably regional textures and patterns.

The layers of a CNN always fully connect with one another. Because of this, the affiliation weight is a vast parameter set, which is counterproductive to learning, if an image has a high-priority and a large number of hidden units. CNN uses the local collecting document to assert the entanglement of a QR picture. Constantly many convolution bits are used. The local gathering field estimation with completely exceptional load between yield maps is a consensus among the convolutional parts. Each convolutional region is capable of performing a convolution on the entire QR image. The parameters, including the convolution bit length, are then determined by the size of the local gathering. A CNN always has several hidden levels. Convolutional layers, and by extension, sub-examining layers, are represented by the opaque layers. The recognisable convolutional components are used for the entire image within the convolutional layer. The graphics are updated to a component map that has more detail. The proposed model CNN processing is shown in Figure 4.

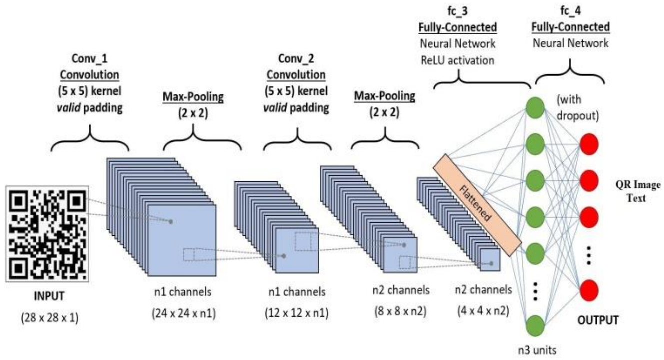

Figure 4. CNN model workflow

In the dataset, each image is 28×28 by 1 size. The sum of all the neurons in the input layer is only 784 (28×28). The considered QR image is 1000 pixels wide and 1000 pixels height; this would require 10^6 neurons in input layer. Initial image dimensions will be scaled to 224×224×3. Convolution reduces the input tensor dimension from 224 by 224 by

3=100,352 to 1 by 1 by 1000, but proceeding without convolution requires 100,352 neurons in the input layer. This implies that the minimum number of neurons in the first layer of a feedforward neural network is merely 1000. A 4×4 image is the result of convolving a 6×6 greyscale image with a 3 by 3 filter. Multiplying a 3×3 filter matrix by a 3×3 greyscale image first, then shifting one column all the way to the end, then shifting one row, and so on. As the input picture is 4 by 4 pixels and the filter is 3 by 3, the resulting convolutional matrix is 2 by 2.

The image recognition process begins with the acquisition of the image and then several actions such as image pre-processing, barcode detection, data sampling, error information rectification [22], information decoding and final output results are performed. Figure 5 depicts the common QR code recognition operation flowchart.

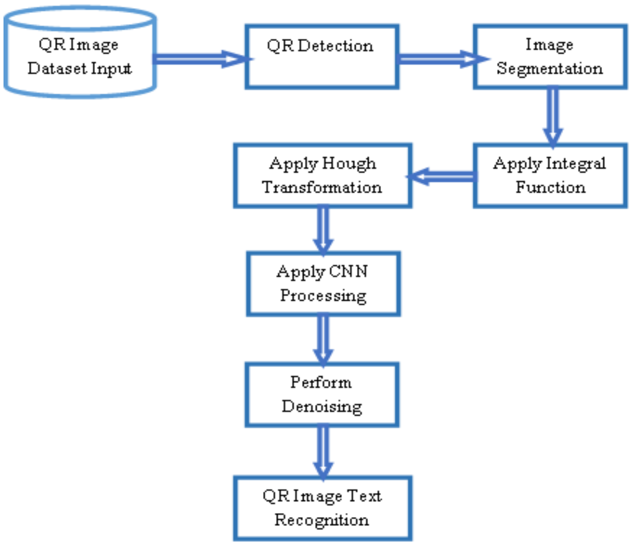

Figure 5. Model framework

Image training is the most important aspect of the complete QR code recognition system. Sampling information, correcting errors in information and decoding information all follow the guidelines. After the picture pre-processing is finished, the Hough Transformation can be used to decode the image. The primary goal of this study is to use QR Code images with Hough Transformation to extract the most important and accurate information. The Hough Transform is a technique used to extract visual features, as well as for computer vision and digital images. Through an elective method, the strategy seeks to find faulty situations in a specific class of forms. This technique is used in an area for parameters from which candidates are derived as a local maximum in a accumulator space formed specifically by the Hough-Computational Algorithm.

