

CAPTCHA RECOGNITION USING DCNN

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Abstract: Completely Automated Public Turing Test to Tell Computers and Humans Apart (CAPTCHA) is an important human-machine distinction technology for websites to prevent the automatic malicious program attack. CAPTCHA recognition studies can find security breaches in CAPTCHA technology. By using the concept of deep learning and computer vision, the very purpose of the CAPTCHAs can be defeated. This test can be passed automatically with the help of Convolutional Neural networks (CNN). A CNN is an algorithm of deep learning which takes an image as input and then assigns some value to various features in the image which further helps to differentiate one feature from the other. Its main purpose is to transform the images into a form which is much easier to process, without losing features which are essential for getting an optimized prediction. The proposed system for this project is to expand this CAPTCHA recognition system for larger and more noisy CAPTCHA containing all the symbols possible, a method based on the Deep Convolutional Neural Network (DCNN) model to identify CAPTCHA and avoid the traditional image processing technology such as location and segmentation. The adaptive learning rate is introduced to accelerate the convergence rate of the model, and the problem of over fitting and local optimal solution has been solved. The multi task joint training model is used to improve the accuracy and generalization ability of model recognition. The experimental results show that the model has a good recognition effect on CAPTCHA with background noise and character adhesion distortion. The future scope of this project lies in technologies where more noisier images can be processed such as license plates, handwriting recognition etc.

1. Introduction

The Completely Automated Public Turing test to tell Computers and Human Apart (CAPTCHA) is a type of test to differentiate between humans and computer programs on Internet websites. CAPTCHA attempts to provide security against bots and can appear in many forms, including text, image, audio and video. Conducting research on recognizing CAPTCHA images is important because it helps identify weak points and loopholes in the generated CAPTCHAs and consequently leads to the avoidance of these loopholes in newly designed CAPTCHA-generating systems, thus boosting the security of the Internet. Text-based CAPTCHAs are still a much popular and powerful tool against malicious computer program attacks due to their extensive usability and easy implementation. The majority of text-based CAPTCHAs consist of English uppercase letters (A to Z), English lowercase letters (a to z), and numerals (0 to 9). Numerous mechanisms have been developed to secure and strengthen text-based CAPTCHAs including background noise, text distortion, rotating and warping, variable string length, and merging of characters. However, due to the rapid evolution of deep learning in the past few years, CAPTCHA recognition systems have become more competent than before in breaking most of the current defense mechanisms of text-based CAPTCHAs [7,8]. As a result, sophisticated security mechanisms need to be developed to make text-

based CAPTCHAs more robust against malicious attacks. Deep learning techniques demonstrate an excellent ability to extract meaningful features from input images and have numerous applications in various areas, such as image restoration and object detection.

These powerful characteristics of deep learning techniques make them a good choice for building robust CAPTCHA recognition networks to perform attacks against text-based.

Tell Computers and Humans Apart (CAPTCHA) is an important human-machine distinction technology for website to prevent the automatic malicious program attack. CAPTCHA recognition studies can find security breaches in CAPTCHA, improve CAPTCHA technology, it can also promote the technologies of license plate recognition and handwriting recognition.

1. Related Works

Segmentation-based CAPTCHA recognition systems are still widely used for CAPTCHA breaking purposes. The segmentation step is the main component in the recognition process of these segmentation-based models. Several algorithms have been proposed to segment text-based CAPTCHAs into separate characters. Zhang et al used the vertical projection technique for CAPTCHA segmentation. They improved the vertical projection to deal with conglutination characters by combining the size features of characters and their locations with the vertical projection histogram. They also covered the segmentation of different

types of conglutination. Chellapilla and Simard used the connected component algorithm to segment several CAPTCHA schemes, including Yahoo and Google, and achieved a success rate between 4.89% and 66.2%. However, vertical projection and connected component algorithms involve numerous preprocessing operations that are computationally expensive and time consuming. Hussain et al. presented another CAPTCHA segmentation method in which the segmentation is based on recognition.

First, an artificial neural network (ANN) was trained to recognize manually cropped CAPTCHA characters, then this trained ANN was used to segment.

