Translation / Transliteration of Vernacular Languages from Signboards

Project ID:21G378383

Review - III

Group Members
RA1711003030378 Vishnu Teja Chikkala
RA1711003030383 Rajpreet Srivastav

Supervised By:
Mr. Sunil Kumar
Assistant Professor

Department of Computer Science & Engineering
Faculty of Engineering & Technology
SRM Institute of Science & Technology

SRM INSTITUTE OF SCIENCE & TECHNOLOGY
Deemed to be University u/s 3 of UGC Act, 1956

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Objective I

- India has 22 constitutionally recognized languages written in 13 different scripts. An average traveler, when travelling to a new region, might often get confused with signboards written in an unfamiliar language. It is also impossible to have every signboard in every city / town / village written in 22 different languages, as there will not be enough room to accommodate more than 2 – 3 scripts.
- The objective of this project is to develop a simple and easy-to-use Android mobile app which provides a two-click, picture-to-text, translation / transliteration service for Indian vernacular languages, using deep neural networks and natural language processing models trained for text detection, recognition and translation tasks on collected and freely-available datasets.

Objective II

- For the scope of this project, we will design a system which works for names (such as road names, city names, shop names, organization names, etc.) which typically are not longer than 4-5 words, and support translation for 1 or 2 languages. Further scope for the project involves including support for more languages and building models to support translation / transliteration of longer pieces of text.

Summary of Literature Review I

- Indian community faces a "Digital Divide" due to dominance of English as mode of communication in higher education, judiciary, corporate sector and Public administration at Central level whereas the government in states work in their respective regional languages [7]
- India has 22 scheduled languages. While 99 % of the population speak one of these scheduled languages in various dialects (which number in the thousands) [1], according to Census 2011, the total percentage of English speakers is at 10 %, and that too is skewed towards the urban population. [10] Hence, there lies a need for developing NLP architectures for facilitating flow of digital content and information in and between local, national and international levels.

Summary of Literature Review II

- The above also means that a large percentage of the literate population is either monolingual or bilingual, and across 22 languages, an accessible, easy-to-use and intuitively developed system is required, which enables intercommunication.
- While traditionally NLP has been approached with statistical methods such as Hidden Markov Machines (HMM), Support vector machine(SVM), Conditional Random Field(CRF), Naive Bayes(NB), etc, which take a large amount of tagged/annotated data (corpus) to statistically analyze and learn the language characteristics [3], the research into deep learning or ‘connectionist approach’ [3] with the use of trained artificial neural networks (ANNs), has gained impetus due to (i) the simplicity of the solution in rapidly prototyping and establishing practically effective systems (ii) the lower cost of annotation of the training data [8], and the fact that they attempt to

Summary of Literature Review III

more closely emulate the learning process of biological brains, among other reasons. [3], [9], [4]

- Particularly, the collection of a uniform corpus and standard datasets for training models remains a challenge across all regional languages. The large number of morphological variations across Indic languages also contributes to this issue.[6], [12]
- Sharma et al., 2017 concluded that almost all existing Indian language machine transliteration systems are based on statistical and hybrid approach [11]
- Kulkarni et al., achieved upto 98% training and 94% testing accuracy on the IndicNLP library for Marathi, using an CNN-LSTM based model architecture. [5]

Summary of Literature Review IV

- Most of the Indian population accesses digital content through smartphones. In 2019, the number of smartphone users in the country passed 500 million [2], and is estimated to increase to 850 million by 2022 [13]. This, hence, also makes smartphones and smartphone apps in particular an ideal platform on which to launch NLP applications for the wider population, and directly help facilitate flow of information past language barriers.

Architectural Design I

- The basic functioning of the app is as follows:
  - User captures a photo of the signboard
  - The image is resized so as to be suitable as input to the model
  - The model takes the image as input. The text within the message is detected, extracted and transcribed to target language.
  - The text output (or error message, in case of failure to generate output within threshold confidence), is displayed on screen.

