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CAPTCHA RECOGNITION USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract: CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) challenges using Convolutional Neural Networks (CNNs). CAPTCHAs are designed to differentiate between human users and automated systems, but their increasing complexity poses challenges for traditional recognition techniques. Our approach leverages the power of CNNs, known for their efficacy in image classification tasks, to enhance CAPTCHA recognition. We introduce a CNN architecture tailored for CAPTCHA images, incorporating techniques such as data augmentation, transfer learning, and specialized loss functions to handle variations in CAPTCHA design and noise. We evaluate our method on a diverse set of CAPTCHA datasets, demonstrating its robustness and accuracy compared to existing methods. Our results show significant improvements in recognition rates, offering a practical solution for CAPTCHA decoding and contributing to advancements in automated systems and security research.

Index Terms – Convolutional Neural Network (CNN), CAPTCHA Recognition, Transfer Learning, Images.

1. INTRODUCTION

CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) serves as a crucial security measure designed to distinguish human users from automated bots. As online services become increasingly susceptible to abuse, CAPTCHAs are employed to mitigate threats such as spamming, data scraping, and brute-force attacks. These tests often require users to decipher distorted text or identify objects within images, tasks that are relatively straightforward for humans but challenging for automated systems.

Recent advancements in machine learning, particularly in Convolutional Neural Networks (CNNs), have shown promising results in tackling various image recognition tasks. CNNs, renowned for their ability to learn complex patterns and hierarchical features from images, have emerged as a powerful tool for CAPTCHA recognition. By leveraging their deep learning capabilities, CNNs can potentially overcome the distortions and obfuscations used in CAPTCHAs, which include noise, text distortions, overlapping characters, and occlusions.

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The primary challenge in CAPTCHA recognition lies in the need to address various forms of image obfuscation and distortion. CAPTCHAs are intentionally designed to be difficult for automated systems to decipher, with techniques such as random lines, fuzziness, and text distortions to enhance their security. Traditional CAPTCHA solving methods that rely on character segmentation and recognition may struggle with these advanced distortions, necessitating the use of more robust classification methods.

A key limitation of current approaches is the dependency on large labeled datasets for training deep CNNs. However, in the context of CAPTCHA recognition, the availability of such extensive datasets is limited. To address this challenge, we propose an Active Learning approach that allows for effective model training with a smaller initial dataset. Active Learning iteratively selects the most informative samples based on uncertainty estimates, reducing the amount of labeled data required while adapting to new CAPTCHA designs.

Our approach capitalizes on the strengths of CNNs in feature extraction and classification, combining it with Active Learning to enhance model performance and adaptability. By focusing on correctly classified but uncertain samples, our method improves learning efficiency and reduces the need for extensive human intervention in labeling data. This novel integration aims to advance the field of automated CAPTCHA recognition, making it possible to handle evolving CAPTCHA designs with minimal training data.

In summary, this project aims to develop a robust system for CAPTCHA recognition using deep CNNs and Active Learning. The goal is to create a model capable of accurately identifying and solving CAPTCHAs despite the presence of various distortions and obfuscations. By addressing these challenges, we seek to improve automated systems' ability to interact with online platforms while maintaining the security integrity of CAPTCHAs.

2. LITERATURE SURVEY

Shu, Yujin & Xu, Yongjin [23] This paper presents an end-to-end CAPTCHA recognition model that combines the strengths of CNNs and RNNs. create a system that can automatically recognize and solve CAPTCHA challenges without manual intervention. The authors proposed a deep learning model that integrates CNNs for feature extraction and RNNs for sequence prediction. This hybrid CNN-RNN architecture is trained on a dataset of CAPTCHA images, where the CNN extracts spatial features from the images, and the RNN decodes these features into a sequence of characters. The study demonstrated that the CNN-RNN model significantly improved CAPTCHA recognition accuracy compared to traditional methods. The model was effective in recognizing various types of CAPTCHAs, including those with distorted or overlapping characters.