The normal picture learning mode is a learning mode and a similar image distortion for distortion correction, which may then be processed. Matching images are utilised to learn during the learning process. The proposed Noise Removal in Quick Response Code Images Using Hough Transformation is detailed and it is used to reduce the noise levels in the QR picture and then access the data held in the QR code image.

Algorithm NRQRCI-HT

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Step 1: Initially the QR image having data stored in it will be provided as input and considered as $DS\{N(QRI_m)\}=\{QRI_{m1}, QRI_{m2},\ldots\ldots, QRI_{mN}\}$

Step 2: The provided input can be analysed for its errors in image detection when the image is scanned. The image analysis process is performed as:

$$\delta_N(N(QRI_m)) = \begin{cases} f'_m(I_i(N)).\left(Inten_j(I_j(N))\right) > Th & then consider image as normal \\ otherwise, & consider image as noisy image \end{cases} \quad (1)$$

here, $f'm(I_i(N))$ is the function considered for the image grey level extraction and Inten is the function used to consider the intensity levels of the image, N is the total images considered. Th is the threshold value that is considered in range of 0 to 255. The proposed model considers threshold value as 200. Pixels with intensity greater than 200 is not considered for pixel intensity enhancement.

Step 3: The QR image is then undergo image segmentation for accurate pixel extraction for analysis of noise levels. The segmentation process is applied as:

$$l_m(I[x_i, y_j]) = \sqrt{\sum_{l=l_m}^{N} \delta_N + min(Th - l_i(I[x, y]))^2} \quad (2)$$

Step 4: The integral function is applied on each segment to verify the change in the structure and shape of the image so that noise location can be detected. The integral function is applied as:

$$f_{integral}(x, y) = \sum_{I_m \in DS} \sum_{I=1} f\,(I(x_i, y_j)) + Th \quad (3)$$

Step 5: The QR code image density and BLOB ratio is considered to identify the accurate error position of the QR image. The process is performed as:

$$Blob.Density[i] = \frac{Number of\ pixels in\ BLOB}{BLOB\ height * width} \quad (4)$$

$$Blob.Ratio[i] = \frac{BLOB\ smallest\ side}{BLOB\ largest\ side} \quad (5)$$

Step 6: The Hough transformation is applied for feature extraction from the QR image is performed as:

$$\mathrm{IHT}(QR(I(x, y))) = \sum_{i=1}^{N} \max\,(Blob.Ratio[i]) + \{\frac{\left\|\left|i_j - \delta_N\right|\right\|}{\left\|\left|j_j - \delta_N\right|\right\|}\}^M + \sum_{i=1} EQ(I(x, y))_{i.j} \quad (6)$$

$$HT = \sum_{i}^{N} f(i, j) + I(i + h, j + w) + \lim_{n\to\infty}\left(1 + \frac{1}{N}\right) + \sum_{i=1}^{N} fi\left(\left(\left(I_i - I_j^{(N)} + Max(IHT(I(x, y))\right)\right) * \vartheta\right)^N \quad (7)$$

here, IHT is the intermediate Hough Transformation, EQ is the equalizer function applied to normalize the intensity levels of the pixels of the considered QR image. HT is the calculated Hough transformation that considers the useful features extracted from the QR image.

Step 7: The noise levels in the QR image can be removed and the quality of the QR image can be enhanced using the following process:

$$QR(I(x,y)) = \left(\max\left(Blob.Ratio[i](\mathrm{I}(x,y)) \right) + \sum_{i \in DS(QR(i))} \sum_{I(i,j)} \frac{|HT^N|}{|\max(IHT)|} * Th_{ij}^{l} \right) \tag{8}$$

here, Th is the threshold value of intensity that is added to the image, HT is the hough transformation set.

Step 8: The CNN model is applied after the image enhancement is applied using integral function and hough transformation. The CNN model makes the task automatic for accurate text detection.

