New Approach Based on Substantial Derivative and LSTM for Online Arabic Handwriting Script Recognition

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Abstract: As some tasks easily performed by man seem to be hard to be accomplished by the machine, the Artificial Intelligence field examines more and more the reproduction of thinking methods and human intuition by studying some mental faculties and substituting them by calculating approaches. Among the major fields of such interest, we can focus on recognizing handwritten characters. However, most handwritten characters are written in Latin, which makes the recognition of Arabic characters handwriting a delicate process compared to other languages, due to the specificity of Arabic words. In this paper, we aim to conceive a framework that offers the ability to recognize online Arabic handwriting applied to a dataset named ADAB (Arabic DAtaBase), using a particular descriptor based on a substantial derivative and a neural network handling Arabic handwritten characters features and then electing the appropriate output for the final decision.

1 INTRODUCTION

Handwriting recognition is among the oldest problems faced by artificial intelligence, since its advent in the 1950s (Mori et al., 1992). An essential playground for new learning algorithms, it represents a real scientific and technical challenge and an imminent need requested by many business sectors.

1.1 Applications

Recognizing handwritten text is being applied in several various human activity fields, including:

- Education (Wu et al., 2021): through the recognition and translation of texts, such as texts in Braille, and writing learning. Photosensors and tactile simulators are used for the blind and low vision (BLV) persons with a sound output.
- Banks and Insurance companies (Singh et al., 2015): through the check authentication (correspondence between amounts and denomination, and between the identity of the signatory and his signature), and verification of insurance contracts.
- Post services (Charfi et al., 2012): through reading postal addresses and automatic sorting of mails.
- Business and Industry (Nagy, 2016): through inventory management and technical documents recognition (electronic diagrams, technical drawings, architectural plans, etc.).
- Office automation (Chherawala & Cheriet, 2014): through indexing and automatic archiving of documents, and for electronic publication.
- Automatic reading of administrative documents and recognition of cartographic maps (Velázquez & Levachkine, 2004).

1.2 Modes of Character Writing

Two writing modes of character writing are used: static mode for characters already written and dynamic mode for handwritten characters to be recognized while writing. Below, we explain both modes in more detail:

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- Static mode (ElKessab et al., 2013): It mainly uses scanners. The scanner scans the text line by line and digitizes each line into a larger or smaller series of dots. The resolution of a scanner, expressed in number of dots per inch (dpi), refers to its ability to digitize fine lines. In OCR, the most common values range from 200 to 400 dpi (Abuhaiba, 2004); a higher resolution does not increase the precision of the digitization; on the contrary it increases the number of points to be processed and generates noise (grain of the paper). Several types of scanners exist on the market offering several input modes: flatbed, drum, or handheld, providing a choice of raster images, binary images, grayscale images and color images.
- Continuous mode (Begum et al., 2021): It uses a graphic tablet which sends coordinates of points to the contact of the pen. Capturing fine lines depends on the regular support of the pen so as not to cause discontinuities in the lines. This mode is quite valuable in OCR because it gives very useful information for recognition such as the number of pencil strokes and therefore the reading direction, and the number of points per pencil stroke significant of the curvature of the line.

1.3 Categories of Handwritten Characters Recognition

Several kinds of handwritten character recognition exist such as:

- Online or offline (Kannan et al., 2008; Tappert et al., 1990): Online recognition is a dynamic recognition that takes place during writing. A slight delay of a word or a character allows the recognition not to encroach on the input. The continuous response of the system allows the user to correct and modify writing directly and instantaneously. Offline or delayed recognition starts after the acquisition of the entire document. It is suitable for printed documents and already written manuscripts. This mode allows the instantaneous acquisition of a large number of characters but imposes costly pre-processing to find the reading order.
- With or without learning (Stremler & Karácsony, 2016): A system with learning includes a module for introducing reference character models. Significant samples of writing (printed or handwritten) in sufficient numbers (tens or even hundreds of samples per character) are entered in manual or automatic mode. In the first case, the user indicates to the system the identity of each sample allowing the system to organize its classes according to the vocabulary which is being studied. For the handwritten script, the ideal would be to learn characters directly from a text, but this presents obvious segmentation problems. In the second case, the samples are grouped automatically from morphological analyses, without knowledge of their name. In a non-learning system, a knowledge base is built into the system and particular analysis algorithms are used.
- Direct, scaled or with labelling (Zhang et al., 2023): In systems with direct recognition, the learning includes a reference model per character. The recognition compares the candidate character to each of these models and retains the closest model. In scaled recognition, learning is divided into progressively selective classification levels. Each level contains separation tests for the different classes represented, allowing recognition to refine its decision if necessary. Labelling in the latter case consists of identifying the different characters in a text, thus distinguishing patterns, and then recognizing them. This mode has the advantage of limiting recognition only to the patterns found and being able to quickly make corrections, but it has the disadvantage of perpetuating any recognition error through all the characters of the same model.

1.4 Challenges

It is not obvious to be able to accurately recognize human writing. Indeed, the form of a handwritten character often varies, reflecting the style of writing, the state of mind, and the personality of the writer, which makes it difficult to characterize.

Among the variations that affect it, we can mention the contour distortion that produces curls and rounding, as well as the inclination that produces a rotation of the base of the character or a flattening of its shape, and the asymmetry generating an occlusion of the character parts or a closure of its cavities, and the poor connection of the lines leading to their sudden extensions and interruptions.

The remnant of this paper is structured as follows: In the following section we provide an overview around the related works and the most known datasets in terms of Arabic handwritten text recognition. Then, we present an innovative approach for features extraction step followed by applying LSTM deep neural model for classification step. Afterwards, we describe the experimentation implemented. A summarized conclusion is provided in the last section.

2 RELATED WORKS

2.1 Standardization and Famous Datasets

Despite the artifacts of handwriting, attempts of standardization have been elaborated. Indeed, committees from different countries have proposed standards of handwritten characters for recognition. In 1974, the American National Standards Institute (ANSI) (Alphabetic Handprint Reading, 1978) developed a character set introducing additional features to remove ambiguities. We can also mention the “Japanese Industry Standard” proposed by the “Japanese OCR Committee” and the standards of the “OCR Committee of Canada”. In order to be able to check the performance of handwritten character recognition systems and to compare them, test datasets were established, containing several samples of different handwritten characters, including uppercase and lowercase letters, digits, and punctuation marks. These databases were created to support research in the field of pattern recognition and machine learning and have been widely used in numerous research papers and projects. The most frequently used datasets are those of Munson (Munson, 1968) and Highleyman (Highleyman, 1961).

The Munson database includes the 46 characters of Fortran II, represented by matrices of size 24 X 24. It includes 12,760 samples of which 6,762 are written by different writers on special sheets. The others were taken either from particular authors or from documents. Munson instructed scripters to strike through the characters O and Z, to print 1 without a slash, and to place horizontal strokes over the I. Highleymann's dataset consists of the 36 alphanumeric characters represented by 12 X 12 size matrices. It includes 1,800 letters and 500 numbers from 50 writers who were instructed to write on grid paper in a writing frame.

We also mention many other recent datasets such as Mori handwriting dataset (Mori et al., 1984) which is a collection of handwritten Japanese characters created by the Mori Laboratory at the University of Tokyo. It contains over 3,000 handwritten characters written by 100 different writers and is widely used in the development of handwriting recognition systems. Moreover, the Modified National Institute of Standards and Technology (MNIST) dataset was introduced in 1998 (Lecun et al., 1998) and is a widely used as a benchmark dataset for handwritten digit recognition. It consists of 60,000 training images and 10,000 testing images of a 28 × 28 size of handwritten digits from 0 to 9. Furthermore, EMNIST (Cohen et al., 2017) dataset is an extension of the MNIST dataset and includes handwritten letters in addition to digits. It contains 240,000 training images and 40,000 testing images. Also, IAM Handwriting dataset (Marti & Bunke, 2002) contains handwritten words and sentences in English including over 5,000 pages of handwritten text from 657 writers.