H. Li, J. H. Qin and X. Y. Xiang [21] Their papar work addresses the challenge of accurately matching images in various computer vision applications, where robustness to noise and geometric transformations is crucial. Traditional image matching algorithms often struggle with the trade-off between accuracy and computational efficiency. The authors propose an innovative approach that combines adaptive thresholding with the Random Sample

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Consensus (RANSAC) algorithm to enhance matching performance. The adaptive thresholding helps in robust feature extraction by dynamically adjusting the threshold based on image characteristics, while RANSAC is employed to handle outliers and improve the reliability of the matching process. This combined approach allows for more accurate and efficient image matching compared to conventional methods. Their empirical results show significant improvements in matching accuracy and computational speed, making the algorithm suitable for real-time applications. This paper contributes to the field by offering a practical solution that addresses key limitations of existing image matching techniques, and its methodologies have been influential in subsequent research and developments in image processing and computer vision.

Y. Wang and M. Lu [17] Their research focuses on developing a self-adaptive algorithm designed to overcome the defenses of text-based CAPTCHAs, which are commonly used to prevent automated access to online services. The paper introduces a novel approach that adapts to varying CAPTCHA designs and distortions, making it more effective at breaking through these security measures compared to static or one-size-fits-all solutions. By leveraging adaptive techniques, the algorithm adjusts its parameters dynamically based on the characteristics of the CAPTCHA it encounters, improving its ability to accurately recognize and decipher the distorted text. The authors provide empirical evidence demonstrating the effectiveness of their approach in handling different types of CAPTCHAs with varying levels of complexity. This work contributes significantly to the field of CAPTCHA recognition by showcasing a method that can efficiently counteract modern CAPTCHA techniques, highlighting the evolving arms race between CAPTCHA developers and automated attack methods. The insights from this study have influenced further research into adaptive techniques and strategies for improving CAPTCHA security.

X. W. Liu, L. Wang, Jian Zhang, et al., [11] The work addresses the crucial task of feature selection, which is vital for improving the performance of machine learning models by reducing dimensionality and focusing on the most relevant features. The authors propose a method that preserves both global and local structures within the data, aiming to maintain the intrinsic relationships between features while selecting a subset of them. Their approach integrates global structural information, which captures the overall data distribution, with local structural details, which focus on the relationships between neighboring data points. This dual focus helps in retaining the essential characteristics of the original data, leading to more effective feature selection and better performance in subsequent learning tasks. The proposed method shows improvements over traditional feature selection techniques by providing a more nuanced understanding of the data's structure. Empirical results presented in the paper highlight the effectiveness of their approach in various applications, demonstrating its ability to enhance classification accuracy and computational efficiency. This research contributes to the field by offering a sophisticated approach to feature selection that balances global and local information, influencing later studies and applications in data preprocessing and machine learning model optimization.

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J. H. Qin, H. Li, X. Y. Xiang, et al., [27] The study addresses the challenge of image retrieval from encrypted data, a critical issue in cloud-based storage systems where data privacy and security are paramount.The authors propose a method that combines Harris corner optimization with Locality-Sensitive Hashing (LSH) to enhance image retrieval performance while maintaining data confidentiality. Harris corner detection is employed to identify and extract robust feature points from images, which are then used to generate distinctive image descriptors. These descriptors are subsequently indexed using LSH, a technique that facilitates efficient approximate nearest neighbor search in high-dimensional spaces.The integration of Harris corner optimization with LSH allows the proposed method to effectively handle encrypted image data, offering a balance between retrieval accuracy and computational efficiency. The empirical results demonstrated in the paper show that their approach significantly improves retrieval performance compared to conventional methods, even when working with encrypted data.