The character recognition module is also considered a crucial component of segmentation-based CAPTCHA recognition systems because it can influence the recognition accuracy of these systems. Sakkatos et al. used the template matching approach to recognize characters by comparing the separate characters with template characters using character's coefficient values. Errors arising from similarities between characters are considered a weak point in recognition via template matching unless more advanced solutions are incorporated. Chen et al introduced a CAPTCHA character recognition method called selective learning confusion class (SLCC). SLCC uses a two-stage Deep Convolutional Neural Network (DCNN) frame to recognize CAPTCHA characters. First, the characters are classified using the all-class DCNN. Then, a confusion relation matrix and a set partition algorithm are used to construct confusion class subsets. This CAPTCHA character recognition method has high character recognition accuracy, especially for confusion-class characters; however, assigning a new DCNN to each confusion class subset could considerably increase the storage size of the whole system. To avoid the drawbacks of ineffective CAPTCHA segmentation algorithms, researchers have recently begun to adopt deep-learning-based segmentation-free CAPTCHA recognition systems for recognizing CAPTCHAs directly without segmentation. The authors of used a segmentation-free CAPTCHA recognition CNN that is trained to recognize all CAPTCHA characters simultaneously. A specific number of neurons (equal to character classes) in the output layer was assigned to each CAPTCHA character for classification. This recognition model has fast recognition speed and avoids CAPTCHA segmentation. However, as the number of CAPTCHA characters increases, the number of neurons in the output layer also increases consequently, the storage size increases as well.. Another segmentation-free multi-label CNN model was presented by Qing et al to recognize CAPTCHAs with connected and distorted characters .The internal structure of this CNN model was designed to consider the correlation between adjacent characters to improve recognition accuracy. However, this model uses a separate set of Convolutional and fully connected layers for

each character on CAPTCHA, which greatly complicates the architecture and increases the storage size of the model when the number of CAPTCHA characters is increased.

1.1 The Proposed Method

The image data is preprocessed and are made into GRAY – SCALE in order to reduce the computational cost and now the model is trained with the preprocessed data. Evaluation will be done in the next step where the comparison with the actual and predicted data is done. Now a dataset is generated which consists of 2000 to 5000 images, which are basically a 4 character CAPTCHA .Now the features are extracted and labeled into various classes for multi-classification. Once the model is trained the model is deployed various test images.

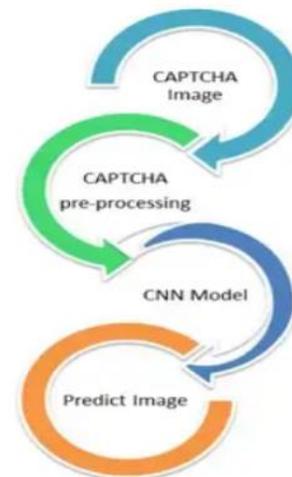
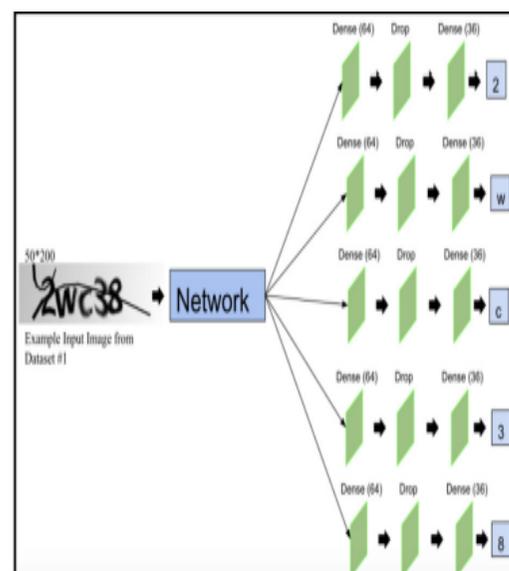


Fig. 3 Flowchart

The given captcha is divided into separate numbers or alphabets by using segmentation algorithm by removing the noise (if any)



3.1 DEEP LEARNING:

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain—albeit far from matching its ability—allowing it to “learn” from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy.