CEDAR dataset (Hull, 1994) is composed of handwritten forms, including surveys, questionnaires, and tax forms. It contains over 1,000 forms with over 50,000 fields. Besides the mentioned, ICDAR is a collection of datasets (Lucas et al., 2003; Lucas, 2005; Shahab et al., 2011) for handwritten text recognition, including Chinese, Japanese, and Arabic text. RIMES (Reconnaissance et Indexation de données Manuscrites et de fac similÉS / Recognition and Indexing of handwritten documents and faxes) (Grosicki et al., 2009) is a modern dataset of handwritten words in French with over 1 million words written by over 1,300 writers. Additionally, the Street View House Numbers (SVHN) (Netzer et al., 2011) is a Google’s dataset of street view house numbers, which includes handwritten digits from 0 to 9. It contains over 600,000 images. One more dataset that we should consider is the ADAB dataset (Arabic DAtaBase) (Kherallah et al., 2011; Tagougui et al., 2012; Boubaker et al., 2012) made up of 15,000 Arabic names of Tunisian towns and villages, handwritten by more than 166 different writers. Figure 1 shows the appearance of some sample images from ADAB database displaying handwritten Arabic names of some Tunisian towns and villages.

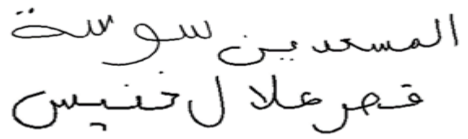

Figure 1: Appearance of some sample images from ADAB dataset.

2.2 Works on Arabic Handwritten Recognition

Various approaches have been used to automate the process of identifying and converting handwritten Arabic text into digital format, which is essential for many applications related to document analysis, text mining, and machine translation. This task mainly relies on using advanced algorithms and machine learning techniques to recognize the unique features of Arabic handwriting, such as the shape and size of letters, the direction of strokes, and the spacing between words. It has become an important research area in the field of computer vision and natural language processing and has the potential to revolutionize the way we interact with Arabic language documents.

There have been numerous research studies and developments in the field of Arabic handwritten recognition. Among the notable works, the comprehensive review of the state-of-the-art techniques and methodologies used in Arabic handwritten recognition (Cheriet, 2007) as well as many studies presented throughout the last decade such as a survey (Tagougui et al., 2012) where different approaches and techniques used for online Arabic handwriting recognition have been exposed. Another system that combines different feature extraction methods and classifiers for Arabic handwritten text recognition was proposed (Al-Maadeed, 2012).

Furthermore, the literature was examined on the most significant work in Arabic optical character recognition (AOCR) and a survey of databases on Arabic offline handwritten character recognition system was provided (Abdalkafor, 2018) as well as a recognition system of Arabic cursive handwriting using embedded training based on hidden Markov models (Rabi et al., 2017).

Later, various papers (Noubigh et al., 2020; Altwaijry & Al-Turaiki, 2020; AlJarrah et al., 2021; Ali & Mallaiah, 2022) presented some deep learning approaches such as convolutional neural networks (CNNs) for Arabic handwritten text recognition.

These works demonstrate the ongoing research and development in the field of Arabic handwritten recognition, and the potential for further advancements in this area.

3 PROPOSED METHOD

Enlightened by a main concept emerging from the physics of fluid mechanics previously explained (Lejmi et al., 2020), we suggest an innovative framework to recognize handwritten text from ADAB dataset. The overall framework phases of the proposed model are depicted in figure 2.

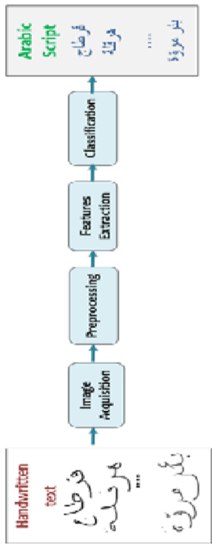

Figure 2: Framework phases of online Arabic handwriting recognition.

