An attention based method for offline handwritten Urdu text recognition

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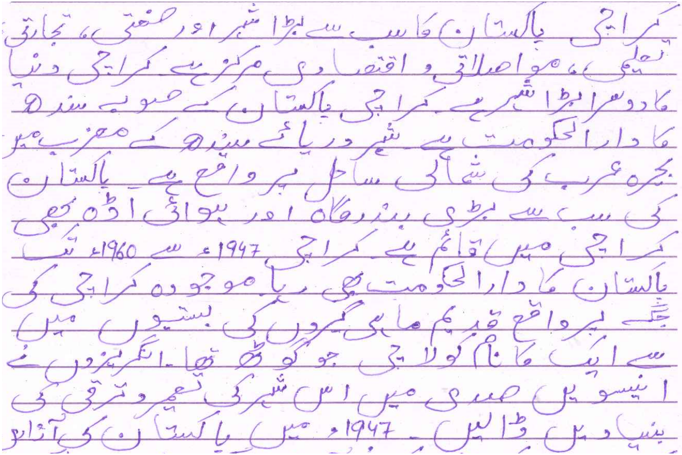
Problem: Offline Handwritten Text Recognition (OHTR) for Urdu

Offline Handwritten Text Recognition (OHTR)

Automatic recognition of text from images of handwritten text.



Urdu is a right-to-left language written in a mixture of mostly cursive and occasionally non-cursive form.

Why is handwritten Urdu recognition difficult?

- Sayre's paradox: cursively written word cannot be recognized without being segmented and cannot be segmented without being recognized.
- Wide range of variations in pen type, writing style, writing size, page background.
- Almost every rule can be violated until text becomes illegible.

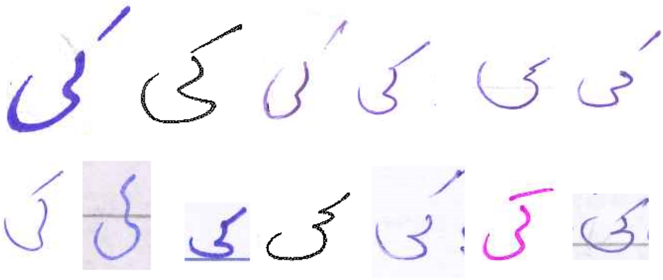


Figure: An Urdu word pronounced as "key" written by 13 different people.

Handwritten vs. Typed Urdu vs. Characters

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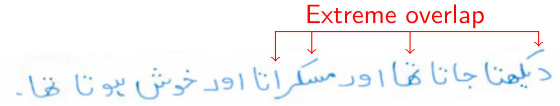
دیکھتا جاتا تھا اور مسکراتا اور خوش ہوتا تھا

د ی ک ھ ت ا ج ا ت ا ت ھ ا ا و ر م س ک ر ا ت ا ا و ر خ و ش ھ و ت ا ت ھ ا

- Within cursive words, characters to be recognized often appear with widely varying ligatures.
- While typed Urdu conforms to some rules, handwriting can be restricted to very few rules.

Challenges of Urdu OHTR



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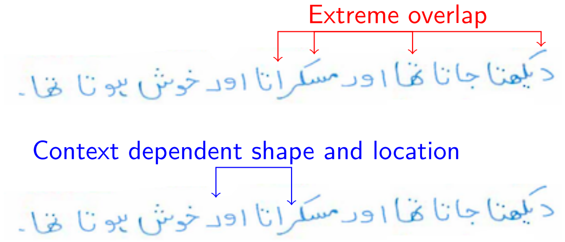
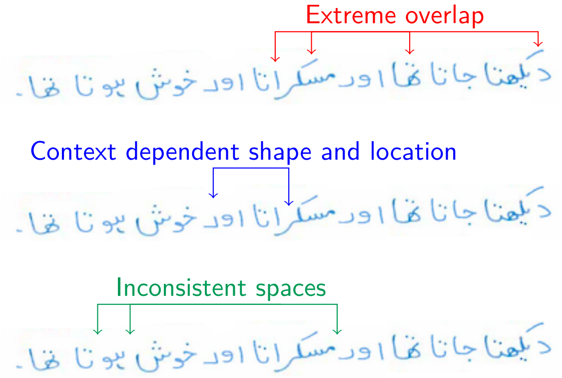


