

E2DIEVS: End-to-End Document Information Extraction and Verification System

Final Project Report

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1 Abstract

As we witnessed rapid digitalization in our country, India, there grows the need for automatic document verification systems. Earlier, the KYC (know your customer) methods were done manually, as opposed to today, we can now perform KYC anywhere on Earth. Traditionally, OCR-based pipelines are getting used extract text, and after applying several rule-based methods, we extract information from it. These methods failed miserably on Indian Identity documents such as Aadhar cards, and Pan cards. LayoutLM is a pre-trained model, known for extracting textual information from scanned documents. We employ that model, fine-tune it on the datasets which only consists of scanned form images and receipts with primary information, that eventually enhanced the performance. But, it faces limitations on scanning and understanding textual information from the Aadhar cards and Pan cards due to unrecognized formats. We overcome this limitation by using YoloV11, pre-trained on the dataset of aadhar cards and pan cards, which gives us text along with its category.

2 Introduction

Extracting information from scanned documents such as forms, invoices, receipts and identity cards has been emerged critically in AI. Microsoft Research introduced LayoutLM (Xu et al., 2019) which brought revolution in this domain. It incorporates spatial awareness in to the transformer which led to the state-of-the-art results on benchmarks such as FUNSD (Jaume et al., 2019) and SROIE (Huang et al., 2019). But it has a drawback of heavily relying on the accurate OCR and bounding box inputs during inference. That makes its multi-modal pre-training computationally expensive

and less effective.

To address limitations faced by the LayoutLM, Donut (Kim et al., 2022) proposed an OCR-free approach. It uses a vision-transformer encoder which is combined with a text decoder to directly generate structured JSON output from raw document images without intermediate text recognition. The drawbacks of Donut are: training on diverse document types, and underperforms on densely formatted or multi-lingual documents, such as Aadhar cards, and Pan cards.

The accurate field extraction from Aadhar cards and Pan cards remains particularly challenging due to multi-lingual content and inconsistent layouts across states. We came across an advanced object detection model, such as YoloV11 (Logasanjeev, 2024), which is finetuned on Indian ID datasets. It is more capable than LayoutLM and Donut for extracting the information from Indian IDs along with their categories. Our project contains the following novel ideas:

- LayoutLM fine-tuned on FUNSD and SROIE datasets showing improved performance.
- A novel pipeline that can extract information from the printed digital forms as well as Aadhar cards or Pan cards, and verify with the ground truth data.

3 Baseline Models

Our baseline model is *layoutlm-base-uncased*. LayoutLM (Xu et al., 2019) is a pre-trained multi-modal transformer which learns textual as well as spatial layout information from images of documents. It is pre-trained on IIT-CDIP dataset (Lewis et al., 2006), which consists of the following different documents:

- Letter
- Handwritten Notes on page
- Memo
- Invoices
- Email
- Advertisement
- File-folder
- Budget
- Form
- And many more.

LayoutLM was proposed by Microsoft Research Asia. A snippet of dataset it was pre-trained on can be seen in Figure 1. There are 400,000 grayscale images in 16 classes, each class accounting 25,000 images. After train, test and validation split, there are 320,000 images in the training set, 40,000 images in the validation set and 40,000 images in the test set. The images are resized such that the largest dimension do not exceed 1000 pixels.

Table 1: Model Specifications of LayoutLM.

Component	Details
Architecture	BERT-like
Input Modalities	Transformer
	1. Text (words)
Pre-training Corpus	2. 2D Layout
Tokenizer	IIT-CDIP
Max Sequence Length	WordPiece (uncased)
Parameters	512
	~110M

The model specification of the pre-trained LayoutLM can be seen in Table 1. The embeddings of the input modalities consists of the following information:

1. Adding 2D spatial embeddings to each token:
 - x-position-embeddings
 - y-position-embeddings
 - h-position-embeddings (height)
 - w-position-embeddings (width)
2. Pre-training on real scanned documents (not synthetic text), preserving:
 - Font styles
 - Table structures
 - Form fields
 - Spatial alignments