Specifically, we suggest performing the features extraction step using the optical flow and the substantial derivative (SD).

The latter describes the rate of change of a particle while in motion with respect to time. Analogically to the particle derivative stemming from the physics of fluid mechanics, we estimate local and convective accelerations from ADAB dataset frames. In fact, the local or temporal acceleration represents the increase rate of a pixel's speed over time at a specific point of the flow. The convective acceleration describes the increase rate of speed due to the change in pixel position.

To estimate local and convective accelerations, we need first to calculate the optical flow (Lejmi et al., 2017). It represents a set of vector fields that relates a frame to an upcoming one (figure 3). Each vector field describes the obvious movement of each pixel from frame to frame.

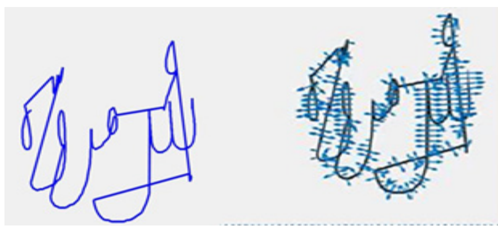

Figure 3: Plot of optical flow vector for an image from ADAB dataset.

Considering the “Brightness Conservation Theorem” which means that "The brightness of an object is constant from one image to another.”:

$$I(x, y, t) = I(x + dx,\ y + dy,\ t + dt) \tag{1}$$

‘I’ represents an image sequence, ‘dy’ and ‘dx’ represent displacement vectors for the pixel with coordinates $[x, y]$ and ‘t’ and ‘dt’ the frame and temporal displacement of the image sequence. The optical flow equation is derived from the above equation as follows:

$$f_x U + f_y V + f_t = 0 \tag{2}$$

‘fx’ , ‘fy’ represent pixel intensity gradients and ‘f_t’ represents the first temporal derivative.

If we solve (2) we obtain a couple of flow vector maps U and V that dictate perceived motion in both the x and y coordinate plane.

For each frame $\{I^t\}_{t=1}^{N}$, the optical flow$\{f^t\}_{t=1}^{N-1}$ represents each pixel’s velocity in x and y directions:

$$F(x, y) = \left(v_x^t, v_y^t\right) \tag{3}$$

When we apply (3), the local acceleration gets the value of the rate of change of velocity over time at a fixed point in a flow field.

Generally, the rate of change of the quantity undergone by an observer who moves with the flow is described in (4) and (5).

$$\frac{Df}{Dt} = \frac{\partial f}{\partial x} * v_x + \frac{\partial f}{\partial y} * v_y + \frac{\partial f}{\partial t} = \vec{v}\,\overrightarrow{\text{grad}}\, f + \frac{\partial f}{\partial t} \tag{4}$$

$$\frac{Df}{Dt} \equiv \underline{v}.\nabla f + \frac{\partial f}{\partial t} \tag{5}$$

Let a_x^t be the local acceleration in an “x” direction and a_y^t the local acceleration at “y” direction as detailed below:

$$a_x^t = v_x^t - v_x^{t-1} \tag{6}$$

$$a_y^t = v_y^t - v_y^{t-1} \tag{7}$$

The calculation of the local acceleration a^{Loc} of a couple of successive optical flows is obtained as follows:

$$a^{Loc} = \sqrt{{a_x^t}^2 + {a_y^t}^2} \tag{8}$$

To obtain the rate of change of velocity with respect to position at a fixed time in a flow field, the convective acceleration should be calculated. It is combined with spatial velocity gradients in the flow field. We consider a_x as the convective acceleration in an “x” direction and a_y as the convective acceleration in a “y” direction:

$$a_x = \left(\frac{\partial v_x}{\partial x} + \frac{\partial v_y}{\partial y}\right) * v_x \tag{9}$$

$$a_y = \left(\frac{\partial v_x}{\partial x} + \frac{\partial v_y}{\partial y}\right) * v_y \tag{10}$$

Let a^{Conv} be the convective acceleration magnitude defined as follows:

$$a^{Conv} = \sqrt{a_x^2 + a_y^2} \tag{11}$$

Overall, the physical interpretation of the substantial derivative (SD) is highlighted in figure 4 indicating the total acceleration of the pixel moving along its trajectory.