Challenges of Urdu OHTR



State of OHTR for Arabic-like scripts

Techniques

- Urdu
  - Raw pixels + Bidirectional LSTM[1]
  - CNN + Bidirectional LSTM[2]
- Arabic
  - CNN + LSTM with context-window[3]
  - Raw pixels + Multidimensional LSTM[4]
- Similar situation for Farsi.
- The concept of **attention has not been explored**.
- Error reporting has been restricted to the level of characters. **World level accuracy is not reported.**

[1] Saad Bin Ahmed et al. "Handwritten Urdu character recognition using one-dimensional BLSTM classifier". In: *Neural Computing and Applications* 31.4 (2019), pp. 1143–1151.

[2] S. Hassan et al. "Cursive Handwritten Text Recognition using Bi-Directional LSTMs: A Case Study on Urdu Handwriting". In: *International Conference on Deep Learning and Machine Learning in Emerging Applications, Deep-ML 2019*. 2019.

[3] Gui et al. "Adaptive context-aware reinforced agent for handwritten text recognition". In: *Proceedings of the British Machine Vision Conference (BMVC)*. 2018.

[4] Riaz Ahmad et al. "KHATT: A deep learning benchmark on Arabic script". In: *14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*. IEEE, 2017. DOI: 10.1109/ICDAR.2017.358.

State of OHTR for Arabic-like scripts
Datasets

- Urdu
  - CENIP-UCCP[5]
  - UCOM/UNHD[6]
  - Hassan et al.[7]
- Arabic
  - IFN/ENIT[8]
  - OpenHaRT[9]
  - KHATT[10]
- Farsi
  - Sadri et al.[11]
- Urdu datasets are **not entirely accessible**.

[5] Raza et al., "An Unconstrained Benchmark Urdu Handwritten Sentence Database with Automatic Line Segmentation".

[6] Ahmed et al., "Handwritten Urdu character recognition using one-dimensional BLSTM classifier".

[7] Hassan et al., "Cursive Handwritten Text Recognition using Bi-Directional LSTMs: A Case Study on Urdu Handwriting".

[8] Pechwitz et al., "IFN/ENIT-database of handwritten Arabic words".

[9] Tong et al., "NIST 2013 open handwriting recognition and translation evaluation".

[10] Mahmoud et al., "KHATT: An open Arabic offline handwritten text database".

[11] Sadri, Yeganehzad, and Saghi, "A novel comprehensive database for offline Persian handwriting recognition".

