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Cursive Handwritten Text Recognition using Bi-Directional LSTMs: A case study on Urdu Handwriting

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***Abstract*—Recognition of cursive handwritten text is a complex problem due challenges like context sensitive character shapes, non-uniform inter and intra word spacings, complex positioning of dots and diacritics and very low inter class variation among certain classes. This paper presents an effective technique for recognition of cursive handwritten text using Urdu as a case study (though findings can be generalized to other cursive scripts as well). We present an analytical approach based on implicit character segmentation where convolutional neural networks (CNNs) are employed as feature extractors while classification is carried out using a bi-directional Long-Short-Term Memory (LSTM) network. The proposed technique is validated on a dataset of 6000 unique handwritten text lines reporting promising character recognition rates.**

***Index Terms*—Cursive handwritten Urdu text, Convolutional Neural Networks, Long Short-Term Memory Networks.**

I. Introduction

Handwriting recognition has remained one of the most investigated pattern classification problems. The problem has witnessed many decades of extensive research and has progressively matured from recognition of isolated characters to complex cursive scripts. Handwriting recognition systems convert handwritten text into machine readable form and work either on offline images (scanned or camera based) or on writing captured directly on a digitizing device (online recognition). Recognition of handwritten text is considered more challenging as opposed to the printed text primarily due to writer-specific preferences in drawing character shapes (allographs) and joining various characters. In addition to these writer-dependent variations, another important factor is the complexity of the writing script under study. While mature recognition systems have been developed for handwriting in the Roman script [18], [26], [30], [38], [39], recognition of handwriting in many cursive scripts still remains a challenging problem.

From the view point of recognition systems for cursive text (like Arabic, Urdu, Persian etc.), recognition of Arabic handwriting has been investigated in a number of studies [7], [19]. A number of International competitions have also been organized on recognition of both offline and online Arabic handwriting [11], [24], [25]. Among recent contributions, deep learning based techniques have been widely employed for recognition of offline [20] as well as online [21] Arabic handwriting and have reported high recognition rates. When compared to Arabic, recognition systems for other similar cursive scripts like Persian, Pashto and Urdu etc. did not receive the same kind of research attention. Among other challenges, a major issue has been the lack of benchmark datasets of printed as well as handwritten texts in these scripts. In the recent years, however, recognition of both printed and handwritten texts in scripts other than Arabic has gained notable research attention of the community. A clear indication of this interest is the support of these languages by recognition systems from Abby and Google etc.

Among various Arabic-derived cursive scripts, the focus of the current study lies on Urdu text. Urdu has more than 100 million native speakers all over the world with major share from Pakistan, India and the middle East. The alphabet of Urdu (39 characters) is a super set of Arabic and the script is influenced by Arabic, Sanskrit and Persian.

Characters in Urdu and other cursive scripts join to form partial words or ligatures and the shape of a character depends upon the context in which it appears. Characters vary shapes as a function of their position (isolated form, beginning, middle or end of a ligature). In some cases, intra-word distances can be greater than inter-word distances and characters of neighboring ligatures overlap. Furthermore, many characters share the same main body and differ only in the number and position of dots and diacritics leading to high inter-class similarity. Few of these challenges are illustrated in Figure 1.

This paper presents an effective recognition system for handwritten Urdu text. The technique employs text lines and relies on implicit character segmentation for recognition. More specifically, we consider each text line as a sequence of strokes (windows). Machine-learned features are extracted from these text lines using a convolutional neural network (CNN) and the feature sequences are classified using a

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bi-directional long short-term memory (LSTM) network. The technique is evaluated on a dataset of 6000 unique handwritten Urdu text lines and promising recognition rates are reported.

The paper is organized as follows. In the next section, we present an overview of the developments towards recognition of printed as well as handwritten Urdu text and the current state-of-the-art on this problem. Section III introduces the developed database while Section IV presents the technical details of the proposed technique. Details of the experiments and the corresponding results are presented in Section V while Section VI concludes the paper.