Deep learning drives many artificial intelligence applications and services that improve automation, performing analytical and physical tasks without human intervention. Deep learning technology lies behind everyday products and services (such as digital assistants, voice-enabled TV remotes, and credit card fraud detection) as well as emerging technologies (such as self-driving cars).

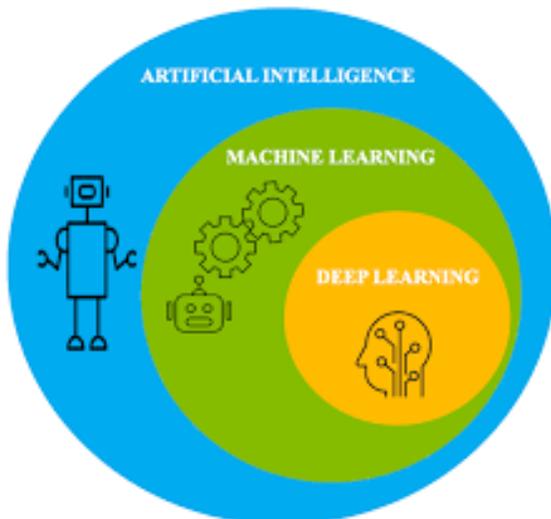


Fig. 5 Domains

3.1.1 How deep learning works

Deep learning neural networks, or artificial neural networks, attempts to mimic the human brain through a combination of data inputs, weights, and bias. These elements work together to accurately recognize, classify, and describe objects within the data. Deep neural networks consist of multiple layers of interconnected nodes, each building upon the previous layer to refine and optimize the prediction or categorization. This progression of computations through the network is called forward propagation. The input and output layers of a deep neural network are called *visible* layers. The input layer is where the deep learning model ingests the data for processing, and the output layer is where the final prediction or classification is made. Another process called backpropagation uses algorithms, like gradient descent, to calculate errors in predictions and then adjusts the weights and biases of the function by moving backwards through the layers in an effort to train the model. Together, forward propagation and backpropagation allow a neural network to make predictions and correct for any errors accordingly.

Over time, the algorithm becomes gradually more accurate. The above describes the simplest type of deep neural network in the simplest terms. However, deep learning algorithms are incredibly complex, and there are different types of neural networks to address specific problems or datasets.

3.2 ARTIFICIAL NEURAL NETWORKS:

Artificial Neural Networks is the architecture involved in our model. Basically there are two kinds of neural networks. Natural and Artificial Neural Networks. Artificial neural networks are the computer software’s which mimic the working of natural neurons in the human brain in order to solve complex problems and implement tough algorithms. Same as natural neurons in the human brain they consist of layers and nodes in each layer. These are classified based on their functionality and applications.

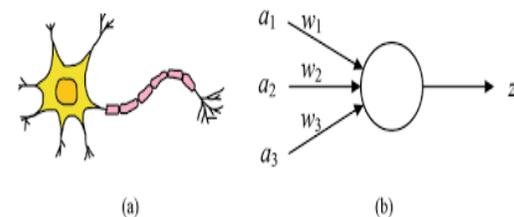


Fig. 6 Neurons and ANN

We have five types of neural networks. They are:

1. Feed forward neural networks
2. Convolutional neural network
3. Radial basis function neural networks
4. Recurrent neural networks
5. Kohonen self organizing neural networks

Convolutional neural networks (CNNs), used primarily in computer vision and image classification applications, can detect features and patterns within an image, enabling tasks, like object detection or recognition. In 2015, a CNN bested a human in an object recognition challenge for the first time.

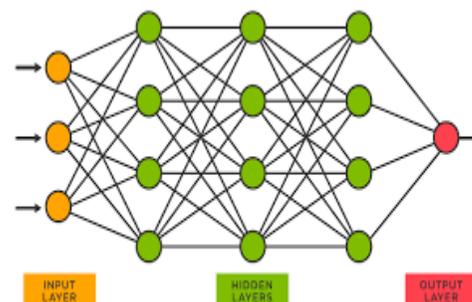


Fig. 7 Basic Neural Network

- **Recurrent neural network (RNNs)** are typically used in natural language and speech recognition applications as it leverages sequential or times series data.