If a x * y convolution layer is considered for the QR image set, and if a f * f filter δ is used, weighted filter attributes are generated for a pooling layer as

$$PollingL[N] = \sum_{i=0}^{N} \sum_{j=0}^{i} \delta_{xy} * (x+i) * (y+j) \tag{9}$$

The hidden layer processing to generate the output is performed as:

$$HidL(\delta) = \sum_{i=1}^{N} \max(PoolingL(i, i+1)) * max(IHT(I(x,y))) + \frac{\sqrt{\frac{|HT^N|}{|\max(IHT)|}}}{\mathrm{size}(QR(I(x,y)))} \tag{10}$$

Step 9: The noise data is removed from the image and the data in the QR code image is extracted as:

$$DA\left(QR(I(x,y))\right) = \sum_{I\,\varepsilon DS(I)} \delta_N + \log HT(y_j = 1|x; \min(IHT)) + \sum_{i \in DS(QR(i))} \log IHT(x_n = 0|y; \min(HT)) \tag{11}$$

Step 10: The absolute mean square error in extracting the data stored is calculated that is the difference among input and output mean of QR images that is calculated as:

$$AMSE = \frac{1}{\delta_N} \mathrm{f}(\mathrm{I}|y-x|) + \min(Blob.Density[i]) \tag{12}$$

Step 11: The Mean Square Error Rate (MSER) is calculated that represents the error rate of the QR image denoising and data accessing is performed as:

$$MSER = \frac{1}{x_i, y_i} \frac{\sum_{i=1}^{N_m} \sum_{y=1}^{N_m} (f(x,y) - \hat{f}(x,y))^2}{\sum_{x=1}^{N_m} \sum_{y=1}^{N_m} (f(x,y))^2} \tag{13}$$

}

4. RESULTS

QR codes with images are used in advertising, product packaging, quick reference guides, and infographics and for storing data. It functions similarly to a standard QR code. However, it differs from the code's content. The proposed model is implemented using python in ANACONDA SPYDER. The QR code images dataset is considered from the link https://www.kaggle.com/coledie/qr-codes. The dataset contains 10000 files. The proposed Noise Removal in Quick Response Code Images using Hough Transformation (NRQRCI-HT) model is compared with the BLOB based Algorithm (BLOBA) [4]. The proposed model performance levels are compared with the traditional method in terms of Noise Removal Time Levels, QR Analysis Time, Hough Transform Calculation Time Levels, Data Detection Time Levels and Accuracy Levels in Data Detection. The noise removal time levels of the proposed and traditional method are represented in Figure 6.

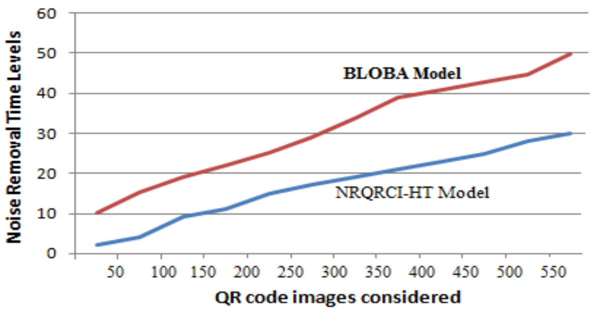

Figure 6. Noise removal time levels

The huge squares just outside of the QR code can be used by a QR reader to identify a normal QR code. When it recognises these shapes, it understands that everything contained within the square is a QR code. The QR scanner then decodes the QR code by dumbing it down into a grid. The QR code analysis time levels of the proposed and existing methods are represented in Figure 7.

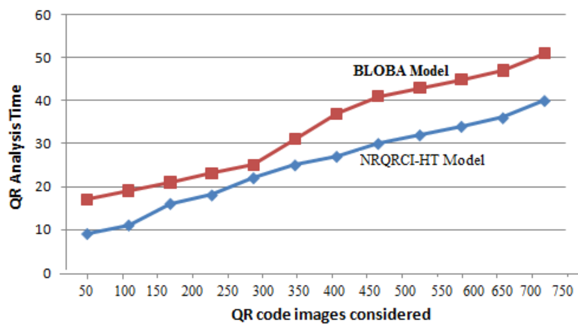

Figure 7. QR analysis time levels

The Hough transform is a method for locating shapes in photographs especially used in QR code images in this research work. It's been used to retrieve lines, circles, and ellipses in particular. Lines have a mathematical definition that is identical to the Radon transform. The Hough Transform Calculation time levels of the proposed and existing methods are represented in Figure 8. The results indicate that the proposed model takes less time in calculation that represents the system performance is better than the existing models.

