Biometric Identification and verification using Deep Learning

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Abstract: Because there has not been much research done on the Arabic language which is thought to be more challenging than other languages due to it has multiple cases and forms for a single letter—there is still interest in developing a system to verification the writer's identity by he/she handwritting. These systems are thought to be essential in resolving complex legal issues involving security agencies and other issues.The foundation of our novel approach is the integration of a Harris corner detector with a Convolutional Neural Network (CNN).We also introduce a data augmentation algorithm to enhance the quality of the data. We tackle several problems related to this point by suggesting a method that can identify handwritten Arabic texts without the need to separate the characters,words to lines and by using upsampling to make the handwritten area of the image larger and more readable and this model work in offline mode with value 99.66% on the KHATT dataset.

Keyword: Handwriting, CNN, Identification, verification.

1. Introduction

A biometric system is a pattern recognition system that verifies the legitimacy of a user's physiological or behavioral characteristic in order to identify the individual. There are two modes of operation for a biometric system: verification and recognition. When a user is in recognition mode,

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the system compares their biometric data with those of all potential users to establish who they are. In the verification mode, the system verifies an individual's identity by comparing a biometric feature that was captured with the same feature in a database that contains the characteristics of various individuals [1].

Researchers' interest in handwriting as a biometric pattern has recently increased [2] Even though the goal of a fully digital future is drawing near, the practicality of digital images for writer recognition makes them interesting. The classification of historical archives [3, 4], signature verification [5], prediction of the writer's genre or age [6, 7], forensic analysis of writing [8], and security and access control [9, 10], and among other examples.

When trying to identify a person from handwriting samples, there is a direct conflict between two significant natural factors: within-writer variability and between-writer variation. Consequently, computer representations (features) that can maximize the separation between different writers while staying stable over samples created by the same writer are required for automatic writer identification [11,12].

A deep learning model utilizing a convolutional neural network (CNN) and a Harris edge detector is presented in this work. It functions without the need for segmentation and also in an offline state by upsampling an image, which is the process of increasing an image's resolution or size (by a factor of 2). The handwritten portion, which is made up of multiple lines from the KHATT dataset, is used in this process. Data augmentation is also used because deep learning requires a lot of images.

It is important to note that this system functions for both writer identification and verification.

The remainder of this paper is organized as follows: presents an extensive review of recently published research on Arabic datasets employed in Section 2. Biometric Systems that have been employed in Section 3.

Background Theory is introduced in Section 4. Section 5 explain the Proposed Method ,Sections 6 discusses the Arabic dataset , The final section concludes the work.

2. Related work

Set of authors in 2017,they outline a technique for reliable one-writer identification. They suggest using densely computed RootSIFT descriptors at the script contours. GMM supervectors are employed as an encoding technique to characterize each scribe's unique handwriting. A background model is modified to fit the distribution of local feature descriptors to produce GMM supervectors. Lastly, they suggest training a document-specific similarity measure with Exemplar-SVMs. They assess the approach using three publicly accessible datasets (KHATT, CVL, and ICDAR) and demonstrate that the method raises the bar for performance on each of the three datasets [13].

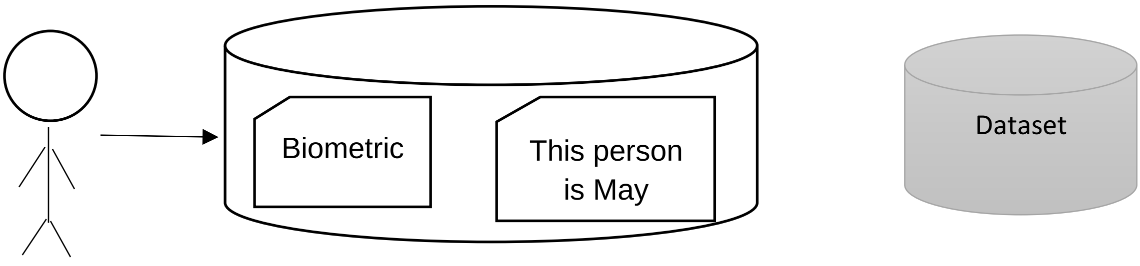
Set of authors in 2017,they distinguish writers from historical and modern manuscripts using a combination of local and global traits. The local handwriting features are extracted using a modified version of the popular contour direction feature, and the global descriptor for the writing style is created by converting key-point-based features (SIFT) into a higher-level representation. Various experiments report an identification rate of 85.5% on 1,000 writers of the KHATT database [14].