One of the most popular types of deep neural networks is known as Convolutional neural networks (CNN or ConvNet). A CNN convolves learned features with input data, and uses 2D convolutional layers, making this architecture well suited to processing 2D data, such as images.

CNNs eliminate the need for manual feature extraction, so you do not need to identify features used to classify images. The CNN works by extracting features directly from images. The relevant features are not pretrained; they are learned while the network trains on a collection of images. This automated feature extraction makes deep learning models highly accurate for computer vision tasks such as object classification.

CNNs learn to detect different features of an image using tens or hundreds of hidden layers. Every hidden layer increases the complexity of the learned image features. For example, the first hidden layer could learn how to detect edges, and the last learns how to detect more complex shapes specifically catered to the shape of the object we are trying to recognize. Deep Learning is a powerful tool which is a sub domain of Machine Learning again which is a part of Artificial Intelligence. Neural Networks are the architecture of Deep Learning which can solve complex problems and implement algorithms by imitating the functionality of the human brain. To implement deep learning in our model we are using tensor flow a popular package provided by python.org. It consists of modules and classes by using which we can implement deep learning in our model.

3.3 IMAGE PROCESSING:

Image Processing is nothing but a method of operating or manipulating images according to our requirements. OpenCV that is “Open Computer Vision” is one of the famous packages available in python for the implementation of image processing in our project. It includes numerous modules and classes in it in order to manipulate different kinds of images in our dataset.

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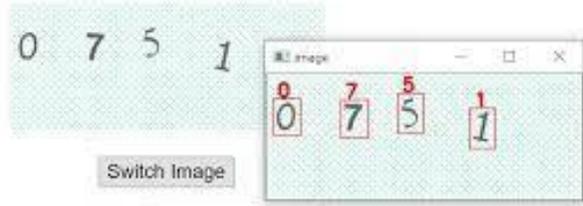


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Fig. 8 Data after preprocessing

Image processing and computer vision are topics covered by many excellent books. Most known (and yet unknown) algorithms can be devised from the hints offered by their authors by conveniently adapting the working principles of their described methods and models to the specific requirements of each application. The main goal of this book is to complement those references in order to provide the reader with a compact description of the most relevant insights of the latest and most successful approaches in super resolution. Whereas this goal is primarily targeted at researchers and developers directly working on super resolution, the book still attempts to provide a sufficiently complete description of contemporary, powerful, and general image models that can also be applied to other image processing and computer vision problems. Last, but not least, the book can also be used as a survey of machine learning models applied to regression applications, which might make it a useful resource even for other signal processing or statistical problems not specifically dealing with image data. Image processing is used for detecting a diseased part of a plant by scanning a collection of images of that plant, which earlier was found decayed. Traditionally, an expert would be hired to examine each plant for disease analysis. Consulting an expert is expensive and many farmers are not able to afford them. The analysis procedure of a hired expert is very time consuming as well. With image-processing technology first the image of the plant is retrieved from an image source such as a camera. Image preprocessing methods are applied to the retrieved images. After preprocessing, the image is segmented into different parts. Analysis techniques are performed on each of the segmented image in which the nature of the disease is identified for all the segmented parts. After that, the plant is classified based on the identified disease. The image of the ones affected is sent to farmers through IoT devices, for indication of diseased plants (as the computerized system is not intelligent enough to decide). Once the farmer verifies it as diseased, then the decision is stored in the database for future reference. Weeds are a challenging issue, as they destroy the crop and lower production. Hand weeding is the traditional method used by farmers for controlling weeds on their land, but practically it is a tedious task and is very time-consuming.