Architectural Design II

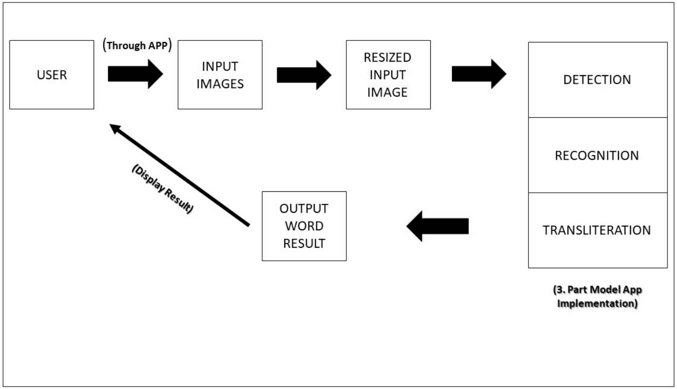


Figure: Functioning of App

Architectural Design III

- The artificial neural network (ANN) behind the core functioning of the app is made up of 3 models performing consecutive tasks. That is, the output of a preceding model will be fed as input to the succeeding model, and thus they act as one model unit.

Architectural Design IV

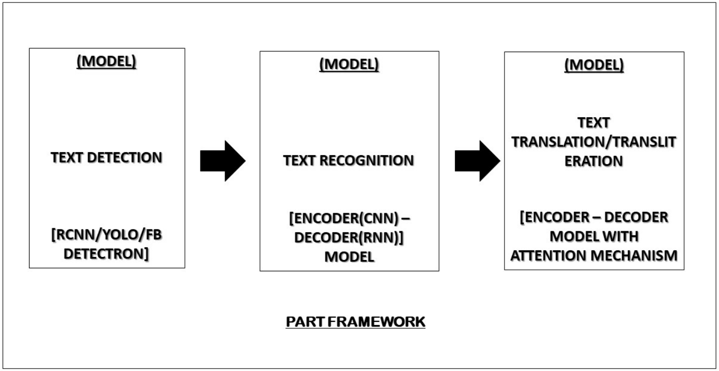
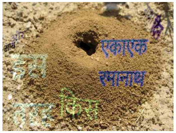

(MODEL)
TEXT DETECTION
[RCNN/YOLO/FB DETECTRON]
(MODEL)
TEXT RECOGNITION
[ENCODER(CNN) – DECODER(RNN)] MODEL
(MODEL)
TEXT TRANSLATION/TRANSLITERATION
[ENCODER – DECODER MODEL WITH ATTENTION MECHANISM
PART FRAMEWORK

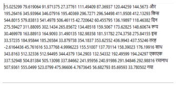
Figure: 3-part model

Dataset Specification I

- The training dataset for the text detection and text recognition tasks consists of a large number of images containing scene text, synthetically generated. Each of the images has a corresponding annotation, listing the bounding boxes and text script present in the images.



(a) Training Set Image



```
15.025299 79.619064 91.971375 27.37761 111.49409 87.36937 120.44259 144.5673 और
195.26416 345.93964 346.07916 195.40369 296.7271 296.54498 411.9508 412.13293 किस
544.8015 579.83813 541.4978 506.46115 42.720642 60.455795 136.19897 118.46382 दिन
275.59427 311.88095 302.1434 265.85672 134.48518 159.5067 173.62825 148.60674 रूप
30.469978 163.88913 164.9093 31.490135 182.98358 181.51782 274.3758 275.84155 इस
33.57235 184.95844 185.26584 33.879738 354.1837 353.62552 436.9943 437.55246 तरह
-2.6164436 45.761616 53.37768 4.9996223 155.51007 137.70114 158.39023 176.19916 साथ
343.8163 512.32336 512.94495 344.4379 134.2903 132.54332 192.49599 194.24297 एकाएक
337.52948 504.81384 505.13098 337.84662 241.95956 240.91986 291.94846 292.98816 रमानाथ
507.9361 555.0499 523.0799 475.96606 4.7673645 56.682793 85.69593 33.780502 गया
```

(b) Set Annotation

Dataset Specification II

- The test dataset for text detection and text recognition tasks consists of actual images containing natural scene text.

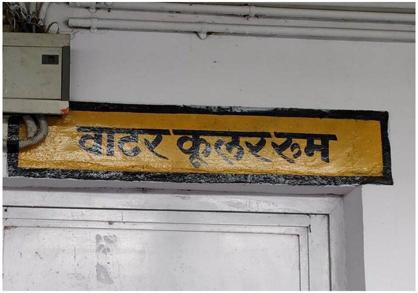
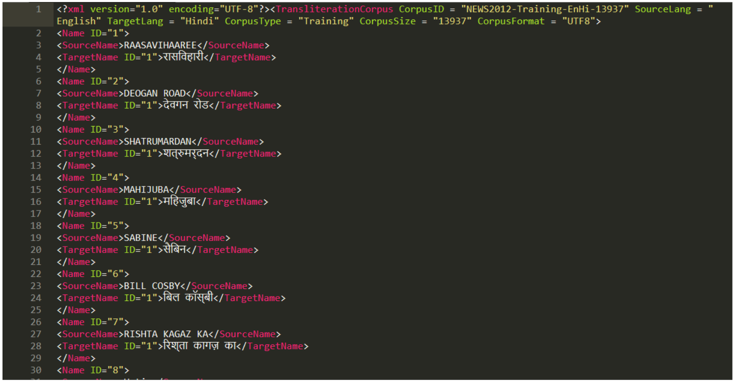