Contributions

Paper Contributions

1. We present the first *attention-based*, encoder-decoder model for recognition of offline handwritten Urdu text.

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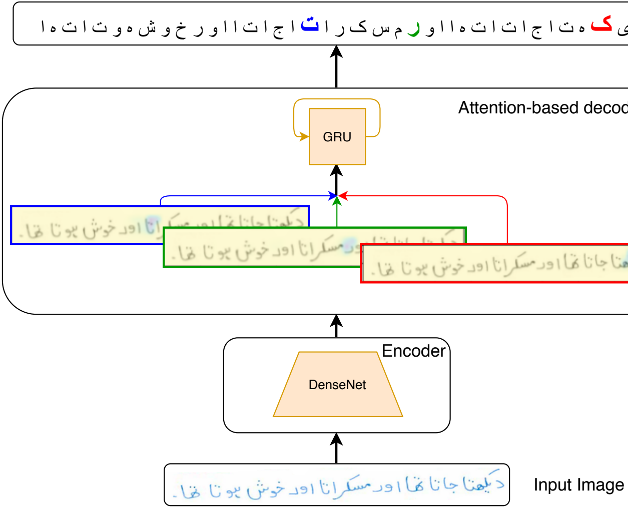
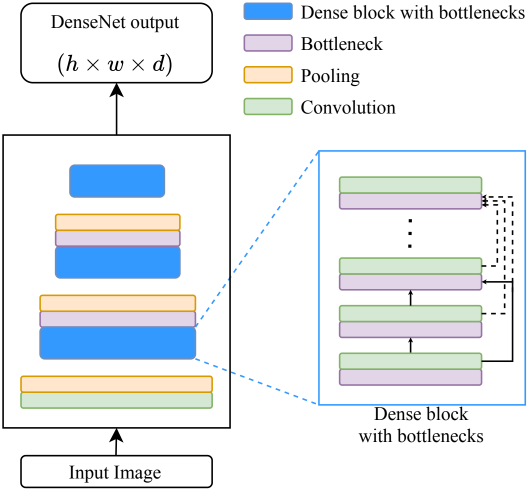
3. For the first time, we report word level accuracy instead of only character level accuracy.
4. We show that attention can enable uni-directional decoders to out-perform bidirectional decoders.
5. Compared to previous approaches, we report close to 2x accuracy improvement at character level and 37x at word level.

Proposed Solution

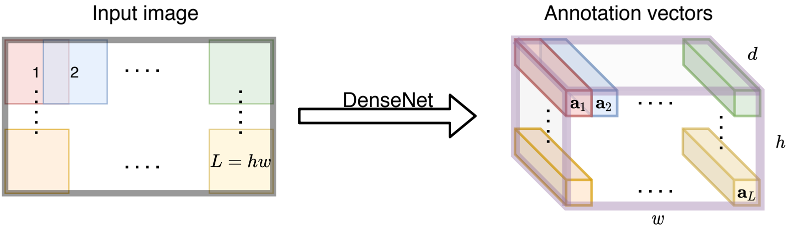
Encoder/Decoder Model



Encoder: DenseNet with bottlenecks



Interpretation of DenseNet Output



Output volume of size $h \times w \times d$ represents d-dimensional *annotation vectors* of $h \times w$ overlapping blocks of the input image.

Decoder: Gated Recurrent Unit (GRU)

Produces text sequence one character at a time conditioned on the previously generated character $\mathbf{y}_{t-1}$ and current hidden state $\mathbf{h}_t$.

$$\begin{aligned}
\mathbf{z}_t &= \sigma(\mathbf{W}_{yz}\mathbf{E}\mathbf{y}_{t-1} + \mathbf{U}_{hz}\mathbf{h}_{t-1}) \\
\mathbf{r}_t &= \sigma(\mathbf{W}_{yr}\mathbf{E}\mathbf{y}_{t-1} + \mathbf{U}_{hr}\mathbf{h}_{t-1}) \\
\widetilde{\mathbf{h}}_t &= \tanh(\mathbf{W}_{yh}\mathbf{E}\mathbf{y}_{t-1} + \mathbf{U}_{rh}(\mathbf{r}_t \otimes \mathbf{h}_{t-1})) \\
\mathbf{h}_t &= (1 - \mathbf{z}_t) \otimes \mathbf{h}_{t-1} + \mathbf{z}_t \otimes \widetilde{\mathbf{h}}_t
\end{aligned}$$

where update gate $\mathbf{z}_t$ and rest gate $\mathbf{r}_t$ and candidate hidden state $\widetilde{\mathbf{h}}_t$ are used to compute the hidden state and GRU output $\mathbf{h}_t$.