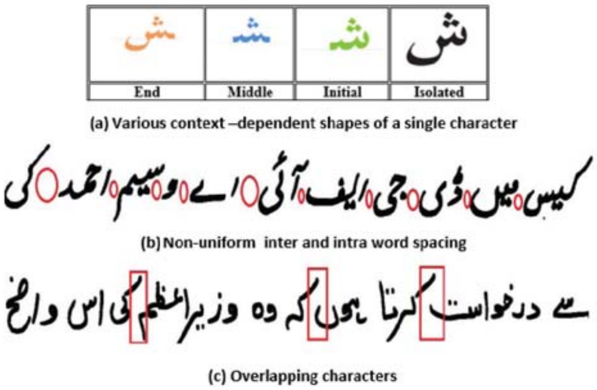

Fig. 1. Recognition challenges in Urdu handwriting

II. RELATED WORK

Recognition techniques for Urdu (and other similar cursive scripts) are traditionally categorized into holistic and analytical methods. While holistic techniques in scripts like Roman refer to word level recognition, in case Arabic and Urdu, these techniques refer to partial words or ligatures (as word boundaries are hard to identify in such cursive scripts). Analytical techniques, on the other hand, refer to character level recognition. This classification is commonly employed both for printed and handwritten texts.

The initial research endeavors towards recognition of Urdu text primarily target printed text (in the common Nastaliq style) and a number of holistic and analytical techniques were proposed in the recent years. The holistic techniques, as mentioned earlier, exploit ligatures as units of recognition. A ligature can be an isolated character or a combination of characters which are joined together. Ligatures are further categorized into primary and secondary components where the former refers to the main body of the ligature while the later refers to dots and diacritics. While holistic techniques do not require the complex character segmentation, a major issue is the very large number of ligature classes (Urdu has more than 25,000 unique ligatures). The problem is normally tackled by considering only frequent set of ligatures or by separately recognizing the primary and secondary ligatures (hence reducing the number of unique classes) and later re-associating them in a post-processing step [10]. Many of the holistic techniques reported for recognition of printed Urdu ligatures employ sliding windows for feature extraction [9], [16], [17]. The feature sequences are typically fed to hidden Markov models for training and subsequent recognition. In a recent study, Ahmed et al. [2] investigated the effectiveness of stacked auto-encoders to recognize printed Urdu ligatures. Likewise in [13], CNNs have been employed for recognition of Urdu ligatures from caption text in video frames.

The analytical recognition techniques proposed for Urdu text either assume pre-segmented characters [3] or mostly rely on implicit segmentation [15], [27], [28] rather than explicitly segmenting the ligatures into characters which is a challenging problem in itself [23]. These methods are based on providing pairs of text lines and corresponding transcriptions to a learning algorithm which is expected to learn various character shapes as well as the segmentation points. A major proportion of such implicit segmentation based recognition techniques exploit various deep (recurrent) neural networks with a connectist temporal classification (CTC) layer [29], [36] reporting high character recognition rates on printed Urdu text.

While recognition of printed Urdu text has matured in the recent years, the literature is fairly limited once it comes to recognition of handwritten text. Among one of the initial studies, Sagheer et al. [33] proposed a system for recognition of pre-segmented handwritten characters and a smallet set of frequent Urdu words. A combination of gradient and structural features was employed in this study with support vector machine (SVM) classifier. The system was evaluated on the CENPARMI Urdu word database and reported high character recognition rates. Among recent studies, Ahmed et al. [5] proposed a recurrent neural network based recognition system for Urdu handwritten text. Handwritten images are first segmented into text lines (using the ground truth information) and fixed sized sliding windows are traversed over these lines to extract pixel value as a features. These pixel values are fed to a recurrent neural network to learn the character shapes (and boundaries) along with the ground truth transcription. The system was evaluated on a very small subset of the UCOM dataset (discussed in the next section) and reported a character recognition rate of 94%. The study was later extended [6] and evaluated on a larger set of writing samples reporting a character recognition rate of 92%.

A critical analysis of the recognition systems for Urdu text reveals that implicit segmentation based techniques tend to be more robust. Though such techniques require relatively larger training sets, they avoid the complex explicit segmentation step and have to deal with a smaller number of unique classes as opposed to holistic techniques. Furthermore, holistic techniques also require ligature images to be grouped into clusters (prior to training) and clustering errors are accumulated in the recognition errors. In our study on recognition of handwritten text, we have also chosen to employ an implicit segmentation based technique. We first discuss the relevant datasets in the next section followed by the details of the proposed technique.