Set of authors in 2019, examines the problem of using Arabic handwriting samples for writer identification. The proposed approach is based on the extraction of short text segments identified by means of two textural descriptors: Histogram of Oriented Gradients (HOG) and Gray Level Run Length (GLRL) Matrices.Calculating the distance between the pieces of two samples that need to be compared is a step in the classification process.Similarity scores derived from GLRL and HOG features are combined using a range of fusion rules. The system is evaluated using three widely used Arabic handwriting databases: the 1,017-writer QUWI database, the 1000-writer KHATT database, and the 411-writer IFN/ENIT database. Fusion uses the "sum" rule to report the highest identification rates, with values of 96.86, 85.40, and 76.27% on the IFN/ENIT, KHATT, and QUWI databases, correspondingly [15].

Set of authors in 2022, they used the DCNN model, they discovered that the Resnet 152 network and Softmax classifier type produced the best results in terms of accuracy when compared to other pre-trained networks. The accuracy of the model, which was tested on four datasets—IAM, CVL, KHATT, and IFN/ENIT— Thus, 98.2%,99.7%, 99.4%, and 99.6% [16].

3. Modes of Operation for Biometric Systems

1. Biometric systems can operate in two modes, such as identification mode and verification mode, which are described below, depending on the type of application.
2. Identification mode is difficult to handle because it compares the provided sample to every biometric template that is currently stored in the central database.
3. Verification mode refers to the process of confirming an individual's identity through a comparison between the stored and enrolled modalities.
4. The identification mode searches for a single user among several identities by using negative recognition.
5. Compared to identification, the verification mode is more affordable and resilient in terms of computation, searching, and complexity.
6. The mode of identification is less intrusive and more convenient.
   See figure 1 showing the difference between Identification (1 : N) and Verification (1 : 1).



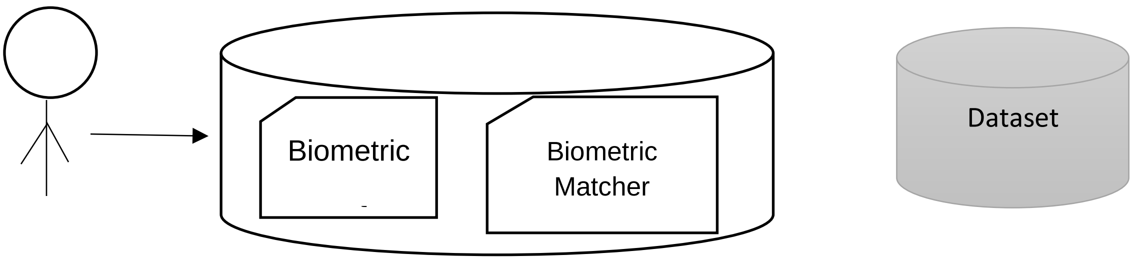


Figure 1. The difference between Identification and Verification.

4. Background Theory

The implemented application in this study is handwritten words verification or handwritten documents verification. Many people think of handwritten word recognition HWR and handwriting word verification as different problems and many of them think the same. The answer is that the idea behind both is the same, just the application area is different [17]. The difference between these two methods can be briefly explained as follows:

Handwriting word verification answers: Is this word (x)?

Whereas, HWR answers: What is this word?

4.1 Handwriting Word Recognition

HWR which is also known as word identification is the process of conversion of handwritten words into machine-readable form. The image of the written word may be recognized online or offline. Online character recognition is the process of recognizing handwriting recorded with a digitizer as a time sequence of pen coordinates. Off-line HWR is the process of recognizing a scanned word and is stored digitally in the greyscale format as in the proposed system [18]. In HWR as shown in Figure 2, the system looks for the written word in a database of words and tries to predict it which is a one-to-many comparison.