Decoder: Gated Recurrent Unit (GRU) with Attention

Produces text sequence one character at a time conditioned on the previously generated character $\mathbf{y}_{t-1}$, current hidden state $\mathbf{h}_t$ and a context vector $\mathbf{c}_t$.

$$
\begin{aligned}
\mathbf{z}_t &= \sigma(\mathbf{W}_{yz}\mathbf{E}\mathbf{y}_{t-1} + \mathbf{U}_{hz}\mathbf{h}_{t-1} + \mathbf{C}_{cz}\mathbf{c}_t) \\
\mathbf{r}_t &= \sigma(\mathbf{W}_{yr}\mathbf{E}\mathbf{y}_{t-1} + \mathbf{U}_{hr}\mathbf{h}_{t-1} + \mathbf{C}_{cr}\mathbf{c}_t) \\
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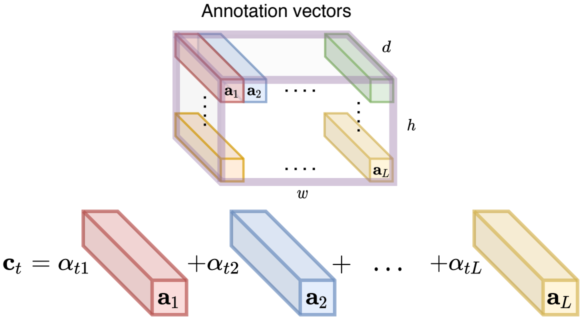
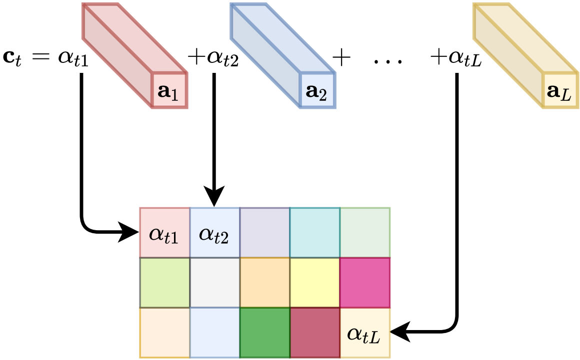
Attention via the context vector

The context vector $\mathbf{c}_t$ is a dynamic representation of the relevant part of the image at time t. Computed as a weighted sum of annotation vectors



Attention via the context vector

Attention weight α_{ti} determines importance of location i in determining context vector $\mathbf{c}_t$.



Attention weights

Standard model

Attention weights α_{ti} computed via softmax over locations

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{j=1}^{L} \exp(e_{tj})}$$

Per-location exponents computed via

$$e_{ti} = \mathbf{v}_a^T \tanh(\mathbf{W}_a \mathbf{h}_{t-1} + \mathbf{U}_a \mathbf{a}_i)$$

depend on

- the hidden state, and
- each location's content encoded in the annotation vector

Computing Attention

- Ideally, we would like our text recognizer to “read” like we do.
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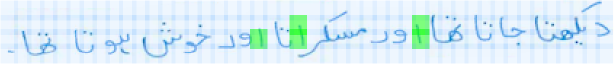


- However, a character or word can appear at multiple locations.
- Nothing stops an attention model from re-attending a previously attended location.
- The decision for attention *in text* needs to depend on the history of attention.

Computing Attention with Coverage

Proposed model

Attention weights α_{ti} computed via softmax over locations

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{j=1}^{L} \exp(e_{tj})}$$

Exponents computed via

$$e_{ti} = \mathbf{v}_a^T \tanh(\mathbf{W}_a \mathbf{h}_{t-1} + \mathbf{U}_a \mathbf{a}_i + \mathbf{U}_f \mathbf{f}_i)$$

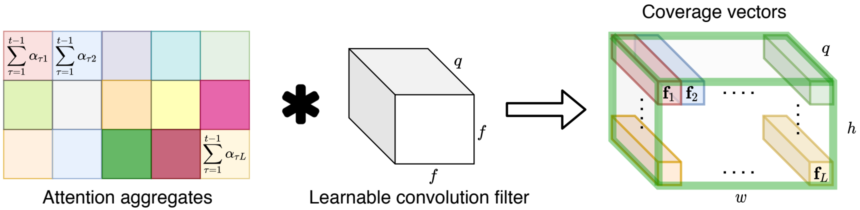
where *coverage vector*[12] $\mathbf{f}_i$ represents history of attention already given to location i.