III. Urdu Text Datasets

Collection and labeling of datasets is a fundamental prerequisite for development and evaluation of a system. Similar to other problem areas, a number of datasets, both printed and handwritten, have been developed for cursive text primarily targeting the evaluation of recognition systems. The most well-known of these is the IFN/ENIT database [31] that has been widely employed to evaluate Arabic handwriting recognition systems. Other known Arabic handwriting datasets include QUWI [8] and KHATT [22]. For printed Urdu text, two benchmark datasets have been commonly employed by researchers, the UPTI database [32] and the CLE database [1].

Recently, a database of Urdu handwriting samples was introduced by Ahmed et al. [5]. The database was named as UCOM and comprises writing samples of 100 writers. The number of unique text lines in the database, however, is very small (only 48). The UCOM dataset was later extended to UNHD dataset [6] that is claimed to contain writing samples of 500 different writers with 700 unique text lines and a total of 10,000 text lines. We acquired the UNHD database, however, it was observed that the number of samples provided was fewer than what was claimed (only 4500 text lines are available). Furthermore, since the number of unique text lines in this database is only 700, it does not truly match the real world recognition scenarios. Consequently, for a robust evaluation of the proposed technique, we collected 6,000 unique text lines from 600 writers as a part of this study. The total number of characters in the dataset is 432,00 with 720 characters on average per writer and each text line is accompanied with its transcription (in UTF-8). Sample images from the database are illustrated in Figure 2 while the statistics are summarized in Table I. The database is also planned to be made publicly available.

TABLE I
STATISTICS OF THE DATASET EMPLOYED IN OUR STUDY

Number of writers	600
Text lines per page	10
Total text lines	6000
Average words per writer	144
Total words	86,400
Total characters	432,000

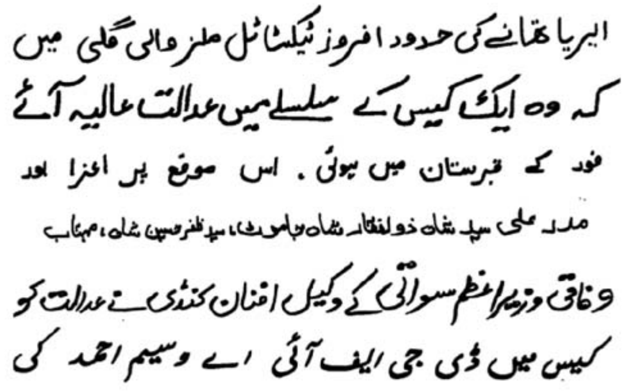

Fig. 2. Sample text line images from the collected writings

IV. Methods

Thanks to the recent advancements in deep neural networks, the last few years have resulted in a paradigm shift from traditional classification pipeline (involving pre-processing, feature extraction and classification) to end-to-end trainable systems [34]. Hand-engineered features are being replaced with data driven machine-learned features. These developments have had a significant impact on document and handwriting recognition community as well. Convolutional neural networks are known to be state-of-the-art feature extractors while recurrent neural networks (and their variants) have been effectively employed to sequence modeling problems. Handwriting represents a sequence of strokes that needs to be mapped to the corresponding transcription. Recurrent nets, hence, offer an attractive choice for handwriting recognition. The effectiveness of recurrent nets has been validated on printed Urdu text where windows sliding over lines of text are employed to feed pixel values [28] or statistical features [27] to the network to learn character shapes and segmentation points. A similar technique [6] was also applied to handwriting images where raw pixel values from columns of text line images are fed to a 1D-LSTM for learning and classification. A step further to this is to replace the raw pixel values (or hand-engineered features) by machine learned features extracted using CNNs. This combination of CNN and LSTM has been previously investigated where the features extracted by CNNs are fed to the recurrent layers for classification [34] and has proved to be an effective solution for recognitin tasks. In our study, we adapt the same combination (CNN+LSTM) for recognition of Urdu handwriting.

An overview of the proposed recognition technique is presented in Figure 3. The input handwriting image is binarized as a pre-processing step, the height of the text line is normalized and the resulting image is fed to the convolutinal layers. The convolutional layers produce a volume of feature maps which is converted to feature sequences using sliding windows and these sequences are fed to the recurrent net. The recurrent net is a bi-directional LSTM. LSTMs are known to outperform the vanilla recurrent nets which suffer from the vanishing gradient problem once attempting to model long term dependencies. The LSTM layers are followed by the CTC layer [12] which aligns the feature sequences with the ground truth transcription during training and decodes the output of the LSTM layer to produce the predicted transcription during the evaluation phase. The system is trained in an end-to-end manner by feeding it with text lines images and the respective ground truth transcriptions (in UTF-8).