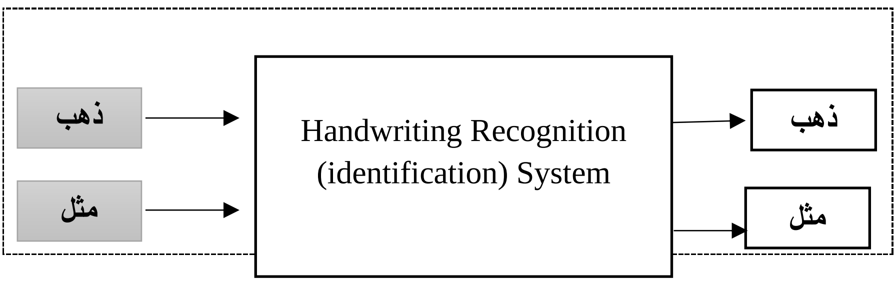


Figure 2. A generic word recognition system.

4.2 Handwriting Word Verification

It can be considered a sub-branch of HWR. As the name suggests, the system tries to authenticate a handwritten word (handwritten documents). It is a one-to-one comparison. Here, the purpose of the system is not to guess the entered word correctly but to verify whether the entered word is correct. As seen in Figure 3, by checking the dataset and applying an algorithm, the system verifies whether the written word is (ذهب) or not.

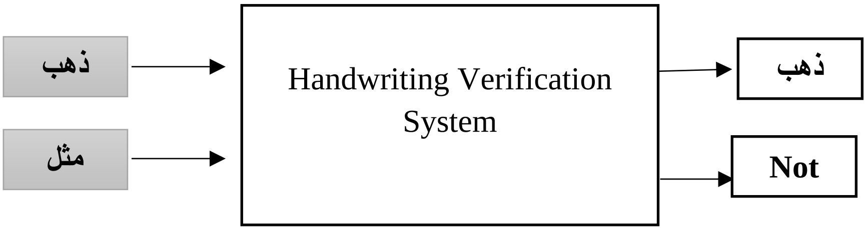


Figure 3. A generic word verification system.

5. The Proposed Method

The suggested approach is built on the CNN model, which belongs to the deep learning class and is frequently used to analyze visual data. It's a model designed to mimic how the human brain works. An input layer, several hidden layers, and one output layer are typically found in a CNN. Convolutional, activation function, pooling, fully connected, and normalization layers are all contained inside the structure of hidden layers. In contrast to alternative classification algorithms, CNN requires significantly less preprocessing and produces better results as the number of training examples rises [19].

Figure 4 displays the CNN sample's network architecture.High recognition accuracy can be achieved by using multiple layers, and this accuracy is unaffected by slight geometric alterations to the input images. CNN is effectively applied to classification tasks on real-world data due to its high recognition accuracy.

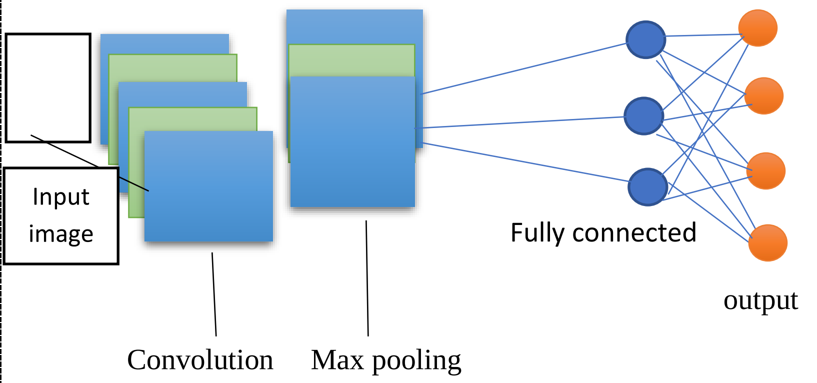


Figure 4. The network architecture of the CNN sample.

the another method that used is The Harris corner detector (Harris & Stephens, 1988), one of the more conventional key point detectors, operates on the simple tenet of tracking changes in image intensity values for minute window displacements in different directions and assigning colors (red, blue, etc.) to these changes in order to identify them.Where a flat region is defined by no (or very little) change in image intensity values in all directions, and an edge is indicated by changes only in one direction (and no change along the edge direction). Similarly, at corner points, the intensity varies significantly in all directions. The mathematical process of finding interest points entails computing the Hessian matrix, which for a given image pixel p, represents the variations in intensity along the x, y, and xy instructions [20].