Fig. 9 Computer Vision Applications

Image processing analysis and neural networks have been widely used for fabric defect detection. The basic principles underlying this technique along with numerous applications are detailed used feed-forward back propagation neural nets to find the relationships between the shrinkage of yarns and the cover factors of yarns and fabrics. a typical multilayer feed-forward network is shown in Beltran *et al* also studied the use of MLP-BP neural networks to model the multi-linear relationships between fiber, yarn and fabric properties and their effect on the pilling propensity of pure wool knitted fabrics. Behera and Muttagi [predicted the low-stress mechanical, dimensional, and tensile properties of woven suiting fabrics using back propagation network (BPN) and radial basis function neural network (RBFN). Fiber, yarn and fabric constructional parameters of wool and wool-polyester blended fabrics were given as input variables. Radial basis function neural networks were found to have better predictability and are faster to train and easier to design than back propagation neural networks. a reverse engineering approach is also reported for prediction of constructional particulars from the fabric properties.

3.4 COMPUTER VISION:

Computer vision is the field of computer science that focuses on creating digital systems that can process, analyse, and make sense of visual data (images or videos) in the same way that humans do. The concept of computer vision is based on teaching computers to process an image at a pixel level and understand it. Technically, machines attempt to retrieve visual information, handle it, and interpret results through special software algorithms.

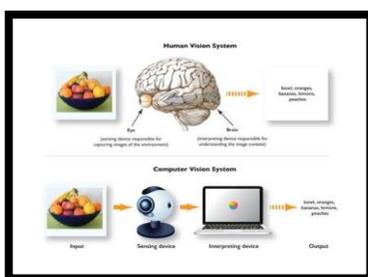


Fig. 10 Vision System comparison

3.4.1 The history of computer vision:

Scientists and engineers have been trying to develop ways for machines to see and understand visual data for about 60 years. Experimentation began in 1959 when neurophysiologists showed a cat an array of images, attempting to correlate a response in its brain. They discovered that it responded first to hard edges or lines, and scientifically, this meant that image processing starts with simple shapes like straight edges. At about the same time, the

first computer image scanning technology was developed, enabling computers to digitize and acquire images. Another milestone was reached in 1963 when computers were able to transform two-dimensional images into three-dimensional forms. In the 1960s, AI emerged as an academic field of study, and it also marked the beginning of the AI quest to solve the human vision problem. 1974 saw the introduction of optical character recognition (OCR) technology, which could recognize text printed in any font or typeface. Similarly, intelligent character recognition (ICR) could decipher hand-written text using neural networks. Since then, OCR and ICR have found their way into document and invoice processing, vehicle plate recognition, mobile payments, machine translation and other common applications. In 1982, neuroscientist David Marr established that vision works hierarchically and introduced algorithms for machines to detect edges, corners, curves and similar basic shapes. Concurrently, computer scientist Kunihiko Fukushima developed a network of cells that could recognize patterns. The network, called the Neocognitron, included convolutional layers in a neural network. By 2000, the focus of study was on object recognition, and by 2001, the first real-time face recognition applications appeared. Standardization of how visual data sets are tagged and annotated emerged through the 2000s. In 2010, the ImageNet data set became available. It contained millions of tagged images across a thousand object classes and provides a foundation for CNNs and deep learning models used today. In 2012, a team from the University of Toronto entered a CNN into an image recognition contest. The model, called AlexNet, significantly reduced the error rate for image recognition. After this breakthrough, error rates have fallen to just a few percent.

3.4.2 How does computer vision work?

Computer vision technology tends to mimic the way the human brain works. But how does our brain solve visual object recognition? One of the popular hypothesis states that our brains rely on patterns to decode individual objects. This concept is used to create computer vision systems.

Computer vision algorithms that we use today are based on pattern recognition. We train computers on a massive

amount of visual data—computers process images, label objects on them, and find patterns in those objects. For example, if we send a million images of flowers, the computer will analyze them, identify patterns that are similar to all flowers and, at the end of this process, will create a model “flower.” As a result, the computer will be able to accurately detect whether a particular image is a flower every time we send them pictures. Machines interpret images as a series of pixels, each with their own set of color values. For example, below is a picture of Abraham Lincoln. Each pixel’s brightness in this image is represented by a single 8-bit number, ranging from 0 (black) to 255 (white). These numbers are what software sees when you input an image.