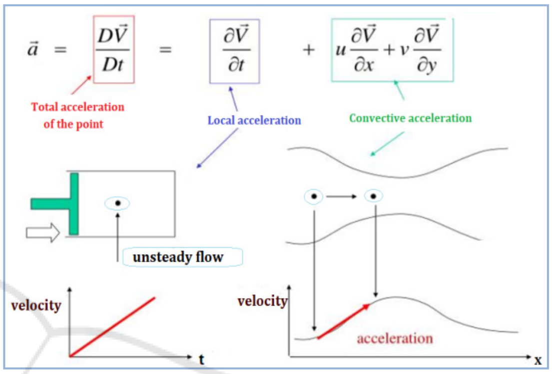

Figure 4: Physical interpretation of the SD concept.

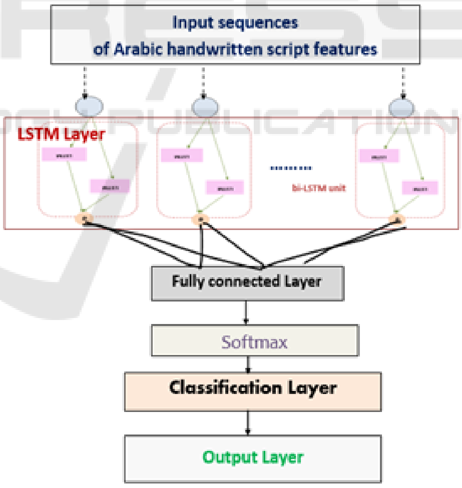

Figure 5: Bidirectional-LSTM classification network (SD-LSTM).

Afterwards, the classification algorithm will be implemented using a recurrent neural network (Long Short-Term Memory LSTM) (Lejmi et al., 2020), which can process both isolated data as well as sequences. This helps avoid long-term dependency issues, by interacting through four layers of neural network and gates indicating which data is useful to keep and which is not. Thus, only relevant data passes through the sequence chain to facilitate prediction. The LSTM deep learning classification technique allows to classify the generated features and to calculate a prediction value for each word.

Figure 5 illustrates how to create a Bidirectional-LSTM (Bi-LSTM) classification network.

We concatenate the extracted features and feed them to a Softmax classifier through a fully connected operator. The classification ability of the model will be later evaluated on confusion matrices which will present the system predictions and their actual labels.

4 EXPERIMENTS

We resorted to MATLAB R2022a software to carry out experimental work on an Intel (R) Core (TM) i9-11980HK, 2.6 GHz and 32 GB RAM under Windows 11 operating system (64-bit).

4.1 ADAB Dataset and Preprocessing

In addition to input files in Tag(ged) Image File Format (TIFF) of ADAB dataset, one more alternative is considering the files in the Ink Markup Language (InkML) format that was created by the W3C (Watt & Underhill, 2011; Xavier et al., 2014) as a standard for data storage ink. Indeed, the features inside them are called “traces” where each one represents a continuous writing curve, as shown in figure 6. Traces consist of series of points. Each