Initially, the writer identification phase involved the application of the aforementioned techniques. This procedure was carried out in a series of sequential steps. The image was manually written and then uploaded into the system. The Harris corner detector was to be used in the second step. The final result of this process is a dotted image, which indicates that the corners were recognized as features that may be referred to at a later time. These images were categorized according to the quantity of users. The process involves defining the condition of each curvature by a specific amount, which is taken as a corner.

In this instance, the KHATT dataset utilized by the system contains a thousand users, which led to the creation of 1000 classes. It's important to note that each user has four handwritten photos. A Softmax classifier was applied in this instance. Following the conclusion of what is regarded as the initial step in the verification process.

Take a look at Figure 5 to see how to identification the writer.

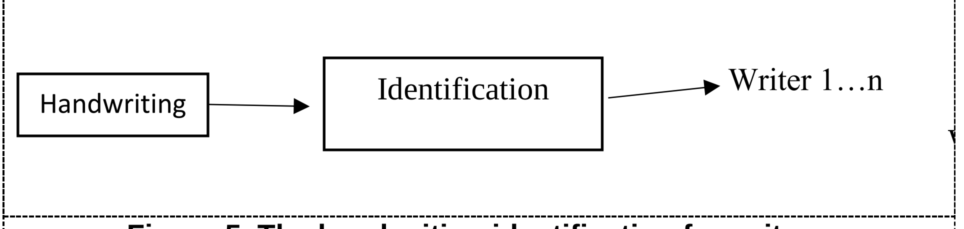


Figure 5. The handwriting identification for writers.

Verifying whether or not this document was written by this person starts the second stage, which is thought of as a derivative of the first stage, after the identification process is finished.Two images are entered into the model to complete this process, and each of the two images has one of the following probabilities: 1. Since the two pictures are alike, they were created by the same author. Herein lies the program's challenge: it takes the expectation percentage (probability) for every class that currently exists, finds the highest percentage, and compares it with the input images. The response will be similar if they are similar. 2. Since the two images are distinct from one another, they each belong to a different person. In this instance, the program responds differently to these two images because the maximum probability rate is also taken and compared with the input images.The response will be different. View the accompanying figure 6 to see how the verification procedure is done.

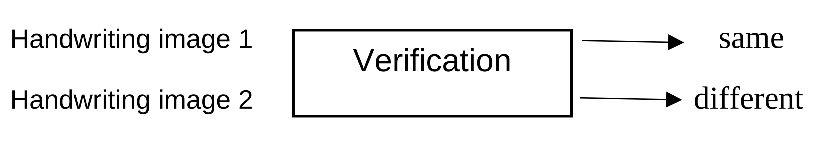


Figure 6. Writer verification.

It is important to note that the dataset underwent several stages during this process, one of which was size adjustment. By making all of the images the same size, this allows for a greater opportunity to reduce the excessive white space. Additionally, the handwritten area was expanded through the use of upsampling, which increases the likelihood of identifying and extracting the font. Important characteristics additionally, in order to improve training and provide satisfactory results for the proposed model, the data augmentation method was employed due to a lack of data.

6. KHATT Dataset

A comprehensive Arabic handwritten text database is necessary for research on Arabic handwritten text recognition. This is especially true for handwritten Arabic text, as there isn't a database like this one.In this paper, we present our large Arabic offline handwritten text database (KHATT).

The handwritten Arabic text dataset (KHATT خط) is owned and protected by copyright by King Fahd University of Petroleum and Minerals (KFUPM).

KHATT was developed by research teams from KFUPM Saudi Arabia, TU Braunschweig, Germany, and TUD Ortmund, Germany.

It consists of handwritten Arabic documents from a thousand writers.The images were scanned at three different resolutions: 200, 300, and 600 dpi.