Figure: Test Set Image

Dataset Specification III

- The train and test datasets are both in form of xml files containing serialized pairs of source language script and corresponding target language script.



```xml
<?xml version="1.0" encoding="UTF-8"?><TransliterationCorpus CorpusID = "NEWS2012-Training-EnHi-13937" SourceLang = "English" TargetLang = "Hindi" CorpusType = "Training" CorpusSize = "13937" CorpusFormat = "UTF8">
<Name ID="1">
<SourceName>RAASAVIHAAREE</SourceName>
<TargetName ID="1">रासविहारी</TargetName>
</Name>
<Name ID="2">
<SourceName>DEOGAN ROAD</SourceName>
<TargetName ID="1">देवगन रोड</TargetName>
</Name>
<Name ID="3">
<SourceName>SHATRUMARDAN</SourceName>
<TargetName ID="1">शत्रुमर्दन</TargetName>
</Name>
<Name ID="4">
<SourceName>MAHIJUBA</SourceName>
<TargetName ID="1">महिजुबा</TargetName>
</Name>
<Name ID="5">
<SourceName>SABINE</SourceName>
<TargetName ID="1">सैबिन</TargetName>
</Name>
<Name ID="6">
<SourceName>BILL COSBY</SourceName>
<TargetName ID="1">बिल कॉस्बी</TargetName>
</Name>
<Name ID="7">
<SourceName>RISHTA KAGAZ KA</SourceName>
<TargetName ID="1">रिश्ता कागज़ का</TargetName>
</Name>
<Name ID="8">
```

Figure: Transliteration Set

Methodology / Algorithms / Techniques to be used I

- The text detection task will be carried out by a Faster Region-based Convolutional Network (Faster R-CNN) with Feature Pyramid Network (FPN; for bounding box tightening) from the FAIR Detectron2 kit, which has been trained for object detection on the COCO dataset. We will fine-tune this model to the task at hand by training and validating further on the above scene text database.

Methodology / Algorithms / Techniques to be used II

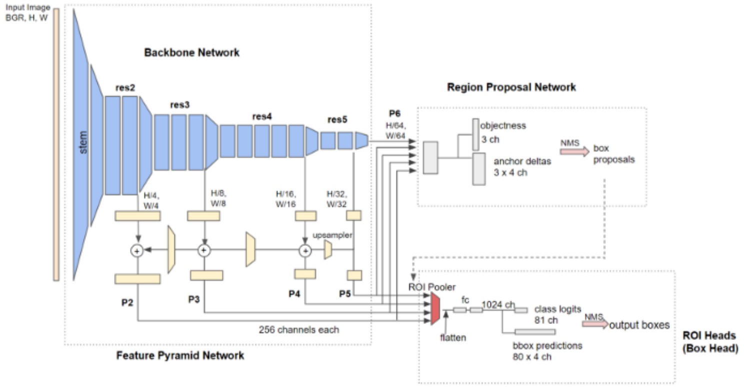


Figure: Faster R-CNN Object Detection Model

Methodology / Algorithms / Techniques to be used III

- The text recognition task will be carried out by an encoder-decoder model setup which takes the cropped bounding box of text as input. The encoder is a Convolutional Neural Network (CNN) while the decoder is a Long Short-Term Memory model (LSTM). Connectionist Temporal Classification (CTC) loss will be used to eliminate duplicate recognition of the same letter by adjacent CNN features.

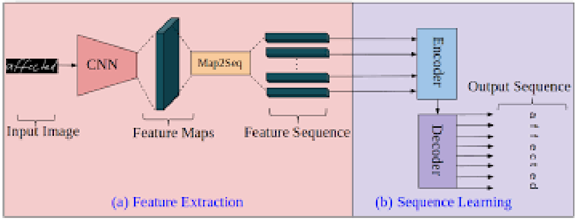


Figure: CNN-LSTM Encoder-Decoder Architecture

Methodology / Algorithms / Techniques to be used IV

- The transliteration task will carried by a LSTM - LSTM encoder-decoder model with attention mechanism, which takes source language script as input and generates target language script as output.