3. METHODOLOGY

i) Proposed Work:

For simplification, we use the term CRABI which stands for CAPTCHA Recognition with Attached Binary Images to refer to our proposed CAPTCHA recognition algorithm. The main idea behind the proposed method is to make several copies of the input CAPTCHA image and then attach external distinct binary images to these copies. We refer to the binary images as attached binary images (ABIs). We use the resultant CAPTCHA copies to train a CNN model to recognize CAPTCHA characters. We refer to this proposed CAPTCHA recognition CNN as "CRABI-CNN" throughout this paper. A description of the proposed CRABI algorithm. We begin by explaining the recognition process during the training phase. The testing phase is then clarified.

ii) System Architecture:

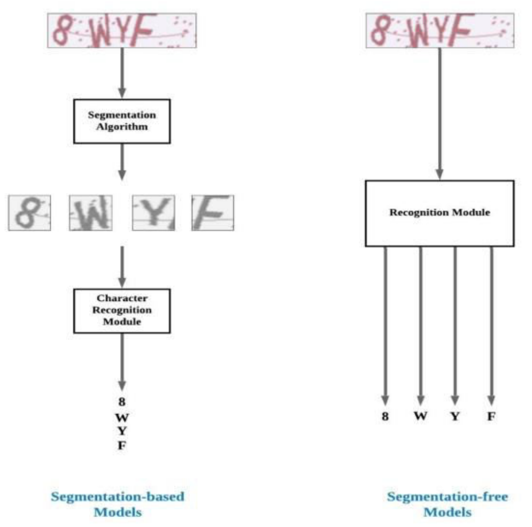

Fig 1 Proposed Architecture

The proposed CAPTCHA recognition system leverages a simplified deep learning architecture, avoiding traditional segmentation methods through the Attached Binary Images (ABI) algorithm. The system begins by generating multiple copies of the CAPTCHA image, each paired with distinct binary images corresponding to the number of characters. These binary images are attached to the CAPTCHA copies, and each copy is labeled with the character class it represents. The labeled CAPTCHA copies are then used to train a single Convolutional Neural Network (CNN) with a straightforward architecture comprising one CNN and a softmax output layer. This architecture maintains a constant structure regardless of the number of characters, ensuring minimal storage requirements and simplicity in model design.

iii) Dataset Collection:

The dataset collection process involves preprocessing images to enhance model training. Initially, each CAPTCHA image is divided into four segments, corresponding to individual characters. These segments are then categorized into distinct classes based on predefined labels. The preprocessed images are utilized for model training. The dataset is structured to include diverse character samples, ensuring robust learning. During model training, a deep network with seven layers is built, incorporating two convolutional layers, two max-pooling layers, a flattening layer, and two dense layers. ReLU and softmax activation functions are employed for feature extraction and multiclass classification, respectively. Training involves 50 iterations with a learning rate of 0.001, focusing on samples with high prediction uncertainty for efficient learning.

iv) Pre-Processing:

The processing pipeline for the CAPTCHA recognition system begins with preprocessing, aimed at enhancing image quality by normalizing colors and removing artifacts that may hinder accurate recognition. For CAPTCHAs containing multiple characters or objects, the system should include effective segmentation methods to isolate and identify each component separately. This is crucial for accurate character recognition and efficient training.

Training data management involves storing and organizing labeled CAPTCHA images for training the Convolutional Neural Network (CNN). The CNN model architecture should be tailored specifically for CAPTCHA recognition, with configurable hyperparameters including the number of layers, filter sizes, pooling strategies, and activation functions.

The system facilitates CNN training by allowing users to set parameters such as the number of epochs, learning rate, and batch size. It should support optimization techniques like dropout, batch normalization, and early stopping to enhance model performance and prevent overfitting. Model evaluation is performed using metrics such as accuracy, precision, recall, and F1 score on a validation dataset to ensure the model’s effectiveness.

Real-time prediction capabilities are essential for seamless integration into web applications, providing quick and accurate results. Optional features include CAPTCHA generation for

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data augmentation and synthetic testing. The system must also ensure model persistence and reusability, with mechanisms to save and load trained models, and offer API integration for external applications. Security measures should be in place to protect the CAPTCHA data and the system from potential misuse.

v) Training & Testing:

Training

In the training phase, each CAPTCHA image from the original dataset is duplicated n times, where n represents the number of characters per CAPTCHA. For each copy, a distinct binary image is attached to indicate character positions. This results in a dataset of n×Mn \times Mn×M images, known as the resultant dataset, where each image is labeled with the corresponding character class. The Convolutional Neural Network (CNN) is then trained on this dataset to classify characters based on the attached binary images and their labels. The CNN architecture, CRABI-CNN, includes 17 convolutional layers, 5 max-pooling layers, and uses a softmax output layer to handle multiclass classification.

