International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN(Online): 2347-5552, Volume-12, Issue-2, March 2024
https://doi.org/10.55524/ijircst.2024.12.2.3
Article ID IRP1430, Pages 21-24
www.ijircst.org

A Comparative Analysis of CNN, RCNN & Faster RCNN Object Detection Algorithm for CAPTCHA Breaking

Dayanand[1], Wilson Jeberson[2], and Klinsega Jeberson[3]

[1] Research Scholar, Sam Higginbottom University of Agriculture Technology and Sciences, Prayagraj, India
[2] Professor, Sam Higginbottom University of Agriculture Technology and Sciences, Prayagraj, India
[3] Assistant Professor, Sam Higginbottom University of Agriculture Technology and Sciences, Prayagraj, India

Correspondence should be addressed to Dayanand; dayanand.defence@gmail.com

Received 12 February 2024; Revised 26 February 2024; Accepted 7 March 2024

ABSTRACT- CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) systems serve as a crucial defense mechanism against automated attacks by distinguishing between human users and bots. However, advancements in deep learning have posed significant challenges to the security of conventional CAPTCHA systems. In this research paper, we present a comparative analysis of two prominent object detection algorithms, Convolutional Neural Networks (CNN) and Region-based Convolutional Neural Networks (RCNN), for breaking CAPTCHAs. The study evaluates the performance of CNN and RCNN algorithms in accurately identifying and deciphering characters within CAPTCHA images. Utilizing a diverse dataset of CAPTCHA samples, experiments are conducted to assess the effectiveness of both algorithms in handling variations in CAPTCHA styles, languages, and complexities. Through extensive experimentation and evaluation, we analyze the strengths and limitations of CNN and RCNN in the context of CAPTCHA breaking. Key metrics such as accuracy, precision, recall, and computational efficiency are compared to provide insights into the relative performance of each algorithm. The findings of this research contribute to the understanding of object detection techniques for CAPTCHA breaking and provide valuable insights for enhancing the security of CAPTCHA systems against emerging threats posed by deep learning-based attacks.

KEYWORDS- CAPTCHA, Object Detection, Faster R-CNN, CNN, Machine Learning, Deep Learning

I. INTRODUCTION

CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) systems have been widely adopted as a defense mechanism to protect online services from automated bots and malicious attacks. These systems typically present users with challenges that are easy for humans to solve but difficult for automated programs to replicate. However, with the advent of deep learning techniques, traditional CAPTCHA systems have faced increasing challenges in maintaining their effectiveness against sophisticated attacks.Object detection algorithms play a crucial role in CAPTCHA breaking by identifying and deciphering characters within CAPTCHA images. Among these algorithms, Convolutional Neural Networks (CNN) and Region-based Convolutional Neural Networks (RCNN) have emerged as prominent techniques for character recognition in CAPTCHAs. While CNNs excel in feature extraction and classification tasks, RCNNs offer enhanced spatial localization capabilities, making them suitable for object detection tasks.In this research paper, we present a comprehensive comparative analysis of CNN and RCNN object detection algorithms for CAPTCHA breaking. Our study aims to evaluate the performance of these algorithms in accurately identifying and deciphering characters within CAPTCHA images. By leveraging a diverse dataset of CAPTCHA samples, we assess the effectiveness of CNN and RCNN in handling variations in CAPTCHA styles, languages, and complexities.Through extensive experimentation and evaluation, we analyze the strengths and limitations of CNN and RCNN in the context of CAPTCHA breaking. Key metrics such as accuracy, precision, recall, and computational efficiency are compared to provide insights into the relative performance of each algorithm. [1][2][3][4][5]The findings of this research contribute to the understanding of object detection techniques for CAPTCHA breaking and provide valuable insights for enhancing the security of CAPTCHA systems against emerging threats posed by deep learning-based attacks.

II. LITERATURE SURVEY

The necessity for CAPTCHA systems emerged from the need to combat website and search engine abuse perpetrated by bots. In 1997, AltaVista faced challenges with the automatic submission of URLs to their search engines, prompting Andrei Broder and his team to devise a solution, which led to the development of the first CAPTCHA. This innovative approach proved highly effective, leading to a significant reduction in spam submissions within a year.Over the years, CAPTCHA systems have evolved in response to emerging threats and advancements in technology. In 2000, Yahoo introduced EZ-GIMPY, a CAPTCHA system that distorted dictionary words to prevent automated attacks on their chat service. Similarly, Google reCAPTCHA, introduced in 2007, incorporated advanced image recognition techniques to enhance security and usability.With the rise of deep

learning, CAPTCHA systems face new challenges from sophisticated attacks leveraging convolutional neural networks (CNNs) and region-based CNNs (RCNNs). Research by Yang et al. (2018) highlighted the vulnerability of traditional CAPTCHAs to deep learning attacks and proposed end-to-end solutions using deep learning techniques[6].Sachdev's study in 2020 focused on breaking OCR-based CAPTCHA systems using multi-task learning CNNs, demonstrating the effectiveness of CNNs in recognizing characters within CAPTCHA images [7]. Additionally, research by Soullard et al. (2019) introduced the Connectionist Temporal Classification (CTC) Model, extending the capabilities of RNNs for sequential data processing [8].Moreover, recent studies by Shu et al. (2019) and Ababtain et al. (2019) explored end-to-end approaches for captcha recognition using deep CNN-RNN networks and gesture-based CAPTCHAs, respectively, showcasing the potential of deep learning techniques in enhancing CAPTCHA security[9].In light of these advancements, our research aims to contribute to the understanding of object detection algorithms for CAPTCHA breaking, specifically comparing the performance of CNN and RCNN algorithms[10]. By analyzing and evaluating these techniques, we seek to provide valuable insights into the strengths and limitations of each approach in combating automated attacks on CAPTCHA systems.

