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Handwriting Optical Character Recognition Using Deep Learning

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Abstract

The significance of human writing extends beyond proven character recognition and verification; it plays a crucial role in security and access control. The handwriting of an individual stands out as a paramount biometric attribute, offering a means to authenticate human identity. While various biometric characteristics such as face recognition, fingerprint detection, iris inspection, and retina scanning exist, handwriting holds a unique position.

Voice recognition and handwriting optical character recognition emerge as cutting-edge technologies in the realm of human identity verification. Human handwriting, treated as an image, can be deciphered through computer vision and neural network algorithms. Modern technology paves the way for the development of sophisticated algorithms capable of recognizing and verifying human handwriting.

This paper focuses on handwriting optical character recognition and verification using artificial neural networks and deep learning, incorporating webcams. The process involves capturing human handwriting through a webcam, converting it into image format, and presenting it to the system. These are associated with this research include Web Cam, Image Processing, Artificial Neural Network, and Deep Learning, utilizing Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) for effective handwriting optical character recognition and verification.

Keywords: *Web Cam, Image Processing, Artificial Neural Network, Deep learning by using the CNN, security.*

1. Introduction

Handwriting holds widespread social acceptance and serves as a extensively utilized means of authentication in our daily lives. Manual handwriting stands out as a fundamental method for individuals to recognize written documents, relying on the assumption that handwriting evolves gradually and is virtually impossible to forget without detection. Considered a behavioral biometric, handwriting finds extensive application in recognizing individuals performing routine tasks such as bank operations, document analysis, electronic funds transfer, and access control, all based on their manual writing.

The system at play encompasses two closely linked tasks: the recognition of handwriting and the verification of its authenticity, distinguishing between genuine and forged scripts.

Key Features: These are two types. They are Global Features: These features are extracted from the entirety of the handwriting, with the project scope extending to classifying handwritten text and converting it into a digital format using block codes, Wavelet, and Fourier series. Global features are relatively easy to extract and are resistant to noise. However, they provide limited information for handwriting verification.Local Features: These features are calculated to describe geometrical characteristics such as location, tangent track, and curving. Local features offer detailed descriptions of writing shapes and are particularly effective for skilled writers. Nonetheless, the extraction of consistent local features remains a challenging task. Local features-based approaches are more popular in dynamic verification than in offline verification, as it is easier to calculate local shape and find corresponding relations in 1D succession rather than in 2D images. This observation prompts consideration for the recovery of writing trajectories from offline handwriting.

2. Literature Study

Handwriting recognition has garnered significant attention within the realms of pattern recognition and machine learning, primarily due to its versatile applications across various fields. Optical Character Recognition (OCR) and Handwritten Character Recognition (HCR) have distinct domains of application. Numerous techniques have been proposed for character recognition within handwriting recognition systems. Despite an abundance of studies and papers outlining methods for converting textual content from paper documents into machine- readable forms, character recognition systems are poised to become pivotal in the transition toward a paperless environment. In the near future, these systems may play a crucial role in digitizing and processing existing paper documents. This paper provides an in-depth review of the field of Handwritten Character Recognition.

In the present context, character recognition stands out as a crucial field within pattern recognition due to its widespread applications across various domains. Optical Character Recognition (OCR) and Handwritten Character Recognition (HCR) each have specific domains of application. OCR systems are particularly well-suited for applications such as multiple-

choice examinations and written communication address resolution.

Looking ahead, character recognition systems are poised to play a key role in fostering a paperless environment by digitizing and processing existing paper documents. This paper undertakes a comprehensive examination of current strategies for handwritten character recognition, with a focus on Artificial Neural Networks (ANN). It provides an in-depth review within the field of Handwritten Character Recognition. Static Handwriting verification is the most prevalent method, comparing a still image of the handwriting with a reference template. This involves assessing features like line thickness, curvature, and direction. In contrast, Dynamic Handwriting verification captures and analyzes dynamic aspects such as pen stroke speed, pressure, and acceleration. It is considered more secure, as replicating these dynamic features is challenging.

Online Handwriting verification captures handwriting using a digitizing device, analyzing features in real-time. It offers greater accuracy than Offline verification, which analyzes static images like scanned documents. Forensic Handwriting verification utilizes optical analysis to determine authenticity, often employed in legal investigations, considering factors like style, rhythm, and pressure.