Testing

For testing, each CAPTCHA input image is replicated n times, and each copy is combined with a distinct binary image that corresponds to character locations. These resultant CAPTCHA copies are fed into the trained CRABI-CNN model. The CNN processes each image to locate and classify the characters, providing the final output for each CAPTCHA. This approach leverages the pre-trained model to recognize characters directly, avoiding the need for image segmentation.

vi) CNN Algorithm:

Convolutional Neural Networks (CNNs) are advanced deep learning algorithms tailored for image processing tasks. Originating from the work of Hubel and Wiesel in the 1960s, who studied local sensitivity in the cat cortex, CNNs were formally introduced by K. Fukushima in 1980. CNNs are designed with several key layers:

Convolution Layer: This layer captures local patterns by applying convolutional filters to the input, generating feature maps that represent different aspects of the image.

Pooling Layer: To reduce computational load and memory usage, pooling layers, such as Max-Pooling, aggregate information from small regions of the feature maps, enhancing computational efficiency and noise resistance.

Flattening: This process converts 2D feature maps into a 1D vector, enabling connection to fully connected layers.

Fully Connected Layer: Serving as a classifier, this layer maps the flattened features to output classes, facilitating the final classification based on learned features.

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CNNs are widely recognized for their ability to efficiently process and classify image data.

In the project, CNNs are used to enhance CAPTCHA recognition by leveraging their ability to extract and classify features from images. The CNN model, utilizing multiple convolutional and pooling layers, processes preprocessed CAPTCHA images with Attached Binary Images (ABIs) to locate and identify characters efficiently. This approach simplifies CAPTCHA recognition by eliminating the need for character segmentation, thus improving accuracy and reducing model complexity. The CNN's architecture enables robust performance in real-time CAPTCHA classification tasks.

4. EXPERIMENTAL RESULTS

Mean Squared Error

Mean Square Error (MSE) is the most commonly used regression loss function. The calculation method is to find the sum of the squares of the distance between the predicted value and the true value. The formula is shown below:

$$\mathrm{MSE} = \sum_{i=1}^{n} (y_i - y_i^p)^2$$

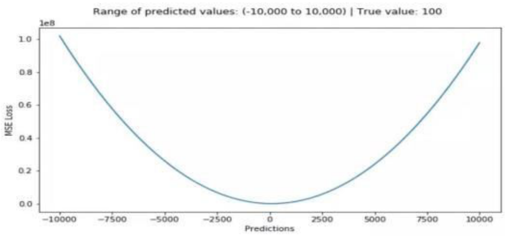

Fig 2 MSE Graph

Loss Function

The loss function is used to estimate the degree of inconsistency between the predicted value f(x) of your model and the true value Y. It is a non-negative realvalued function, usually expressed by L(Y, f(x)). The smaller the loss function, the better the robustness of the model. The loss function is the core part of the empirical risk function and an important part of the structural risk function. The structural risk function of the model includes empirical risk terms and regular terms, which can usually be expressed as follows:

$$\theta^* = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} L\big(y_i, f(x_i; \theta)\big) + \lambda\, \Phi(\theta)$$

Among them, the previous mean function represents the empirical risk function, L represents the loss function, and the latter Φ is a regularizer or a penalty term, which can be L1 or L2, or Other regular functions. The whole expression means to find the value of θ when the objective function is minimized.