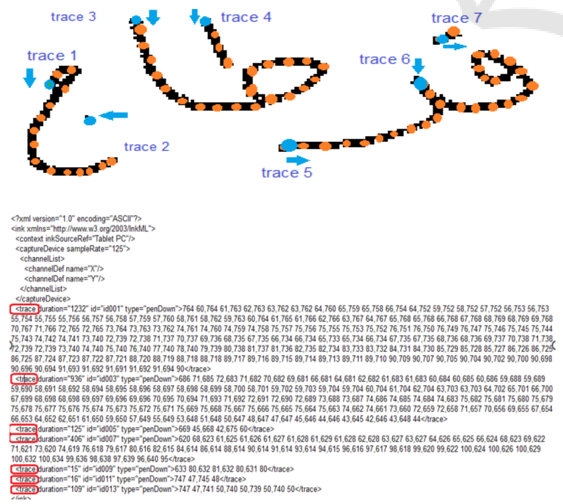

Figure 6: Schematization of one handwritten script from ADAB dataset generated by connecting the dots of 7 stored InkML traces. The displayed lines of the inkml file below represent the 7 traces of this Arabic word.

represents a number of coordinate values whose meanings are provided by a <traceFormat> element.

These coordinates are able to give us information on values for quantities like pen position, angle, tip force, button state, etc. More clearly, the data is recorded in consecutive elements within <trace> tags.

Each one includes a comma-separated "coordinate" tuple representing points pairs (x , y). For each point, the pair (x , y) describes the position of the pen relative to the origin (0 , 0) placed in the upper left corner of the screen. Thus, we read the files into the ADAB dataset composed of three sets (set1, set2 and set3) containing the names of 937 Tunisian towns and villages written in Arabic and in more than one handwriting, and presented in Ink Markup Language (InkML) files.

The hypothesis of our research is to read the ADAB online Arabic handwriting dataset in order to perform the main procedures below:

- Calculating substantial derivative equations and then getting features using optical flow and taking advantage of the results to compute convective and local acceleration in order to get local and convective features which will be concatenated to obtain the total ones.
- Using total features with taxonomic information in order to train and test the obtained characteristics before utilizing them for classification based on the LSTM recurrent neural network.

A first difficulty in obtaining meaningful features (Al-Helali & Mahmoud, 2016; Wilson-Nunn et al., 2018) using optical flow, is that it accepts input datasets only in video format. We, therefore, need to find a technique to convert the INKML files of our dataset into a suitable form that can efficiently compute and calculate the optical flow.

One more important issue is the need for an approach to prepare files names, so that we can read them and associate each INKML file with its intended label. The latter can be found in the UPX file having the same name, precisely in the "alternative value tag", for example in the case of the name "باب سعدون المحطّة", or as depicted in line 17 of the example previously shown in figure 5. We also need to take into consideration, when preparing the file name, the association of the INKML file with all the other ones having the same label, i.e. the same "alternative value tag". In addition, we need to prepare these names based on their occurrences in the dataset so that they are easy to read and to use during the training and classification phases.

4.2 Features Extraction Using Substantial Derivative and Acceleration Features

The traces marks are selected in order to convert data into video with an AVI (Audio Video Interleave) format and then deduce the dimensions of the x and y coordinates from the InkML files so that the video starts drawing the word from the first point of its intersection and continues until this word is completed as a whole. First, we managed to use the *.inkml files and extract x and y coordinates from traces which represent the words, in order to store the source files names and their coordinates in the file *'inkmlFileName_X_Y.mat'* and use them later. This is performed for dataset set1 while making sure, through two subsequent steps for set 2 and set 3 of this same dataset, to store the results later in the matrices '*inkmlFileName_X_Ys2.mat'* and '*inkmlFileName_X_Ys3*'. Then, the generated *inkmFileName_X_Y.mat* will be used to read and convert data from inkml files to AVI video file with the same name, using the coordinates for each file to extract each video in a new way: The graphics axis limits will be set according to the actual x and y point limits without affecting the size of the output video. This starts by exploiting the current coordinates and changing them according to the following ones to adapt simultaneously to the successive coordinates as depicted in figure 7.

Figure 7: An example of converting the data read from inkml file in case of the word "وادي الرّمل" which represents one file.

Through the first part of the following figure, we highlight a new way of reading Arabic writing in order to benefit from the largest possible number of video image coordinates, unlike the usual way where most of the video image remains empty or stationary, particularly for short words, as shown for example in the case of the word "رمادة" (figure 8).