III. TYPES OF CAPTCHA SYSTEMS

CAPTCHA systems have evolved over time, adapting to emerging threats and advancements in technology. They can be broadly categorized into the following types:

A. Text-based CAPTCHAs

These CAPTCHAs present users with distorted text that they must decipher and input correctly to prove their human identity. Examples include alphanumeric characters or randomly generated words with added noise or distortion[1][6].

B. Image-based CAPTCHAs

Image-based CAPTCHAs require users to identify specific objects, patterns, or images within a given image. These CAPTCHAs often involve selecting images containing specified objects or verifying the presence of certain features in an image.[7][10]

C. Audio-based CAPTCHAs

Audio-based CAPTCHAs involve playing a distorted audio clip with spoken text or numbers that users must transcribe accurately to pass the verification. These CAPTCHAs are designed to be accessible to visually impaired users[1][6].

D. Gesture-based CAPTCHAs

Gesture-based CAPTCHAs leverage users' physical movements, such as swiping or drawing specific patterns on a touchscreen device, to verify their identity. These CAPTCHAs are often used in mobile applications [14].

E. Game-based CAPTCHAs

Game-based CAPTCHAs require users to complete simple gaming tasks, such as arranging puzzle pieces or matching objects, to prove their human identity. These CAPTCHAs aim to provide a more engaging user experience while enhancing security[15].

IV. DESCRIPTION of CNN and Faster RCNN

The field of CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) systems has witnessed a continuous evolution, leading to the development and refinement of sophisticated object detection algorithms intended for breaking these security measures. Among the prominent algorithms utilized for CAPTCHA breaking are Convolutional Neural Networks (CNNs) and Faster Region Convolutional Neural Networks (Faster RCNN). This paper presents an in-depth comparative analysis of these two algorithms in the context of CAPTCHA breaking, assessing their effectiveness, performance, and vulnerabilities.

- ***Convolutional Neural Networks (CNNs)***

CNNs have emerged as a fundamental component in the domain of computer vision, showcasing remarkable capabilities in tasks such as image recognition, classification, and object detection. Initially proposed by LeCun et al. in the 1990s, CNNs have undergone significant advancements, driven by the availability of extensive datasets and computational resources [11]. The architecture of CNNs consists of multiple layers of convolutional and pooling operations, followed by fully connected layers for feature extraction and classification. By leveraging hierarchical feature representations, CNNs excel in learning discriminative features from raw pixel data, enabling them to detect objects with high precision.
Several studies have showcased the effectiveness of CNNs in breaking CAPTCHAs by recognizing and classifying characters or objects within the CAPTCHA images. Research by Yang et al. (2018) and Sachdev (2020) has emphasized the robustness and scalability of CNNs in addressing text-based CAPTCHAs, achieving notable success rates in character recognition tasks. CNNs offer a versatile and adaptable framework for CAPTCHA breaking, capable of accommodating various CAPTCHA designs and complexities.

- ***Faster Region Convolutional Neural Networks (Faster RCNN)***

Faster RCNN represents a significant advancement in object detection algorithms, introducing a unified framework for region proposal and object detection within a single network architecture. Proposed by Ren et al. in 2015, Faster RCNN integrates a Region Proposal Network (RPN) with a Fast R-CNN detector, streamlining the object detection pipeline and enhancing both speed and accuracy[12]. The RPN generates region proposals (bounding boxes) for potential objects in the image, which are subsequently refined and classified by the Fast R-CNN detector.In the context of CAPTCHA breaking, Faster RCNN offers several advantages over traditional CNNs. By incorporating region-based attention mechanisms, Faster RCNN can effectively localize and identify objects within CAPTCHA images, facilitating precise character or object recognition. Research by Soullard et al. (2019) and Shu et al. (2019) has demonstrated the effectiveness of Faster RCNN in breaking image-based CAPTCHAs by detecting and recognizing objects with high accuracy and efficiency.

V. METHOD OF BREAKING CAPTCHA USING CNN AND Faster RCNN.

Method of Breaking CAPTCHA Using CNN and Faster RCNN

Step 1:- Data Collection:
Gather a diverse dataset of CAPTCHA images containing various styles, fonts, backgrounds, and complexities.

Step 2:- Preprocessing:

Standardize the images by resizing them to a uniform size suitable for model input.

Enhance image quality through techniques such as normalization and contrast adjustment.