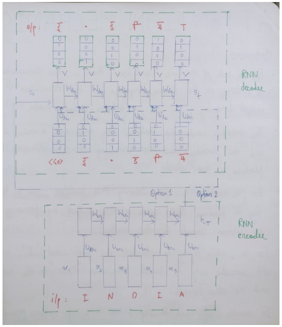
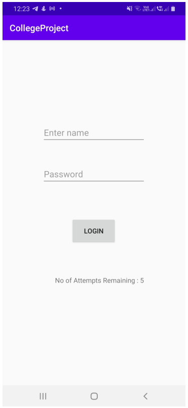


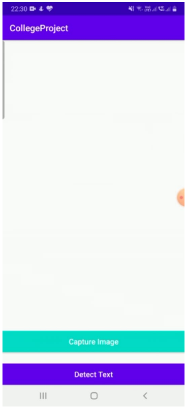
Figure: LSTM-LSTM Encoder-Decoder Architecture

Methodology / Algorithms / Techniques to be used V

- The app will make use of Google Firebase API to provide UI functionality and user services.
- The model will be mounted on and integrated with the app with the help of Tenserflow Lite.

Partial Implementation I





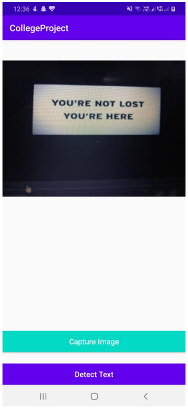
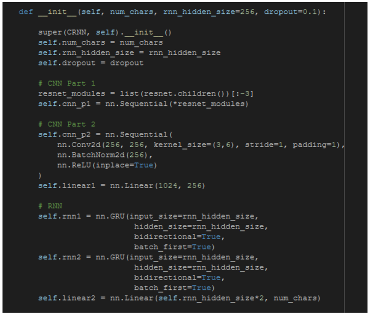


Figure: Skeleton App

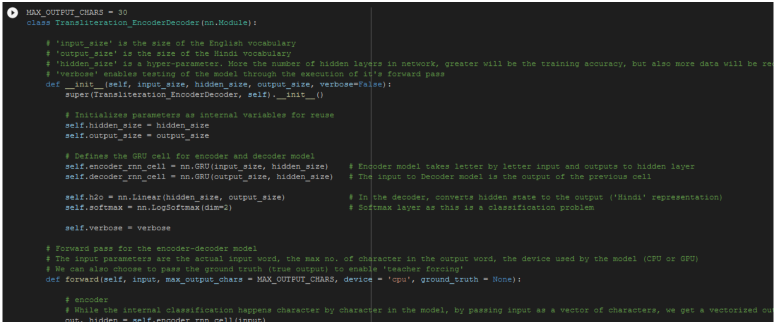
Partial Implementation II



```
def __init__(self, num_chars, rnn_hidden_size=256, dropout=0.1):

    super(CRNN, self).__init__()
    self.num_chars = num_chars
    self.rnn_hidden_size = rnn_hidden_size
    self.dropout = dropout

    # CNN Part 1
    resnet_modules = list(resnet.children())[:-3]
    self.cnn_p1 = nn.Sequential(*resnet_modules)

    # CNN Part 2
    self.cnn_p2 = nn.Sequential(
        nn.Conv2d(256, 256, kernel_size=(3,6), stride=1, padding=1),
        nn.BatchNorm2d(256),
        nn.ReLU(inplace=True)
    )
    self.linear1 = nn.Linear(1024, 256)

    # RNN
    self.rnn1 = nn.GRU(input_size=rnn_hidden_size,
                        hidden_size=rnn_hidden_size,
                        bidirectional=True,
                        batch_first=True)
    self.rnn2 = nn.GRU(input_size=rnn_hidden_size,
                        hidden_size=rnn_hidden_size,
                        bidirectional=True,
                        batch_first=True)
    self.linear2 = nn.Linear(self.rnn_hidden_size*2, num_chars)
```