This data is provided as an input to the computer vision algorithm that will be responsible for further analysis and decision making. Histogram equalization (HE) is one of the most commonly used methods for image contrast enhancement because of its high efficiency and simplicity (Gonzalez and Woods, 2008). The HE techniques use linear cumulative histogram of the input image and distribute its pixel values over its dynamic intensity range. HE-based enhancement finds applications in medical image processing (Sundaram et al., 2011), speech recognition (De la Torre et al., 2005), satellite image processing (Ganesan and Rajini, 2014), and others. Various HE methods have been proposed in the literature. The weighted thresholder HE (WTHE) method is an improved method for contrast enhancement (Wang and Ward, 2007). It modifies the probability distribution function of an image by weighting and thresholding before the HE is performed. Optimization of the weighting constrains is a hard optimization problem.

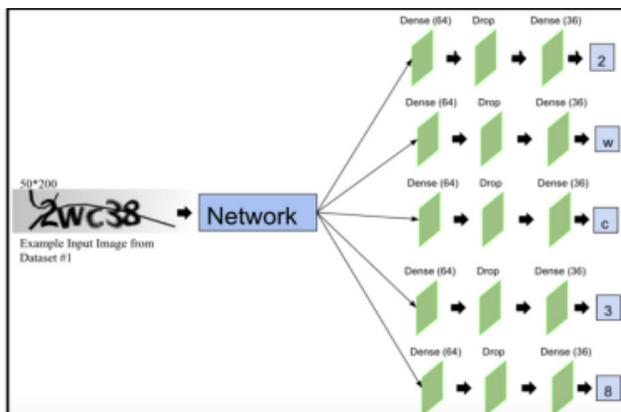


Fig 11 The image in internal system

computer vision systems can be used for:

- **Object classification.** The system parses visual content and classifies the object on a photo/video to the defined category. For example, the system can find a dog among all objects in the image.

Object identification. The system parses visual content and identifies a particular object on a photo/video. For example, the system can find a specific dog among the dogs in the image.

4. Experiments

4.1 Generate Dataset:

Firstly we have to create the folder called Generate_Captcha.png. Whenever we run the generate captcha shell in the shell it will generate the Captchas based on the size provided. All generated Captchas will be stored in Generated_Captcha folder.

4.2 Preprocessing the data:

After the captcha is selected the preprocessing will be started on specific captcha and whole dataset. The preprocessing will separate the each character in the captcha and counts no of specific characters and puts specific characters in specific folders. This preprocessing will help easily to identify the Captchas more easily.

4.3 Selecting captcha :

After Captchas are generated then the system selects one captcha randomly and performs various actions on it.

4.4 Training data:

After preprocessing the training of specific captcha be started and the cnn will deeply study the captcha and it finds the accuracy of each captcha if accuracy was low it trains the data and improves the accuracy.

4.5 Finding Accuracy and Loss:

It find the accuracy and loss of specific captcha. It improves the accuracy based on the captcha generated. If low accuracy found it trains the data more and more and improves accuracy.

4.6 Evaluate Model:

The graphs following graphs that the training model will improves the accuracy as shows in first graph and reduces the loss as shows in the second graph.