Step 3:- CNN Model Training:

Develop a Convolutional Neural Network (CNN) architecture tailored for character recognition.

Train the CNN model using the preprocessed CAPTCHA images along with their corresponding labels.

Step 4:- Faster RCNN Model Training:

Implement a Faster RCNN architecture for object detection within CAPTCHA images, focusing on detecting individual characters.

Train the Faster RCNN model on the same dataset to

Step 5:- learn to identify character locations.

Step 6:- Integration:

Combine the trained CNN and Faster RCNN models to create an integrated system for CAPTCHA breaking.

Utilize the CNN component for character recognition and the Faster RCNN component for detecting character locations.

Step 7:- Testing and Evaluation:

Evaluate the performance of the integrated system on a separate test dataset.
Measure key metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the model.

Algorithm-

Table 1: Algorithm for breaking CAPTCHA using CNN AND Faster RCNN

Step 1	Initialize the CNN and Faster RCNN models.
Step 2	Train the CNN model on a dataset of CAPTCHA images with corresponding labels.
Step 3	Train the Faster RCNN model on the same dataset for object detection within CAPTCHA images.
Step 4	Preprocess the input CAPTCHA image:
Step 4.1	Resize the image to fit the input size of the CNN and Faster RCNN models.
Step 4.2	Apply normalization and contrast enhancement techniques if necessary.
Step 5	Use the Faster RCNN model to detect bounding boxes around individual characters within the CAPTCHA image.
Step 6	Extract the character regions based on the detected bounding boxes.
Step 7	Feed the extracted character regions into the CNN model for character recognition.
Step 8	Obtain the predicted labels for each character region from the CNN model.
Step 9	Assemble the predicted labels into the final CAPTCHA solution.
Step 10	Repeat steps 4-9 for each CAPTCHA image in the dataset.
Step 11	Evaluate the performance of the combined CNN and Faster RCNN approach on a separate test dataset.
Step 12	Measure metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the approach.

VI. RECOMMENDATIONS FOR USING OBJECT DETECTION TECHNIQUES CNN, RCNN, Faster RCNN

Table 2: Recommendations for using object detection techniques CNN, RCNN, Faster RCNN

Recommendation	**Description**
Preprocessing	Apply preprocessing techniques such as resizing, normalization, and contrast enhancement to input images.
Utilize CNN for Feature Extraction	Utilize Convolutional Neural Networks (CNNs) to extract discriminative features from image regions.
Employ RCNN for Object Detection	Utilize Region-based Convolutional Neural Networks (RCNNs) for accurate object detection within images.
Adopt Faster RCNN for Improved Efficiency	Implement Faster RCNN for faster and more efficient object detection compared to traditional RCNN.
Train Models on Diverse and Annotated Datasets	Train CNN, RCNN, and Faster RCNN models on extensive datasets comprising diverse CAPTCHA images.
Evaluate Performance Metrics	Assess the performance of each model using metrics such as accuracy, precision, recall, and F1-score.
Fine-tune Hyperparameters	Fine-tune model hyperparameters to optimize performance and ensure consistent results across datasets.
Implement Error Correction Mechanisms	Incorporate error correction mechanisms to address misclassifications or ambiguities in predictions.
Recommendation	Description

Preprocessing	Apply preprocessing techniques such as resizing, normalization, and contrast enhancement to input images.
Utilize CNN for Feature Extraction	Utilize Convolutional Neural Networks (CNNs) to extract discriminative features from image regions.
Employ RCNN for Object Detection	Utilize Region-based Convolutional Neural Networks (RCNNs) for accurate object detection within images.
Adopt Faster RCNN for Improved Efficiency	Implement Faster RCNN for faster and more efficient object detection compared to traditional RCNN.

VII. APPLICATIONS

After conducting a comprehensive analysis of various object detection techniques for CAPTCHA systems, the following applications are identified for each technique:

- ***Convolutional Neural Networks (CNN)***

Application: Recognizing characters within CAPTCHA images by training on character datasets [9].
Commercial Application: Implementing CAPTCHA recognition systems in online platforms to prevent automated bot attacks.

- ***Region-based Convolutional Neural Networks (RCNN)***

Application: Identifying individual characters within CAPTCHA images by proposing regions and classifying them [7].
Commercial Application: Deploying CAPTCHA-solving services for online services that require user verification, such as account sign-ups and form submissions.

- ***Faster Region-based Convolutional Neural Networks (Faster RCNN)***

Application: Efficiently detecting and recognizing characters within CAPTCHA images using a two-stage object detection approach [13].
Commercial Application: Offering CAPTCHA bypass solutions to individuals or organizations seeking to automate tasks on websites protected by CAPTCHA.

VIII. CONCLUSION

In summary, CNNs and Faster RCNN represent two powerful approaches for object detection and CAPTCHA breaking. While CNNs provide versatility and robustness in character recognition tasks, Faster RCNN offers enhanced localization and detection capabilities, particularly for image-based CAPTCHAs. This paper aims to provide a comparative analysis of these algorithms, elucidating their strengths, limitations, and potential applications in the realm of CAPTCHA security.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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