Figure: Text Recognition Model

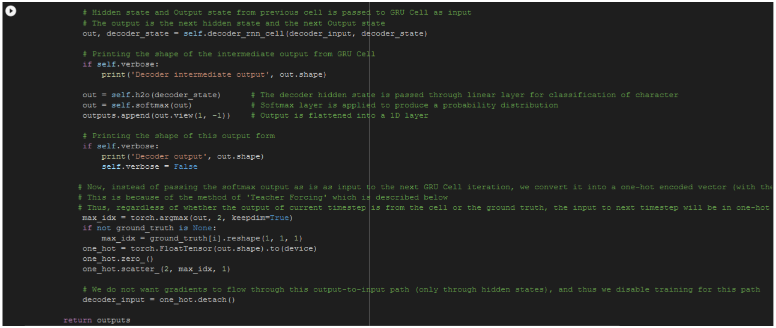
Partial Implementation III



```
MAX_OUTPUT_CHARS = 30
class Transliteration_EncoderDecoder(nn.Module):

    # 'input_size' is the size of the English vocabulary
    # 'output_size' is the size of the Hindi vocabulary
    # 'hidden_size' is a hyper-parameter. More the number of hidden layers in network, greater will be the training accuracy, but also more data will be re
    # 'verbose' enables testing of the model through the execution of it's forward pass
    def __init__(self, input_size, hidden_size, output_size, verbose=False):
        super(Transliteration_EncoderDecoder, self).__init__()

        # Initializes parameters as internal variables for reuse
        self.hidden_size = hidden_size
        self.output_size = output_size

        # Defines the GRU cell for encoder and decoder model
        self.encoder_rnn_cell = nn.GRU(input_size, hidden_size)    # Encoder model takes letter by letter input and outputs to hidden layer
        self.decoder_rnn_cell = nn.GRU(output_size, hidden_size)   # The input to Decoder model is the output of the previous cell

        self.h2o = nn.Linear(hidden_size, output_size)             # In the decoder, converts hidden state to the output ('Hindi' representation)
        self.softmax = nn.LogSoftmax(dim=2)                        # Softmax layer as this is a classification problem

        self.verbose = verbose

    # Forward pass for the encoder-decoder model
    # The input parameters are the actual input word, the max no. of character in the output word, the device used by the model (CPU or GPU)
    # We can also choose to pass the ground truth (true output) to enable 'teacher forcing'
    def forward(self, input, max_output_chars = MAX_OUTPUT_CHARS, device = 'cpu', ground_truth = None):

        # encoder
        # While the internal classification happens character by character in the model, by passing input as a vector of characters, we get a vectorized ou
        out, hidden = self.encoder_rnn_cell(input)
```

Figure: Text Transliteration Model

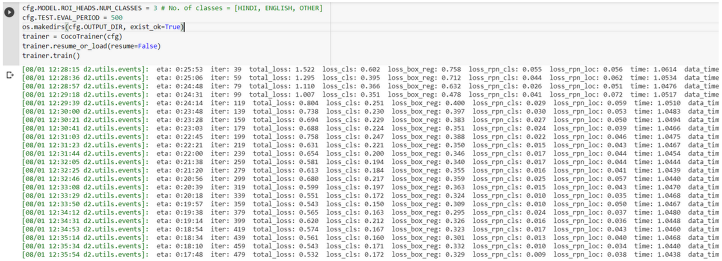
Partial Implementation IV



```
            # Hidden state and Output state from previous cell is passed to GRU Cell as input
            # The output is the next hidden state and the next Output state
            out, decoder_state = self.decoder_rnn_cell(decoder_input, decoder_state)

            # Printing the shape of the intermediate output from GRU Cell
            if self.verbose:
                print('Decoder intermediate output', out.shape)

            out = self.h2o(decoder_state)      # The decoder hidden state is passed through linear layer for classification of character
            out = self.softmax(out)            # Softmax layer is applied to produce a probability distribution
            outputs.append(out.view(1, -1))    # Output is flattened into a 1D layer

            # Printing the shape of this output form
            if self.verbose:
                print('Decoder output', out.shape)
                self.verbose = False

           # Now, instead of passing the softmax output as is as input to the next GRU Cell iteration, we convert it into a one-hot encoded vector (with the
           # This is because of the method of 'Teacher Forcing' which is described below
           # Thus, regardless of whether the output of current timestep is from the cell or the ground truth, the input to next timestep will be in one-hot
            max_idx = torch.argmax(out, 2, keepdim=True)
            if not ground_truth is None:
                max_idx = ground_truth[i].reshape(1, 1, 1)
            one_hot = torch.FloatTensor(out.shape).to(device)
            one_hot.zero_()
            one_hot.scatter_(2, max_idx, 1)

            # We do not want gradients to flow through this output-to-input path (only through hidden states), and thus we disable training for this path
            decoder_input = one_hot.detach()

        return outputs
```