The network architecture comprises seven convolutional layers followed by two B-LSTM layers. Pooling, batch normalization and drop-out layers are also added in between. A summary of the convolutional and recurrent layers of the network is presenetd in Table II.

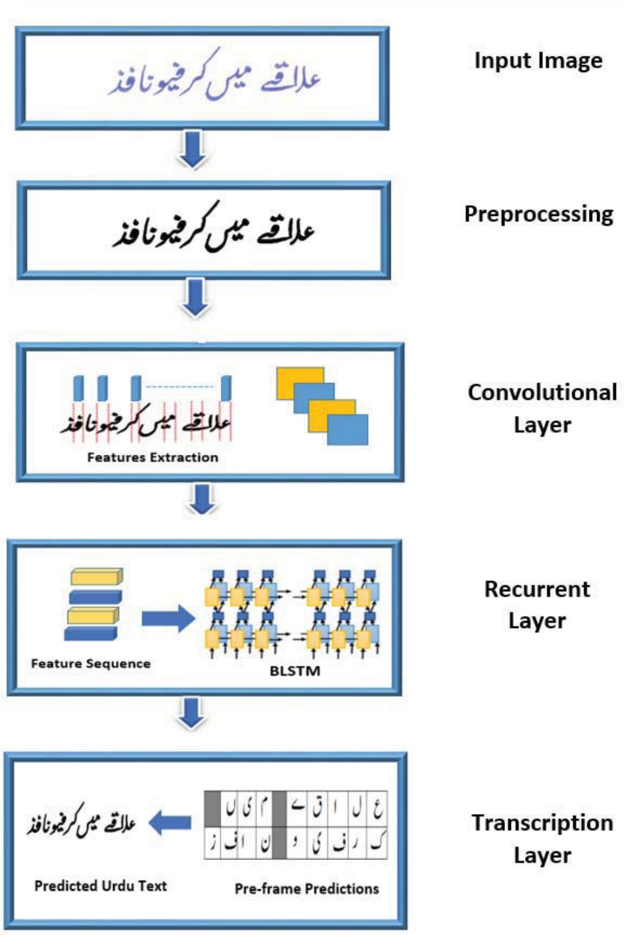

Fig. 3. An overview of the recognition system

V. Results and Discussion

This section presents the details of the experiments carried out to evaluate the effectiveness of the proposed recognition system. As discussed in Section III, the dataset under study comprises a total of 6000 unique text lines. We employed 4000 of these in the training set and 1000 each in the validation and test sets. Cross validation is employed and the average recognition rates of three runs are reported. The (character) recognition rates are computed by calculating the Lavensthein distance between the ground truth and the predicted transcription. The CNN-LSTM combination reported an average character recognition rate of 83.69% on 1000 test lines.

For comparison purposes we summarize few of the recent studies on recognition of printed and handwritten Urdu text (along with the realized results) in Table III. The recognition rates on printed text are naturally high and are provided as a baseline only. Among techniques targeting recognition of handwritten text, Sagheer et al. [37] report a recognition rate of 97%. The technique, however, is evaluated on isolated characters and a very small subset of frequently used (isolated) Urdu words and hence cannot be employed in real world recognition scenarios. Recognition rate of 94% is reported in [5] on small set of 50 text lines in training and 20 in the test. Recognition with LSTMs on raw pixels reports a recognition rate of 92% in [6] on 1840 test lines. It is however important to note that though the dataset is claimed to have 10,000 text lines, the number of unique lines is only 700 implying that text lines in train and test sets have same semantic content. Though our system reports a recognition rate of 83%, all 6000 text lines in our dataset are unique and no text line is common in training and test sets to match the challenging real world scenarios. Considering the complexity of the script and the challenging experimental setup, the reported recognition rate is indeed very promising. We are in process of collecting and labeling more data which is likely to enhance the recognition rates as can be observed from Figure 4 where recognition rates are plotted as a function of size of training data.