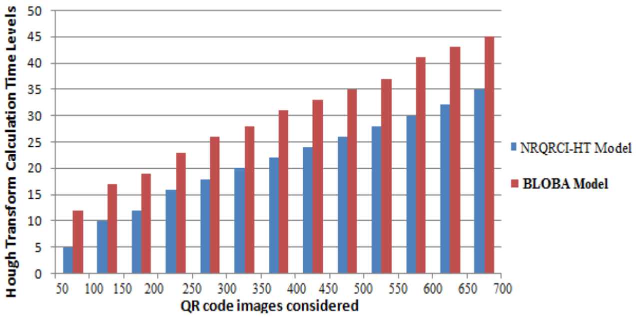

Figure 8. Hough transform calculation time levels

QR codes could include any kind of information including coupons, internet URLs, train schedules, and even music and video samples. Consumers might receive information with advertising with QR codes instantaneously. Another useful use of the QR code could be enhancing based localization systems that can more accurately estimate the present position. The data detection levels in QR code images of the proposed and existing models are represented in Figure 9.

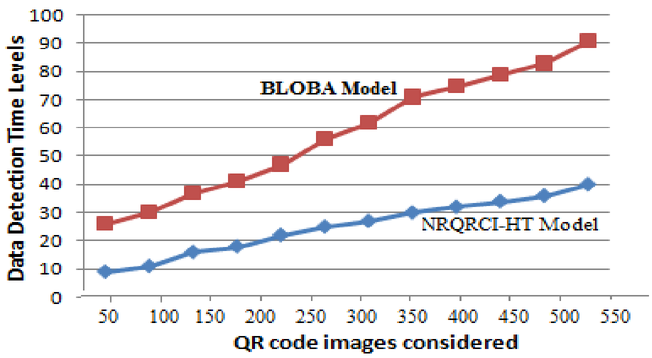

Figure 9. Data detection time levels

Although there are so many possibilities of QR code usages, there are several problems to existing methods for code recognition and decoding. The recognised QR decoders, in particular, need the correct placement of the code on the image frame. For successful deconstruction, the symbols should represent more than 30 percent of the entire image. QR decoders are sensitive to interference, rotation, blurredness, lighting or distortions of perspective. Due to those real-life conditions, decoders could fail. The proposed model is very helpful in removing the noise from the QR images and the extract the data stored in the image. The proposed model after denoising and image quality enhancement, the QR data will be accurately detected without loss that is used to know the hidden information of the QR image. The accuracy levels in the data detection of the proposed and existing models are indicated in Figure 10.

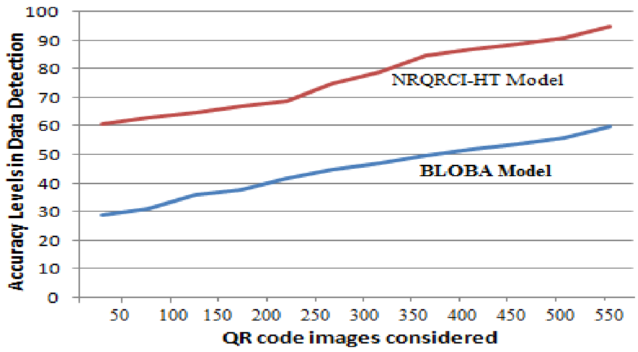

Figure 10. Accuracy levels in data detection

5. CONCLUSIONS

The primary goal of this research is to recognize QR codes that are severely deformed, particularly those printed on goods that are prone to harm. In this case, the QR code's recognition rate is very low or non-existent, and the data stored in it is inaccessible. The use of QR codes in trademarks as an effective two-dimensional code is bound to be an important development trend. As a result, it is critical in special circumstances to improve the recognition rate of the QR code, and better recognition rate can also considerably encourage the use of QR codes. The Hough Transformation is used in this research to effectively remove noise from Quick Response Code images. In the realm of deep learning algorithms, a CNN is the network design of choice for QR image text recognition and other tasks that require processing pixel data. The proposed research makes use of CNN model for accurate denoising of QR images that provides best accuracy. The proposed model achieves 97% accuracy in text recognition from QR image. The test results reveal that, even with a high noise density in the image, this technique has a decent filtering and denotation influence. Furthermore, the image after this procedure is filtered and denounced is quite noteworthy in terms of data protection. Extensive analysis of QR code symbol image preprocessing work prior to QR code decoding, followed by detailed analysis and investigation of existing QR code preprocessing methods. The use of all methods is compared in order to correct the distortion, in particular while identifying QR codes written on the surface of objects prone to crinkles. The technique is further optimized in future to improve the detection rate for the application for the QR code detection.

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