[12] Zhang, Du, and Dai, "Multi-scale attention with dense encoder for handwritten mathematical expression recognition".

Coverage vectors

2-step computation of coverage vectors $\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_L$ at time t

1. Compute aggregated attention $\sum_{\tau=1}^{t-1} \alpha_{\tau i}$ at each location i.
2. Convolve attention aggregates with q filters of size $f \times f$.



Attention and coverage

Attention of location i

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{j=1}^{L} \exp(e_{tj})}$$

$$e_{ti} = \mathbf{v}_a^T \tanh(\mathbf{W}_a \mathbf{h}_{t-1} + \mathbf{U}_a \mathbf{a}_i + \mathbf{U}_f \mathbf{f}_i)$$

depends on

- hidden state,
- description of location i, and
- attention already given to location i.

Output Character Probability

Conditional probabilities of next character computed via softmax

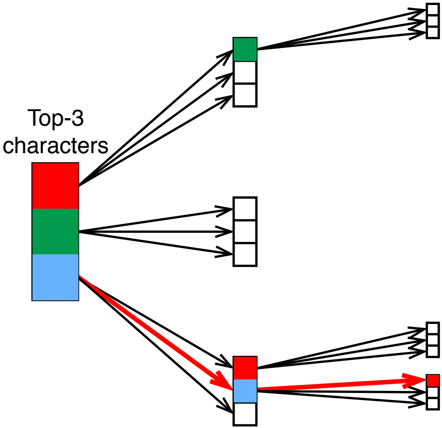
$$p(\mathbf{y}_t|\mathbf{y}_{t-1};\mathbf{X}) = \text{softmax}(\mathbf{W}_o(\mathbf{E}\mathbf{y}_{t-1} + \mathbf{W}_h\mathbf{h}_t + \mathbf{W}_c\mathbf{c}_t))$$

depend on

- previous output character $\mathbf{y}_{t-1}$,
- hidden state $\mathbf{h}_t$, and
- context $\mathbf{c}_t$ which
  - encodes localized image region(s),
  - based on a history of localizations/coverage.

Optimal character sequence

Optimal sequence of characters $\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_c$ is found via beam search.



$t = 1$ $t = 2$ $t = 3$

New Dataset

New Dataset

Statistics

- 7,309 offline handwritten Urdu text lines.
- 78,870 words written by 100 different writers.
- 98 unique Urdu characters.

Collection

- 100 undergraduate students between the ages 20-24 years.
- Requested to submit
  - any handwritten Urdu text, and
  - a corresponding ground-truth text file.
- No restriction on pen type, page type, and ink colour.
- No restriction on what to write.
- Pages scanned at 200 DPI and text lines manually segmented.
- No deskewing.
- Submitted ground-truth was thoroughly checked and corrected/completed by a team of 3 persons.

Comparison of datasets

Dataset	Total Lines	Total Words	Total characters	Total Writers	Vocabulary Size
UCOM/UNHD[13]	10,000	312,000	1,872,000	500	59
CENIP-UCCP[14]	2,051	23,833	-	200	-
Hassan et al.[15]	6,000	86,400	432,000	600	-
Proposed	**7,309**	**78,870**	**283,664**	**100**	**98**

[13] Saad Bin Ahmed et al. "Handwritten Urdu character recognition using one-dimensional BLSTM classifier". In: *Neural Computing and Applications* 31.4 (2019), pp. 1143–1151.