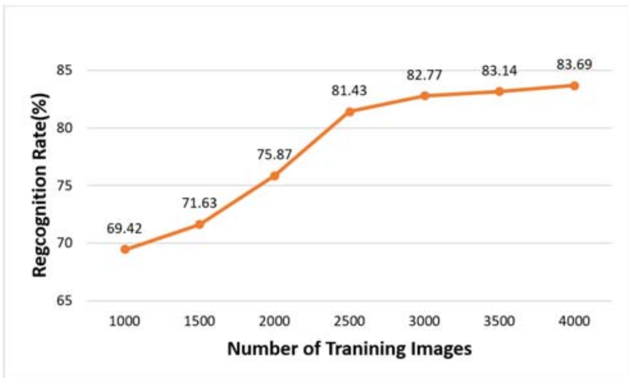

Fig. 4. Recognition rates as a function of size of training data

TABLE II
SUMMARY OF CONVOLUTIONAL AND LSTM LAYERS

Layers	Filter Size	No.of Filters
CNN Layer 1	3×3	64
CNN Layer 2	3×3	128
CNN Layer 3	3×3	256
CNN Layer 4	3×3	256
CNN Layer 5	3×3	512
CNN Layer 6	3×3	512
CNN Layer 7	2×2	512
BLSTM Layer 1	Hidden Units: 256	
BLSTM Layer 2	Hidden Units: 256	

TABLE III
RECOGNITION RATES OF NOTABLE STUDIES ON (PRINTED AND HANDWRITTEN) URDU TEXT

Type	Study	Technique	Database	Experiments	Results
Printed	Hussain et al. [14]	DCT with HMMs	CLE	5249 primary ligatures	87.44%
	Ahmed et al. [4]	Raw pixels with BLSTM	UPTI	Training: 12,415 lines, Test: 2,836 lines	96%
	Naz et al. [28]	Statistical features with MD-RNN	UPTI	Training: 6800 lines, Test: 1600 lines	96.40%
	Din et al. [35]	CNN	CLE & UPTI	2782 Ligature classes	88% /95%
Handwritten	Sagheer et al. [37]	Gradient and structural features with SVM	CENPARMI	1817 Handwritten words	97%
	Ahmed et al . [5]	Raw pixels with BLSTM	UCOM	Training:50 text lines Test:20 text lines	94%
	Ahmed et al . [6]	Raw pixels with BLSTM	UNHD	Training:6400 text lines Test:1840 text lines	92.07%
	Proposed Study	CNN with BLSTM	Custom data set	Training:4000 text lines Test:1000 text lines	83.69%

To provide an insight into recognition errors we also illustrate few of the errors in Figure 5 where it can be seen that in most cases, the ground truth and the predicted characters have very similar shapes. In some cases, the main body of the character is correctly identified but the wrong number of dots lead to recognition errors.

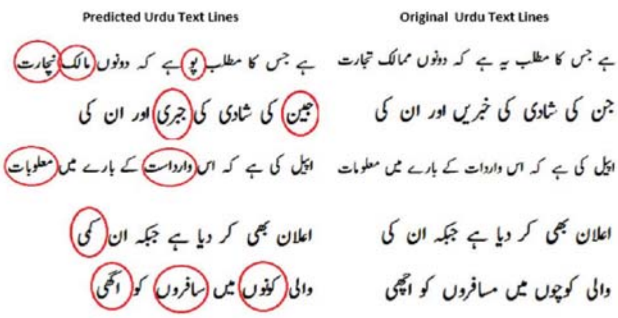

Fig. 5. Examples of recognition errors

VI. CONCLUSION

We presented an effective technique for recognition of cursive handwritten Urdu text. The technique relies on implicit segmentation of characters where the ground truth transcription and the text line images are fed to the learning algorithm to learn character shapes and the segmentation points. We employed a combination of convolutional and recurrent neural networks where features extracted by convolutional layers are fed to a bidirectional long short-term memory network for classification. Experiments on a dataset of 6000 unique text lines reported an average character recognition rate of more than 83%.

As discussed earlier, the process of data collection and labeling continues and we intend to collect a dataset of around 25000 labeled text lines. In our further investigations on this problem, we aim to compare the performance of implicit segmentation based recognition with ligature (partial word) level recognition. Furthermore, separate recognition of main body ligatures and dots can also be explored to reduce the number of character classes.

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