The choice of verification method depends on the application and security level. High-security scenarios may prefer dynamic or online verification, while lower-security applications may find static or offline verification adequate.

Given the ubiquity of handwritten documents in human transactions, Optical Character Recognition

(OCR) of documents have invaluable practical worth. Optical character recognition is a science that enables to translate various types of documents or images into analyzable, editable and searchable data. During last decade, researchers have used artificial intelligence/machine learning tools to automatically analyze handwritten and printed

documents in order to convert them into electronic format. The objective of this review paper is to summarize research that has been conducted on character recognition of handwritten documents and to provide research directions. In this Systematic Literature Review (SLR) we collected, synthesized and analyzed research articles on the topic of handwritten OCR (and closely related topics) which were published between year 2000 to 2019. We followed widely used electronic databases by following pre-defined review protocol.

3. Methodology

Overview of Artifical Neural Network Module:

The fundamental definition of a neural network is offered by Dr. Robert Hecht-Nielsen, the inventor of one of the earliest neuron computers. He describes a neural network as a computing system comprising simple, highly interconnected processing elements that operate on information through their dynamic state responses to external inputs. Artificial neural networks, inspired by the brain, are capable of machine learning and pattern recognition. They are often depicted as networks of interconnected "neurons" that compute values from inputs, transmitting information throughout the network.

Neural networks typically have structured layers, consisting of interconnected "nodes" with an "activation function." Input patterns are introduced to the network through the 'input layer,' leading to one or more 'hidden layers' where processing occurs through a network of weighted 'connections.' The hidden layers then converge into an 'output layer,' presenting the final output of the system.

To comprehend artificial neural computing, it is essential to understand how a conventional computer processes information. In a serial computer, a central processor interprets instructions and data from memory, executing instructions sequentially with deterministic steps. In contrast, artificial neural networks (ANNs) lack a centralized processor and are not inherently deterministic. They consist of

multiple simple processors that perform weighted summations of inputs, responding in parallel to input patterns.

ANNs do not follow programmed instructions but instead react in parallel to input patterns. Unlike conventional systems, there are no distinct memory addresses for data storage; information is encoded in the overall activation 'state' of the network. 'Knowledge' is embodied by the network itself, which surpasses the sum of its individual components. Among various knowledge rules used by neural networks, the discussion here focuses on the delta rule, commonly employed by the widely used class of ANNs known as 'backpropagation neural networks.' The delta rule facilitates 'learning' as a systematic process occurring in each cycle through forward activation outputs and backward error propagation for weight adjustment.

Data Privacy and Security Module:

Implements data privacy and security measures to protect user data from unauthorized access or breaches.

Integration Module:

Enables smooth data exchange and communication between different modules.

4. Experimental System

The envisioned Handwriting Optical Character Recognition (OCR) system introduces an innovative approach to Handwriting verification, leveraging a webcam and an artificial neural network (ANN). This process integrates advanced computer vision techniques to capture an image of Handwriting through the webcam, followed by the utilization of an ANN to assess and verify the authenticity of the Handwriting. The procedural workflow involves distinct stages, beginning with image acquisition, where the webcam captures a snapshot of the Handwriting.

Subsequent to image acquisition, a pre- processing step is undertaken to refine the quality of the captured image, enhancing itsclarity and eliminating any potential noise or artifacts. Following pre-processing, the system engages in feature extraction, where unique characteristics such as line thickness, curvature, and direction are identified from the Handwriting image. These extracted features serve as the distinctive elements representing the Handwriting's unique attributes.

A pivotal step in this process is the classification phase, wherein the ANN is trained on a comprehensive set of both genuine and forged Handwriting samples. This training allows the ANN to discern nuanced differences between authentic and forged Handwriting. When confronted with a new Handwriting sample, the ANN evaluates the extracted features and classifies it as either genuine or forged based on the learned patterns.