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Existing datasets:

- Unreliable statistics. Only 700 lines in UCOM/UNHD are unique.
- Either publicly unavailable or only partially available.

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Proposed dataset publicly available in full at

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Experiments and Results

Attention Visualization

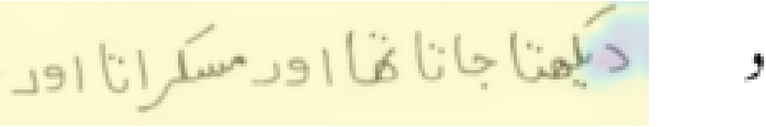

Figure: Our model implicitly segments and recognizes every character by focusing only on localized, relevant areas. It also learns to focus in context.

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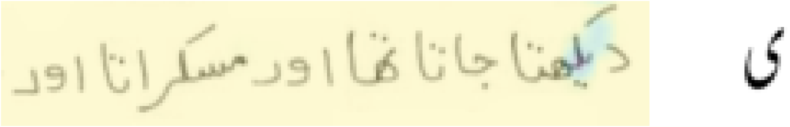

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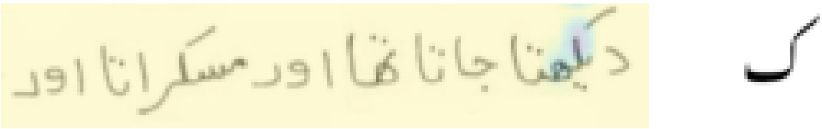

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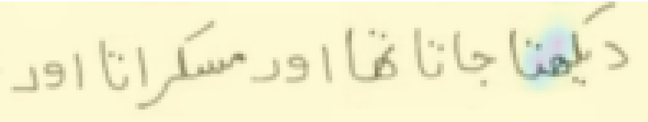

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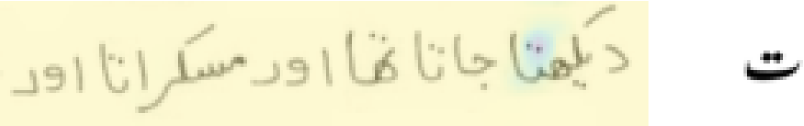

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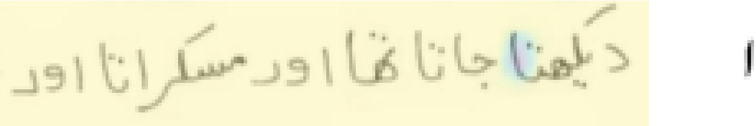

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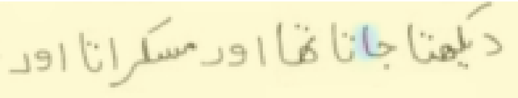
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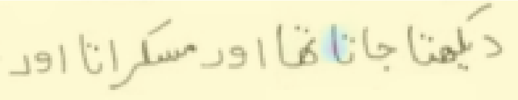
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Evaluation Metrics

Character Level

$$\text{CER} = \frac{\text{ins} + \text{sub} + \text{del}}{\text{n}} \times 100$$

Percentage of insertions, substitutions and deletions required to transform target of length n into the output.

$$\text{CLA} = 100 - \text{CER}$$

Word Level

Same formulae as above but with role of characters replaced by words.

Comparison of different models

Models	CLA	WLA
CNN+GRU	39.79	1.24
CNN+LSTM	39.26	1.40
CNN+BGRU	41.45	1.41
CNN+BLSTM[16]	40.90	1.17
DenseNet+GRU+ Attention	**77.05**	**43.35**

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DenseNet+GRU+ Attention	**77.05**	**43.35**

Reasons for improvement

- More diverse features learned by DenseNet compared to CNN.
- Attention reduces the need for bidirectional decoding.
- Coverage captures right-to-left nature of Urdu.

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- New publicly accessible dataset of >7K text lines consisting of around 79K words written by 100 writers.

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Thank you for your attention.

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