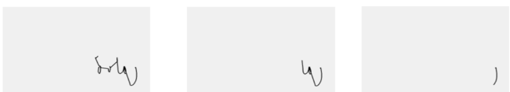

Figure 8: Example of empty part of video image in case of ADAB short words.

This helps us to collect more features in the next step. This new method is beneficial in terms of homogeneity of the data used for analysis, as all the video files and their frames have the same size and line thickness. This will help us to achieve more accurate results in the classification process.

4.3 Classification Results

This section presents our experimentation in the field of multilingual online handwriting script recognition. First, we introduce the datasets used in our study. Then, we provide an in-depth discussion of the results. Both kinds of acceleration features are mixed and then divided into a Training set and a test set. In this context, it is noteworthy to mention the number of frames that have been processed.

To deal with challenging aspects of online handwriting recognition (Mahmoud et al., 2018), it is recommended to use a standardized database that accommodates different writing styles and encompasses various classes in the target language.

To evaluate the performance and effectiveness of our proposed system, we used ADAB dataset (Boubaker et al., 2012), tailored for Arabic words which collectively serve as pivotal components of our experimentation.

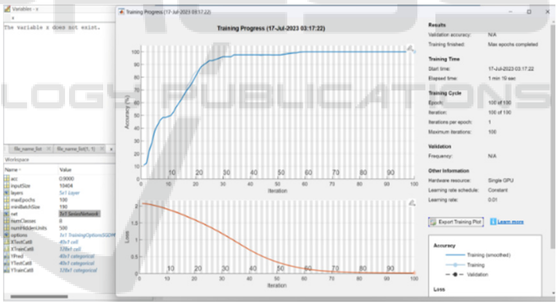

Figure 9: LSTM minimizes loss function for total acceleration features.

This ADAB dataset, consisting of over 33,000 handwritten Arabic words by 170 different writers, has been widely utilized in the literature. It contains 937 names of Tunisian towns and villages. This database is segmented into six distinct sets, originally collected for the ICDAR 2011 online Arabic handwriting recognition competition (Elleuch et al., 2016).

To improve the training accuracy, we applied some data augmentation techniques (Hamdi et al., 2021) and we focused on sets 1, 2, and 3 which altogether contain more than 45,158 words for the training process. When testing the network, the recognition rate was quite high for the Bi-LSTM neural network trained with an SGDM optimizer and a learning rate of 0.01 during 100 epochs (figure 9). Indeed, the accuracy was around 90% and 95%. Specifically, for the Training set, it reached 99%. Based on features extraction results, further implementation is on the way to enhance the classification performance. Indeed, we are planning to increase the size of the ADAB dataset as it currently has a considerable imbalance in terms of content occurrences. We believe that this will significantly improve the results. Besides, we performed a comparative analysis of the suggested system against other ones that have been experimented in the field of online Arabic character recognition. The results are summarized in Table 1. Regarding the ADAB dataset, our results are like the state of the art.

Table 1: Comparison of recognition rate between the suggested approach and some existing models.

Models	Recognition rate (%)
Elleuch et al. (2016)	97,5
Abdelaziz and Abdou (2014)	97,1
Tagougui and Kherallah (2017)	96,2
SD-LSTM	**95,3**

5 CONCLUSIONS

In this paper, we presented various well-known datasets and crucial works underlying the approaches of handwritten recognition and we specially outlined those used to process identifying Arabic handwriting as well. Then, enlightened by a main concept of fluid mechanics, we presented a novel model based on an initial phase of spatio-temporal features extraction using the optical flow and the substantial derivative to calculate local, convective and total accelerations. Afterwards, we suggested a classification model relying on the deep learning LSTM neural network. The last part was mainly devoted to the experiments we performed on ADAB dataset as well as the implementation of the descriptor and the technical tricks that we proposed in order to effectively classify the Arabic characters. We believe that further research on this can lead to fruitful results.

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