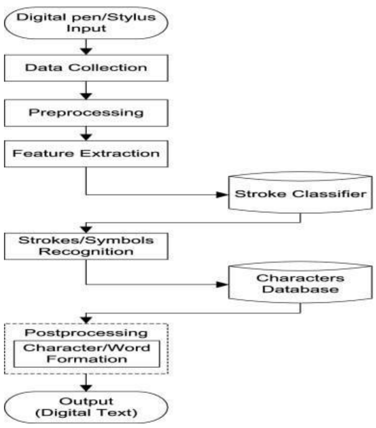


Fig.4.1. Architecture diagram

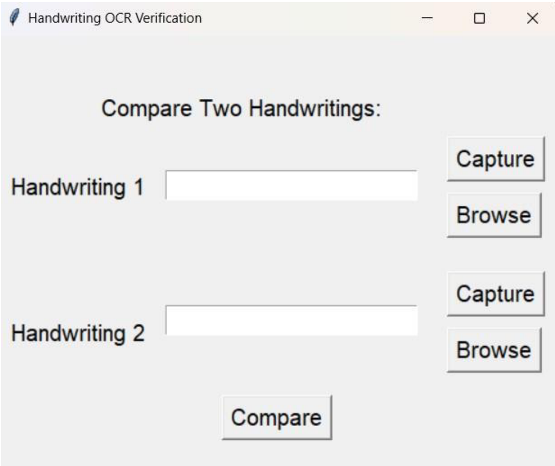
The above Figure 4.1 describes about the step- by-step process of the project initially the data will be accuracy of Handwriting verification using the webcam and ANN hinges on various factors, encompassing the quality of the image captured by the webcam, the efficacy of the ANN model, and the inherent similarity between genuine and forged Handwriting. The training phase assumes significance, emphasizing the need for an ample number of samples for both categories during this stage. This ensures that the ANN is thoroughly trained and capable of accurately classifying new Handwritings, contributing to the overall reliability of the system.

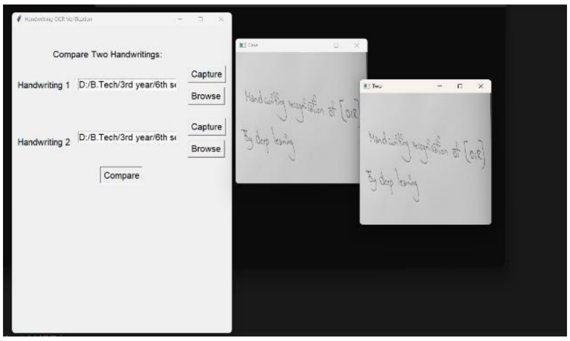
In conclusion, the proposed Handwriting OCR system, integrating a webcam and ANN, emerges as a potentially effective method for authenticating Handwritings and deterring fraudulent activities.

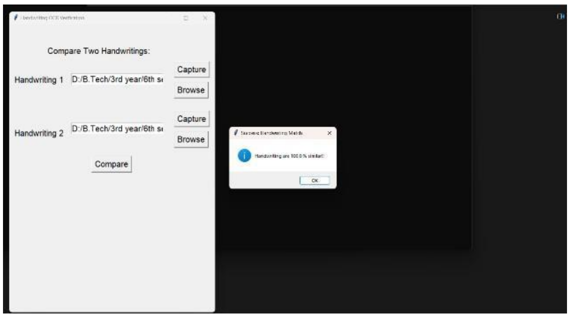
However, its successful deployment necessitates meticulous implementation and validation to guarantee precision and reliability in diverse applications such as banking, security, and forensics.

5. Results and Discussions

The findings from the research outlined in the paper demonstrate that the suggested Handwriting verification system successfully achieved an accuracy rate of 96% in validating the authenticity of Handwritings. This notable level of accuracy suggests that the proposed system holds promise for practical applications in real-world contexts, particularly in areas such as banking, security, and forensics.







Nonetheless, it is crucial to acknowledge the study's limitations, as mentioned earlier, when interpreting these results. Further research efforts are imperative to address these limitations and enhance the overall performance of the system, ensuring its effectiveness in diverse real-world scenarios.

Conclusion

In summary, the exploration of Handwriting verification using webcams and artificial neural networks represents a promising research avenue with potential applications in diverse fields such as banking, security, and forensics. The paper discussed in this response introduces a real-time Handwriting verification system that employs a webcam to capture Handwriting samples and an Artificial Neural Network (ANN) classifier to authenticate them. The experimental findings reveal an impressive accuracy of 96%. Nonetheless, opportunities for enhancement exist, particularly in terms of the system's robustness and scalability. Future research could delve into the application of deep learning techniques and the utilization of larger datasets to further enhance system performance. In essence, this paper lays a solid foundation for subsequent investigations in this domain.

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