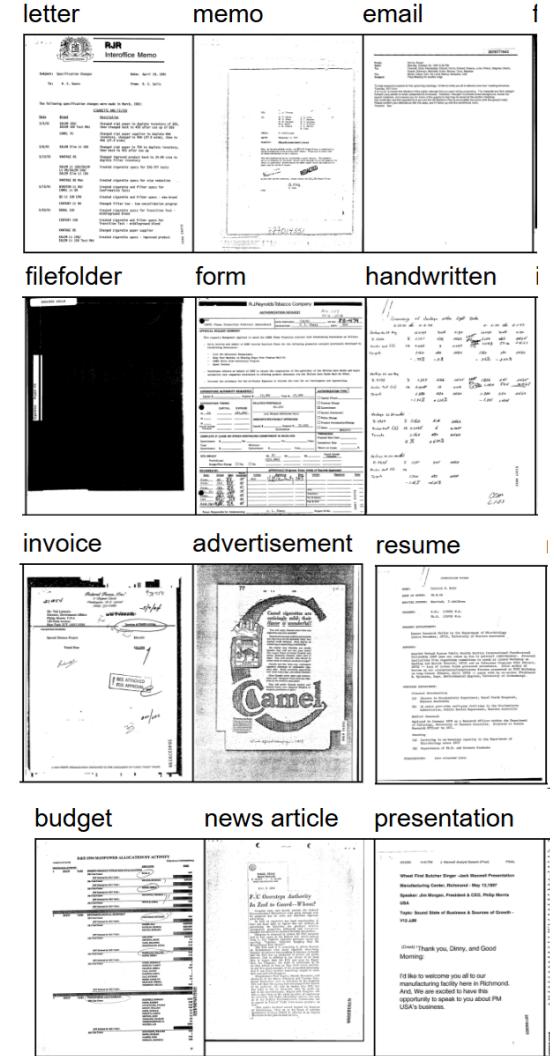


Figure 1: IIT-CDIP train dataset snippet. There 16 different types of scanned documents in the dataset.

4 Proposed Model

4.1 Dataset Configuration

1. FUNSD ([Jaume et al., 2019](#)): A dataset for understanding the forms in noisy scanned documents. There are 149 datapoints in train-set and 50 datapoints in test-set. The language in forms is majorly English. More details can be seen in Table 2.

2. SROIE ([Huang et al., 2019](#)): The full-form is Scanned Receipts OCR and Information Extraction. This is used for OCR and key information extraction from scanned receipts. It consists of 626 images in train-set and 347 images in test-set. The language in receipts is English. More details can be seen in Table 3.

¹

¹Github Repo: <https://github.com/ManishPraa24/End->

Table 2: FUNSD dataset configuration.

Attribute	Details
Total Images	199 scanned forms
Word-level annotations	30,000
Entities	10,000
Entity Types	Header, Question, Answer & other
Annotation Format	BIO tagging + bounding boxes + key-value links
Image Resolution	100 DPI grayscale

Table 3: SROIE dataset configuration.

Attribute	Details
Total Images	1,000 scanned receipts
Key Entities	4
Image resolution	Varied
Annotations	OCR bounding boxes and key-value pairs

4.2 Model Configuration

LayoutLM introduced a powerful pre-training paradigm for scanned documents. However, downstream evaluation was constrained. Earlier work fine-tuned the model on FUNSD and test-set of the SROIE dataset corpora. We find our enhancement far from being trivial for the following reasons:

1. The objectives of pre-training operate at the representation level and do not expose the model to task-specific BIO schemas.
2. Pre-training data consist primarily of scanned books and articles from IIT-CDIP, exhibiting fundamentally different spatial statistics.
3. Character-level fidelity as a Proxy for deployment success.

Thus, our work including the fine-tuning, completes the experiment from the original paper. The model configuration can be seen in the Table 4.

As described in Table 4, we choose 15 number of labels, which represent the BIO-schema heads: HEADER, QUESTION, ANSWER,

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Table 4: Model configuration for fine-tuning on the dataset corpora of FUNSD and SROIE.

Parameter	Value
Number of labels	15 (BIO-schema)
Max. sequence length	512
Batch Size	8
Learning rate	5e-5
Optimizer	AdamW
Epochs	30

COMPANY, DATE, ADDRESS, TOTAL, etc. We kept the value of the maximum sequence length same as pre-training. To be memory efficient with the bounding box embeddings, we kept the batch-size as 8. Optimizer is AdamW with weight decay of 0.01. Initially, we kept model warmup comprising of 10% of the steps in order to stabilize the training. For collating the data, we use dynamic padding that gives no batch size errors, and ensures no data loss.