Figure: Text Transliteration Training

Expected Outcomes I

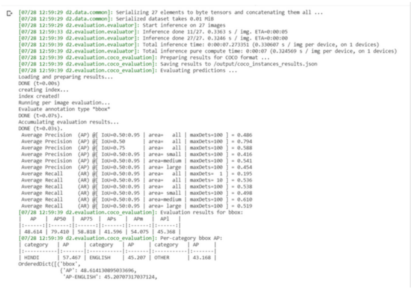


```
cfg.MODEL.ROI_HEADS.NUM_CLASSES = 3 # No. of classes = [HINDI, ENGLISH, OTHER]
cfg.TEST.EVAL_PERIOD = 500
os.makedirs(cfg.OUTPUT_DIR, exist_ok=True)
trainer = CocoTrainer(cfg)
trainer.resume_or_load(resume=False)
trainer.train()
```

```
[08/01 12:28:15 d2.utils.events]:  eta: 0:25:53  iter: 39  total_loss: 1.522  loss_cls: 0.602  loss_box_reg: 0.758  loss_rpn_cls: 0.055  loss_rpn_loc: 0.056  time: 1.0614  data_time
[08/01 12:28:36 d2.utils.events]:  eta: 0:25:06  iter: 59  total_loss: 1.295  loss_cls: 0.395  loss_box_reg: 0.712  loss_rpn_cls: 0.044  loss_rpn_loc: 0.062  time: 1.0534  data_time
[08/01 12:28:57 d2.utils.events]:  eta: 0:24:48  iter: 79  total_loss: 1.110  loss_cls: 0.366  loss_box_reg: 0.632  loss_rpn_cls: 0.026  loss_rpn_loc: 0.051  time: 1.0476  data_time
[08/01 12:29:18 d2.utils.events]:  eta: 0:24:31  iter: 99  total_loss: 1.007  loss_cls: 0.351  loss_box_reg: 0.478  loss_rpn_cls: 0.041  loss_rpn_loc: 0.072  time: 1.0517  data_time
[08/01 12:29:39 d2.utils.events]:  eta: 0:24:14  iter: 119  total_loss: 0.804  loss_cls: 0.251  loss_box_reg: 0.400  loss_rpn_cls: 0.029  loss_rpn_loc: 0.059  time: 1.0510  data_tim
[08/01 12:30:00 d2.utils.events]:  eta: 0:23:48  iter: 139  total_loss: 0.738  loss_cls: 0.230  loss_box_reg: 0.397  loss_rpn_cls: 0.030  loss_rpn_loc: 0.053  time: 1.0483  data_tim
[08/01 12:30:21 d2.utils.events]:  eta: 0:23:28  iter: 159  total_loss: 0.694  loss_cls: 0.229  loss_box_reg: 0.383  loss_rpn_cls: 0.027  loss_rpn_loc: 0.050  time: 1.0494  data_tim
[08/01 12:30:41 d2.utils.events]:  eta: 0:23:03  iter: 179  total_loss: 0.688  loss_cls: 0.224  loss_box_reg: 0.351  loss_rpn_cls: 0.024  loss_rpn_loc: 0.039  time: 1.0466  data_tim
[08/01 12:31:03 d2.utils.events]:  eta: 0:22:45  iter: 199  total_loss: 0.758  loss_cls: 0.247  loss_box_reg: 0.388  loss_rpn_cls: 0.022  loss_rpn_loc: 0.046  time: 1.0475  data_tim
[08/01 12:31:23 d2.utils.events]:  eta: 0:22:21  iter: 219  total_loss: 0.631  loss_cls: 0.221  loss_box_reg: 0.350  loss_rpn_cls: 0.015  loss_rpn_loc: 0.043  time: 1.0467  data_tim
[08/01 12:31:44 d2.utils.events]:  eta: 0:22:00  iter: 239  total_loss: 0.654  loss_cls: 0.200  loss_box_reg: 0.346  loss_rpn_cls: 0.017  loss_rpn_loc: 0.044  time: 1.0454  data_tim