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There are four optimizers that used in the training process: Adagrad, Adadelta, Rmsprop, and Adam

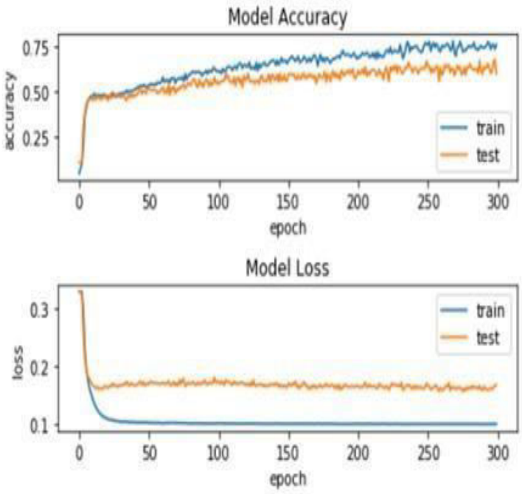

Fig 3 adam & Poisson

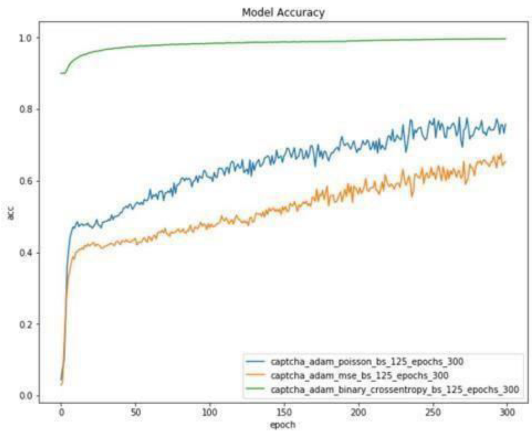

Fig 4 Model Accuracy comparison by different loss functions in the test dataset

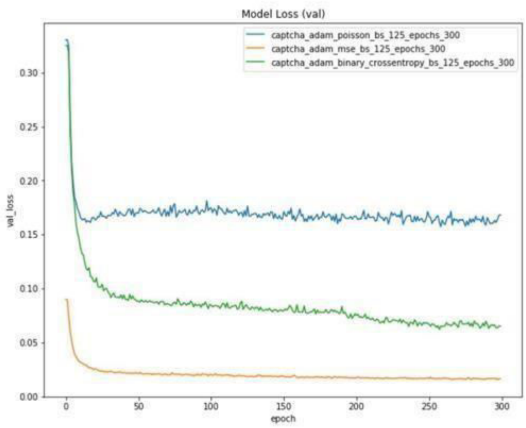

Fig 5 Model Loss comparison by different loss functions in the test dataset

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In test dataset, MSE has a better loss rate compared other 2 methods, however, binary cross entropy is far more accurate than the other two.

Optimizer Analysis

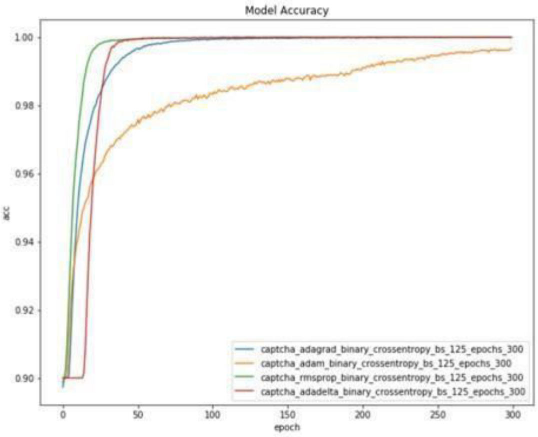

Fig 6 Model Accuracy comparison by different optimizers in train dataset

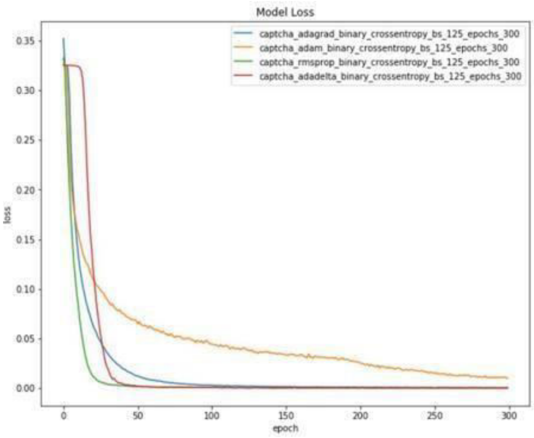

Fig 7 Model Loss comparison by different optimizers in train dataset

Except for Adam methods, those other three reached the highest accuracy and lowest loss rate in training set are quite similar, but Adam has better continuous learning ability than the other three methods.

