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HAND JOTTED NUMERAL REALISATION USING CNN

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ABSTRACT

The issue of verifying registration numbers has remained an open question in legal standards for years. Some believe neural systems possess remarkable capabilities in manipulating information. This article aims to propose an effective strategy for confirming the emergence of composite content by analyzing available models. It focuses on Convolutional Neural Networks (CNNs), which are known for their efficiency but can sometimes weaken the framework. In machine learning, neural systems can be utilized for tasks such as code traversal. By utilizing the MNIST database and integrating it with CNNs, a clear progression strategy was developed. Essential libraries like NumPy, Pandas, TensorFlow, and Keras are key to this modeling approach. The MNIST dataset contains about 70,000 images of digits 0-9, categorized into 10 classes. This data is split into training and test sets, with each image represented as a 28x28 grid of grayscale pixels.

Keywords: Data processing,Convolutional neural networks(CNN),MNIST(Modified National Institute of Standard and Technology),TensorFlow,Keras,Numpy,Pandas

I. INTRODUCTION

The issue of code validation has recently gained significant attention, leading to various preparatory efforts and calculations. One of the main challenges in validating composite codes is that these codes differ from a single, standard code due to their creation by multiple users. This introduces variations in measurement, interpretation, line weight, rotation, and distortion, all of which are influenced by the user's input, computer images, and other factors. Researchers have applied different methods to assemble codes from various counterfeit devices, utilizing machine learning and neural network techniques to interpret and make decisions based on visual data. As noted by Khotan et al. (1998), code recognition can be a complex problem for neural machine learning, presenting opportunities to enhance advanced techniques such as deep learning.

Handwritten Text Recognition (HTR) refers to a computer's ability to process and extract legible written content from various sources, such as stored data or touchscreen input. Composite images of written text can be extracted from archives using optical character recognition (OCR) or through intelligent content or user input methods. This article explains how to use TensorFlow to recognize handwritten digits (0-9) from the widely-used MNIST dataset with Python. The user enters a specific code, and the system retrieves the correct result based on the trained model, demonstrating an effective approach for recognizing composite numbers in a real-world scenario.

ModulesDescription:

1. **Data:** An input dataset is generated in the initial module for both training and testing purposes.

2. **Import Core Libraries**: Essential libraries such as Keras for building graphical models, and others like Pandas, NumPy, and Matplotlib for transforming images into numerical representations, should be imported.

3. **Image Restoration:** Images and their corresponding labels will be restored for processing.

4. **Dataset Distribution:** The dataset should be divided into training and testing sets, with 80% allocated for training and 20% for testing.

III. LITERATURE REVIEW

TITLE : Iris liveness detection using a batch-normalized convolutional neural network
AUTHOR **:**Long, M.; Yan, Z.
YEAR **:** 2019
DESCRIPTION
To address presentation attacks in iris recognition systems, a new iris liveness detection method based on a batch-normalized convolutional neural network (BNCNN) is proposed to enhance the reliability of iris authentication. The BNCNN model consists of 18 layers, including convolutional, batch-normalization (BN), ReLU, pooling, and fully connected layers, designed to differentiate between genuine and fake irises.

Initially, the iris image undergoes preprocessing, which includes segmentation and normalization to a 256×256 pixel resolution. Then, the BNCNN model extracts distinctive iris features. These features are processed in a decision-making layer to classify the iris as either genuine or fake. The use of batch normalization in the BNCNN helps prevent overfitting and alleviates issues related to vanishing gradients during training.

The proposed approach is evaluated using three widely-used databases: the CASIA Iris Lamp, CASIA Iris Syn, and Ndcontact databases. Experimental results demonstrate that the proposed method is effective in extracting fine-grained iris texture features, achieving higher detection accuracy than several traditional iris liveness detection techniques.

TITLE **:** Improving handwriting-based gender classification using ensemble classifiers. Expert systems with applications

AUTHOR **:** Ahmed, M., Rasool, A. G., Afzal, H., & Siddiqi

YEAR **:** 2017

DESCRIPTION

This paper proposes a system for predicting the gender of individuals based on offline handwriting samples. The method involves extracting a range of textural features from handwriting samples of male and female writers, and using these features to train various classifiers to distinguish between gender classes. The features include local binary patterns (LBP), histogram of oriented gradients (HOG), statistics derived from the gray-level co-occurrence matrix (GLCM), and features obtained through segmentation-based fractal texture analysis (SFTA).

For classification, a variety of machine learning algorithms are utilized, including artificial neural networks (ANN), support vector machines (SVM), nearest neighbor classifiers (NN), decision trees (DT), and random forests (RF). These classifiers are further combined using ensemble techniques such as stacking and voting to enhance the overall system performance. Experimental results show that the proposed method achieves significantly higher classification accuracy compared to existing state-of-the-art systems, validating the effectiveness of the approach.

IV.SYSTEM ARCHITECTURE

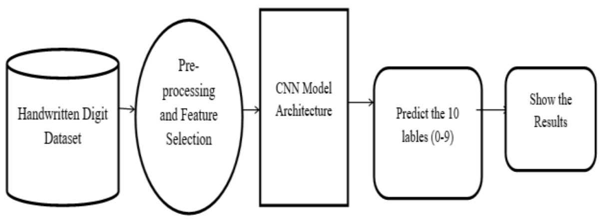
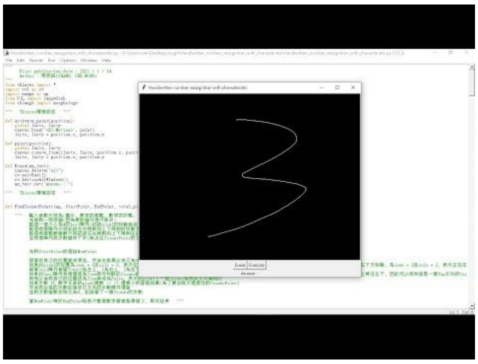


Fig: System Architecture

V.SYSTEM RESULT

Input Image



Output Image

VI.CONCLUSION

This study investigates the impact of modifying neural network connectivity to enhance character recognition performance while addressing issues such as pre-planning, over-elimination, and uncertain (combinational) model recognition. Extensive evaluations were conducted using the MNIST dataset, identifying key factors for improvement. The research demonstrates that adjusting hyperparameter boundaries plays a crucial role in boosting the performance of convolutional neural network (CNN) features. By using the Adam optimizer, the proposed approach achieved a verification rate of 99.89%, surpassing the performance of the latest models in the MNIST repository.

VII. FUTURE ENHANCEMENT

Future research could explore various CNN architectures, particularly hybrid models such as CNN-RNN and CNN-HMM, as well as explicit space recognition frameworks. Additionally, further investigation into optimization techniques for refining CNN learning parameters, such as the number of layers, learning rate, and kernel sizes in convolutional layers, could lead to improved performance.

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