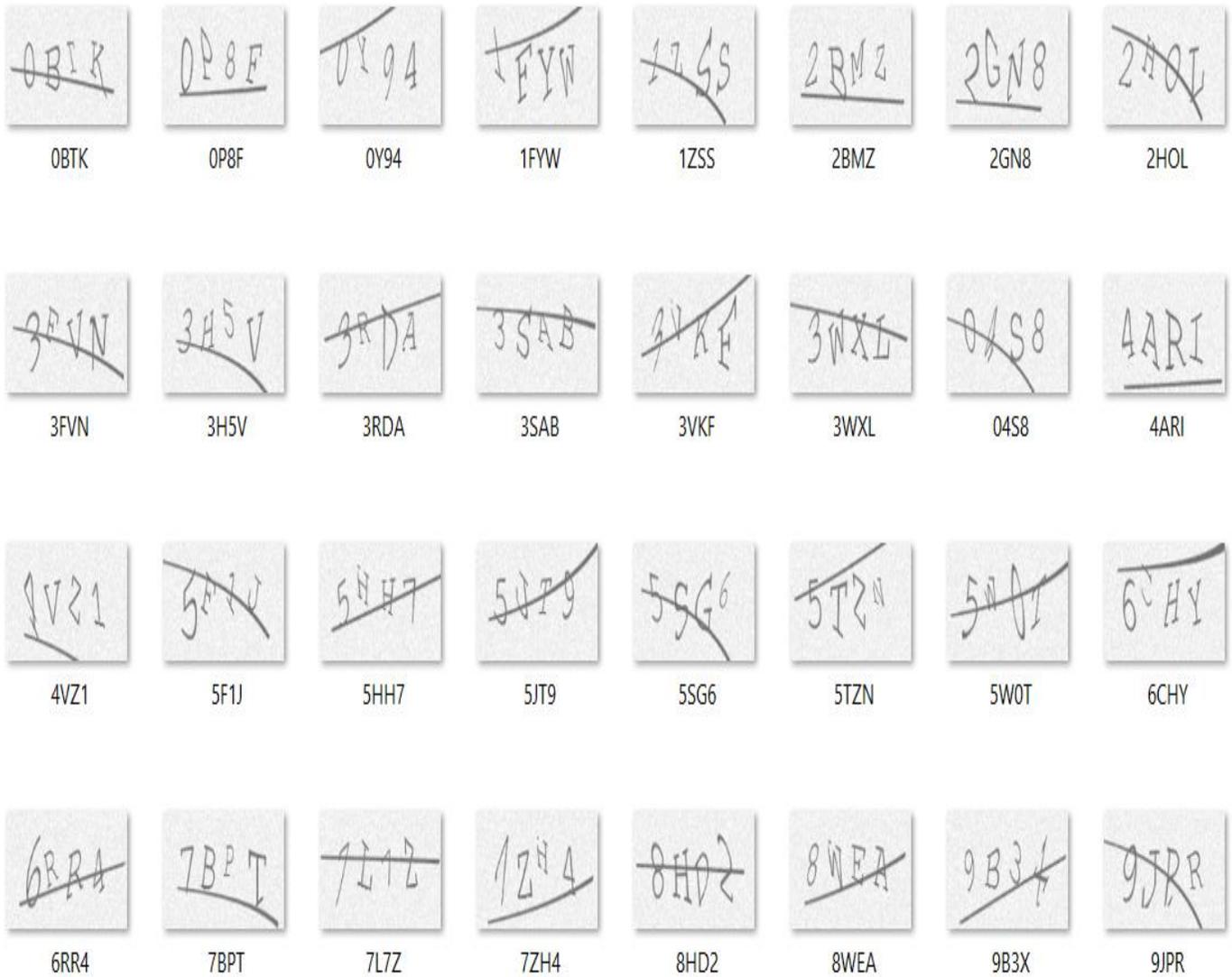


Figure6:RandomgeneratedCAPTHCA.