[08/01 12:32:05 d2.utils.events]:  eta: 0:21:38  iter: 259  total_loss: 0.581  loss_cls: 0.194  loss_box_reg: 0.340  loss_rpn_cls: 0.017  loss_rpn_loc: 0.044  time: 1.0444  data_tim
[08/01 12:32:25 d2.utils.events]:  eta: 0:21:20  iter: 279  total_loss: 0.613  loss_cls: 0.184  loss_box_reg: 0.355  loss_rpn_cls: 0.016  loss_rpn_loc: 0.041  time: 1.0439  data_tim
[08/01 12:32:46 d2.utils.events]:  eta: 0:20:56  iter: 299  total_loss: 0.680  loss_cls: 0.217  loss_box_reg: 0.359  loss_rpn_cls: 0.025  loss_rpn_loc: 0.057  time: 1.0440  data_tim
[08/01 12:33:08 d2.utils.events]:  eta: 0:20:39  iter: 319  total_loss: 0.599  loss_cls: 0.197  loss_box_reg: 0.363  loss_rpn_cls: 0.015  loss_rpn_loc: 0.043  time: 1.0470  data_tim
[08/01 12:33:29 d2.utils.events]:  eta: 0:20:18  iter: 339  total_loss: 0.551  loss_cls: 0.172  loss_box_reg: 0.324  loss_rpn_cls: 0.010  loss_rpn_loc: 0.035  time: 1.0468  data_tim
[08/01 12:33:50 d2.utils.events]:  eta: 0:19:57  iter: 359  total_loss: 0.543  loss_cls: 0.150  loss_box_reg: 0.309  loss_rpn_cls: 0.010  loss_rpn_loc: 0.050  time: 1.0467  data_tim
[08/01 12:34:12 d2.utils.events]:  eta: 0:19:38  iter: 379  total_loss: 0.565  loss_cls: 0.163  loss_box_reg: 0.295  loss_rpn_cls: 0.024  loss_rpn_loc: 0.037  time: 1.0480  data_tim
[08/01 12:34:31 d2.utils.events]:  eta: 0:19:14  iter: 399  total_loss: 0.620  loss_cls: 0.212  loss_box_reg: 0.326  loss_rpn_cls: 0.016  loss_rpn_loc: 0.036  time: 1.0448  data_tim
[08/01 12:34:53 d2.utils.events]:  eta: 0:18:54  iter: 419  total_loss: 0.574  loss_cls: 0.167  loss_box_reg: 0.323  loss_rpn_cls: 0.017  loss_rpn_loc: 0.043  time: 1.0460  data_tim
[08/01 12:35:14 d2.utils.events]:  eta: 0:18:34  iter: 439  total_loss: 0.561  loss_cls: 0.160  loss_box_reg: 0.301  loss_rpn_cls: 0.013  loss_rpn_loc: 0.040  time: 1.0468  data_tim
[08/01 12:35:34 d2.utils.events]:  eta: 0:18:10  iter: 459  total_loss: 0.543  loss_cls: 0.171  loss_box_reg: 0.332  loss_rpn_cls: 0.010  loss_rpn_loc: 0.034  time: 1.0440  data_tim
[08/01 12:35:54 d2.utils.events]:  eta: 0:17:48  iter: 479  total_loss: 0.532  loss_cls: 0.172  loss_box_reg: 0.329  loss_rpn_cls: 0.009  loss_rpn_loc: 0.038  time: 1.0438  data_tim
```