The writers were selected based on their educational background, hand (left or right), nationality, gender, and age.

Because there were no restrictions on writing techniques when these naturally occurring writings were created, they are unique.

The database is available for free use by researchers worldwide to investigate a range of handwritten-related topics, such as text recognition, form analysis, writer identification and verification, preprocessing, and segmentation. Numerous international research groups and investigators have obtained the database to date for their research needs.

The dataset is arranged with four pages for each individual. The author has written paragraphs on the first, second, third, and fourth pages [21,22]. A handwritten sample is displayed in Figure 7.

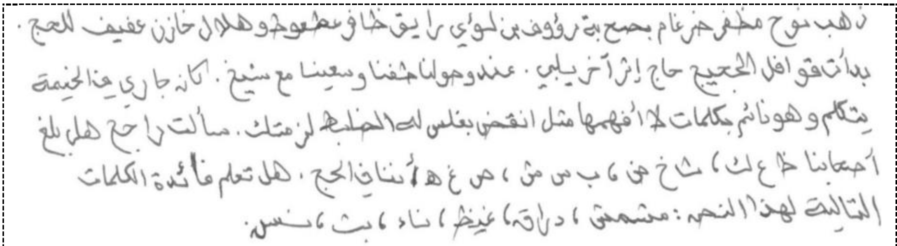


Figure 7. A handwritten sample.

7. Results

The writer identification and verification performance on the KHATT dataset is shown in Table 1.

Table 1. The related works for writer verification

Model	Regional and Global Character - istics	GLRL+ HOG	DCNN	(Our models) CNN+ Corner detector
Accuracy	85.5%	85.40%	99.4%	99.66%

The table above leads us to the conclusion that there is a certain amount of restriction in research sources due to the paucity of studies on the Arabic language.

8. Conclusion

We have looked into the issues with writer verification in this communication. Because it provides the only means of individual rejection (writer) in cases where a writer is not recognized by the system, it is a necessary and complementary approach to any identification approach. Our focus was on the writer verification process using two input images into the system and get the answer which be one of two is same or different. Our system consists of a Harris corner detector and a convolutional neural network, which together provide an accuracy for the KHATT dataset—one of the challenging datasets that includes Arabic text documents and manuscripts—that is almost 99.66%.

A universal strategy does not work for all languages because they are unique and each has unique characteristics that pose unique challenges. We observed that, in contrast to Latin scripts, which have been widely employed for writer identification and verification, Chinese and Arabic scripts—including Arabic, Urdu, Persian, and others—have received much less attention.

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تحديد القياسات الحيوية والتحقق منها باستخدام التعلم العميق

مهند تحرير يونس
البريد الالكتروني

ميس زيدان خليف
البريد الالكتروني

المستخلص: نظرًا لعدم إجراء الكثير من الأبحاث حول اللغة العربية التي يُعتقد أنها أكثر تحديًا من اللغات الأخرى نظرًا لوجود حالات وأشكال متعددة للحرف الواحد، فلا يزال هناك اهتمام بتطوير نظام للتحقق من هوية الكاتب من خلاله. / هي الكتابة اليدوية. يُعتقد أن هذه الأنظمة ضرورية في حل المشكلات القانونية المعقدة التي تتعلق بالوكالات الأمنية وغيرها من القضايا. أساس نهجنا الجديد هو دمج كاشف زاوية هاريس مع الشبكة العصبية التلافيفية (CNN). كما نقدم خوارزمية زيادة البيانات تعزيز جودة البيانات. قمنا بمعالجة العديد من المشاكل المتعلقة بهذه النقطة من خلال اقتراح طريقة يمكن من خلالها التعرف على النصوص العربية المكتوبة بخط اليد دون الحاجة إلى فصل الحروف والكلمات عن السطور وباستخدام upsampling لجعل المساحة المكتوبة بخط اليد من الصورة أكبر وأكثر قابلية للقراءة ويعمل هذا النموذج في وضع غير متصل بالشبكة بقيمة ٩٩,٦٦٪ في مجموعة بيانات KHATT.

الكلمات المفتاحية : الكتابة اليدوية، CNN، التحديد، التحقق.

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