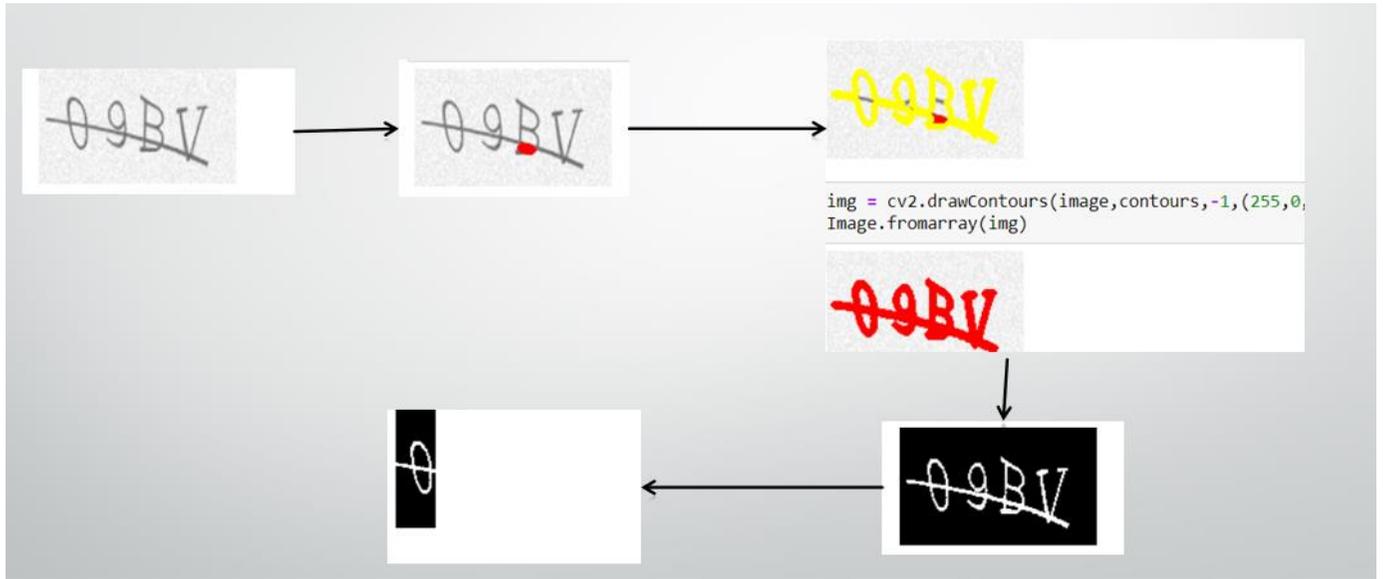


Fig PreProcessing steps

epoch_accuracy

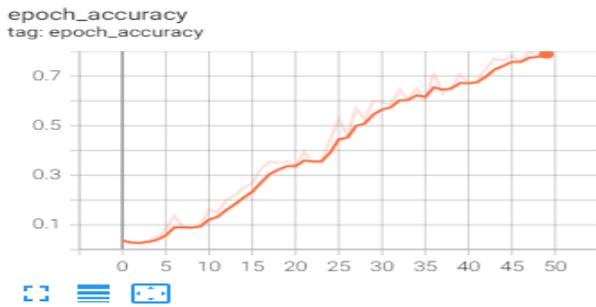


Fig Accuracy Graph

epoch_loss

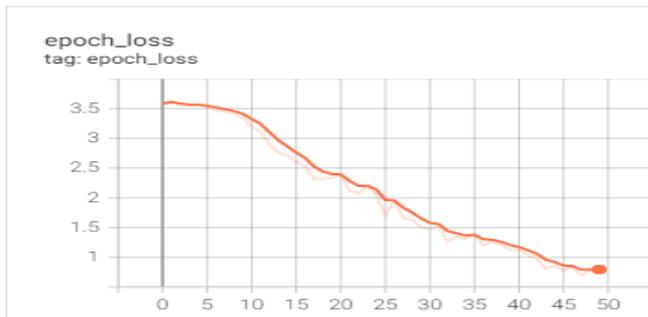


Fig Loss Graph

Conclusion

This paper proposes a Convolutional neural network method based on focal loss for CAPTCHA recognition. Deep learning helps computers to derive meaningful links from a plethora of data and make sense of unstructured data. Here, the mathematical algorithms are combined with a lot of data and strong hardware to get qualified information. CAPTCHA was designed to improve the security of the systems but deep learning algorithms defeated its very purpose. Here, we used Convolutional Neural networks for CAPTCHA recognition. Firstly, preprocessing such as graying, binarization, demising, segmentation, and labeling is carried out, and then a simple neural network model is constructed by using Keras library; in addition, an end-to-end neural network model is constructed for the complex CAPTCHA with high adhesion and more interfering pixels. The test results on three different CAPTCHA datasets show that the proposed method has certain advantages over the traditional methods and has higher recognition rate, robustness, and good generalization ability. In the future, we will study more types of CAPTCHA recognition.

Data Availability

The data used to support the findings of this study are included with in the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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