Figure: Text Detection Training

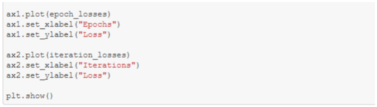
Expected Outcomes II



```
[07/28 12:59:29 d2.data.common]: Serializing 27 elements to byte tensors and concatenating them all ...
[07/28 12:59:29 d2.data.common]: Serialized dataset takes 0.01 MiB
[07/28 12:59:29 d2.evaluation.evaluator]: Start inference on 27 images
[07/28 12:59:33 d2.evaluation.evaluator]: Inference done 11/27. 0.3363 s / img. ETA=0:00:05
[07/28 12:59:39 d2.evaluation.evaluator]: Inference done 27/27. 0.3246 s / img. ETA=0:00:00
[07/28 12:59:39 d2.evaluation.evaluator]: Total inference time: 0:00:07.273351 (0.330607 s / img per device, on 1 devices)
[07/28 12:59:39 d2.evaluation.evaluator]: Total inference pure compute time: 0:00:07 (0.324569 s / img per device, on 1 devices)
[07/28 12:59:39 d2.evaluation.coco_evaluation]: Preparing results for COCO format ...
[07/28 12:59:39 d2.evaluation.coco_evaluation]: Saving results to /output/coco_instances_results.json
[07/28 12:59:39 d2.evaluation.coco_evaluation]: Evaluating predictions ...
Loading and preparing results...
DONE (t=0.00s)
creating index...
index created!
Running per image evaluation...
Evaluate annotation type *bbox*
DONE (t=0.07s).
Accumulating evaluation results...
DONE (t=0.03s).
 Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.486
 Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.794
 Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.588
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.416
 Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.541
 Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.454
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.195
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.536
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.538
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.498
 Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.610
 Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.519
[07/28 12:59:39 d2.evaluation.coco_evaluation]: Evaluation results for bbox:
|   AP   |  AP50  |  AP75  |  APs   |  APm   |  APl   |
|:------:|:------:|:------:|:------:|:------:|:------:|
| 48.614 | 79.410 | 58.818 | 41.596 | 54.075 | 45.368 |
[07/28 12:59:39 d2.evaluation.coco_evaluation]: Per-category bbox AP:
| category   | AP     | category   | AP     | category   | AP     |
|:-----------|:-------|:-----------|:-------|:-----------|:-------|
| HINDI      | 57.467 | ENGLISH    | 45.207 | OTHER      | 43.168 |
OrderedDict([('bbox',
              {'AP': 48.614130895033696,
               'AP-ENGLISH': 45.20707317037124,
```

Figure: Text Detection Testing

Expected Outcomes III



```
ax1.plot(epoch_losses)
ax1.set_xlabel("Epochs")
ax1.set_ylabel("Loss")

ax2.plot(iteration_losses)
ax2.set_xlabel("Iterations")
ax2.set_ylabel("Loss")

plt.show()
```

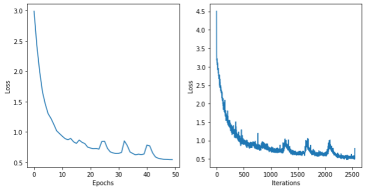
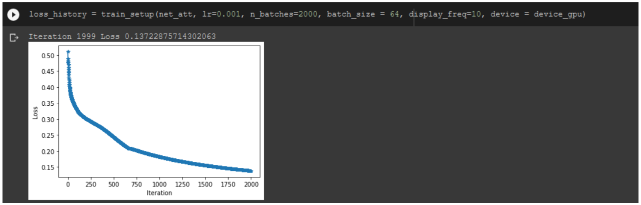


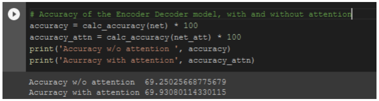
Figure: Text Recognition Training and Testing

Expected Outcomes IV



```
loss_history = train_setup(net_att, lr=0.001, n_batches=2000, batch_size = 64, display_freq=10, device = device_gpu)

Iteration 1999 Loss 0.13722875714302063
```

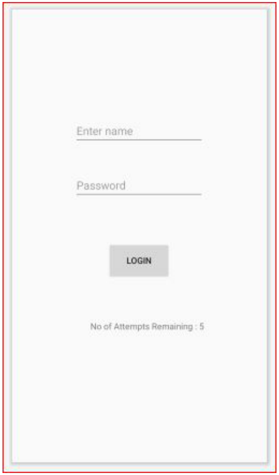
Figure: Text Transliteration Training



```
# Accuracy of the Encoder Decoder model, with and without attention
accuracy = calc_accuracy(net) * 100
accuracy_attn = calc_accuracy(net_att) * 100
print('Accuracy w/o attention ', accuracy)
print('Acurracy with attention', accuracy_attn)

Accuracy w/o attention  69.25025668775679
Acurracy with attention 69.93080114330115
```

Figure: Text Transliteration Testing

Expected Outcomes V



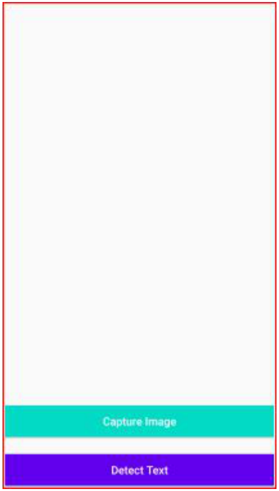


Figure: App Result

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Thank You