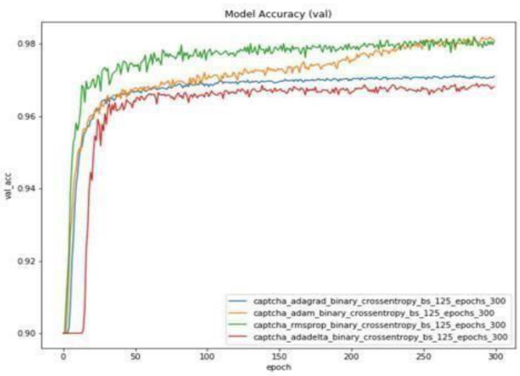

Fig 8 Model Accuracy comparison by different optimizers in the test dataset

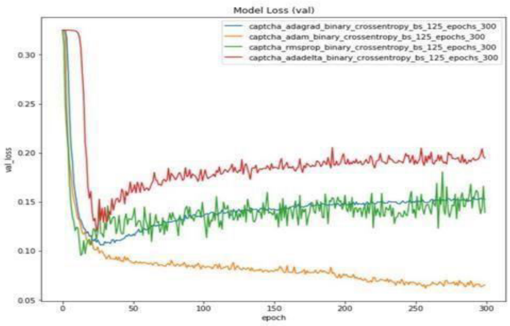

Fig 9 Model Loss comparison by different optimizers in the test dataset

However, after 150 epochs training, in the test dataset, Adam performs far better than the other three with the lowest loss rate. The other three reached a lower loss rate but rebounded to a higher value after about 50 epochs, which means that with Adagrad, Adadelta, and Rmsprop, the model is overfitting with the training set that cannot continue to perform well on the test set or some general situations. By comparing the performance within three loss functions and 4 optimizers, Adam with Binary Cross Entropy is more comprehensive on the test set, which will be used when deploying to real applications.

Fig 10 Output Screen

5. CONCLUSION

In this thesis, a CAPTCHA recognition system is developed, by using convolutional neural network, which is a popular technique in deep learning field and can be deployed to a humanoid NAO robot and web service to execute recognition service. During the establishment and the training process, there are some issues found that can be improved in future development. As the label text is translated to vector by one-hot encoding system, there are 36 of zeros and 4 of ones containing in the NumPy array. Because of this feature, if our model predicts the correct position of each zero, the accuracy would rise to a high level. When I was training the model, accuracy started at 90%, which is not an accurate number for the initial training moment. In the future, maybe another encoding system could be used to solve this problem. Another thing that can be improved is that the CAPTCHA image only contains numbers as the text because of the huge amount of data if we introduced letters and other characters in our dataset (624 combinations if we introduce uppercase and lowercase letters). It can be improved if computing capability is increased in the future. In this project, establishing the convolutional neural network and designing the training model are the core parts. CAPTCHAs are becoming more and more difficult to crack nowadays, but with the deep learning algorithm developing, more advanced neural network will be developed to cope with increasingly complex CAPTCHA algorithms.

6. FUTURE SCOPE

The future scope of captcha recognition using Convolutional Neural Networks (CNN) is promising, as there are several potential areas of improvement and application. The future scope of CAPTCHA recognition using Convolutional Neural Networks (CNNs) is poised for significant advancements. As CAPTCHA systems become increasingly complex, CNNs are expected to evolve with more sophisticated architectures that enhance their accuracy and adaptability. Future developments may include improving CNNs' ability to generalise across various types of CAPTCHAs, such as image-based, text-based, and hybrid forms, while also enabling real-time processing for faster recognition. Another crucial area of focus will be enhancing the robustness of CNNs against adversarial attacks and CAPTCHA modifications. Additionally, integrating CNNs with other AI techniques, like reinforcement learning or natural language processing, could further refine CAPTCHA-solving capabilities. As the technology advances, addressing privacy and ethical concerns related to AI- driven CAPTCHA recognition will also be essential to ensure responsible use.

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