4.3 Embeddings and Encoding

We have used the original pipeline of LayoutLM pre-training which contains the following strategies:

1. Text Encoding:

- Input: List of words (from OCR: Tesseract for SROIE, ground-truth for FUNSD).
- Tokenizer: *AutoTokenizer* (WordPiece, uncased) with *is_split_into_words = True*.
- Sub-words of the first token for each word inherits the BIO label.

2. Layout (2D Position) Encoding

- Bounding boxes are normalized for every document, making them the size of [0, 1000] x [0, 1000].
- Formula:

$$x' = \left\lfloor \frac{x \cdot 1000}{\max(x)} \right\rfloor, \quad y' = \left\lfloor \frac{y \cdot 1000}{\max(y)} \right\rfloor$$

where x and y are the dimensions of the images.

- Four coordinates are fed into the learned 2D position embeddings as in (Xu et al., 2019).

3. Input representation

- Each token receives:
 $[CLS] + \text{Token Embedding} + \text{Segment Embedding} + 2\text{-D Position Embedding } (x_1, y_1, x_2, y_2) + [SEP]$.

4.4 Evaluation Method

4.4.1 Training and Evaluating Loss

During the fine-tuning, we optimize the standard token classification objective by incorporating cross-entropy loss over the predicted logits and ground-truth labels. For a sequence of length T , the loss for a particular instance is calculated as:

$$\mathcal{L} = -\frac{1}{|\mathcal{A}|} \sum_{t \in \mathcal{A}} \log \left(\frac{\exp(\text{logit}_{y_t}[t])}{\sum_{c=1}^C \exp(\text{logit}_c[t])} \right), \quad (1)$$

where:

- $\mathcal{A} = t \mid y_t \neq -100$ is set the of active positions.
- $y_t \in \{0, 1, \dots, C-1\}$ is the ground-truth label at position t .
- $C = 15$ is the number of classes in our unified BIO schema.
- $\text{logit}_c[t]$ is the model’s un-normalized score for class c at position t .
- The positions corresponding to the subword continuations, and special tokens ($[CLS]$, $[SEP]$, $[PAD]$) are assigned label **-100**. This is ignored by the loss function.

Our objective function is similar to that in (Xu et al., 2020).

4.4.2 Token-level Accuracy

For document-image understanding tasks, the token-level accuracy is defined as:

$$\text{Accuracy} = \frac{\sum_{t \in \mathcal{A}} \mathbb{1}\{\hat{y}_t = y_t\}}{|\mathcal{A}|} \quad (2)$$

4.4.3 Macro F1 Score

This is computed for more than 15 BIO classes:

$$F1_c = \frac{2P_cR_c}{P_c + R_c}, \quad \text{Macro-F1} = \frac{1}{C} \sum_{c=1}^C F1_c$$

where P_c and R_c are the precision and recall for class c .

5 Results

The results for baseline LayoutLM on the dataset of FUNSD can be seen in Table 5, and on the dataset corpora of SROIE can be seen in Table 6.

Table 5: Evaluation of FUNSD dataset on baseline LayoutLM model

Metric	Value
Recall	0.041
Precision	0.254
F1	0.068

Table 6: Evaluation of SROIE dataset on baseline LayoutLM model

Metric	Value
Recall	0.271
Precision	0.249
F1	0.249

The macro-F1 score on FUNSD dataset is 0.068 and, that on SROIE dataset is 0.249. Both the scores are very low, compared to that we obtained upon fine-tuning the model on the FUNSD and SROIE datasets. Our fine-tuned model achieved the best macro-F1 score of 0.638 at epoch 19, and best evaluation accuracy of 95.169% at epoch 7. The trajectory of macro-F1 and evaluation accuracy can be seen in Figure 2. We obtained the least validation loss at epoch 5 having value of 0.1544. The trajectory of evaluation loss and training loss during fine-tuning can be seen in the Figure 3.

6 Inference

We parsed three random images, taken from FUNSD, SROIE and Aadhar card dataset, in order to observe the change in inference of the model after fine-tuning.

FUNSD: The inference of pre-trained LayoutLM model on the one of the instance of FUNSD dataset can be seen in Figure 4. Comparing to the inference of the fine-tuned LayoutLM model which can be seen in Figure 4, the pre-trained model fails to classify the text such as ‘TO’, ‘FAX NUMBER’, etc. as keys. However, the fine-tuned model classifies the parsed text such as ‘TO’, ‘FAX NUMBER’, etc., and ‘George Baroody’, ‘(336) 335-7392’, etc., as corresponding key-value pairs.

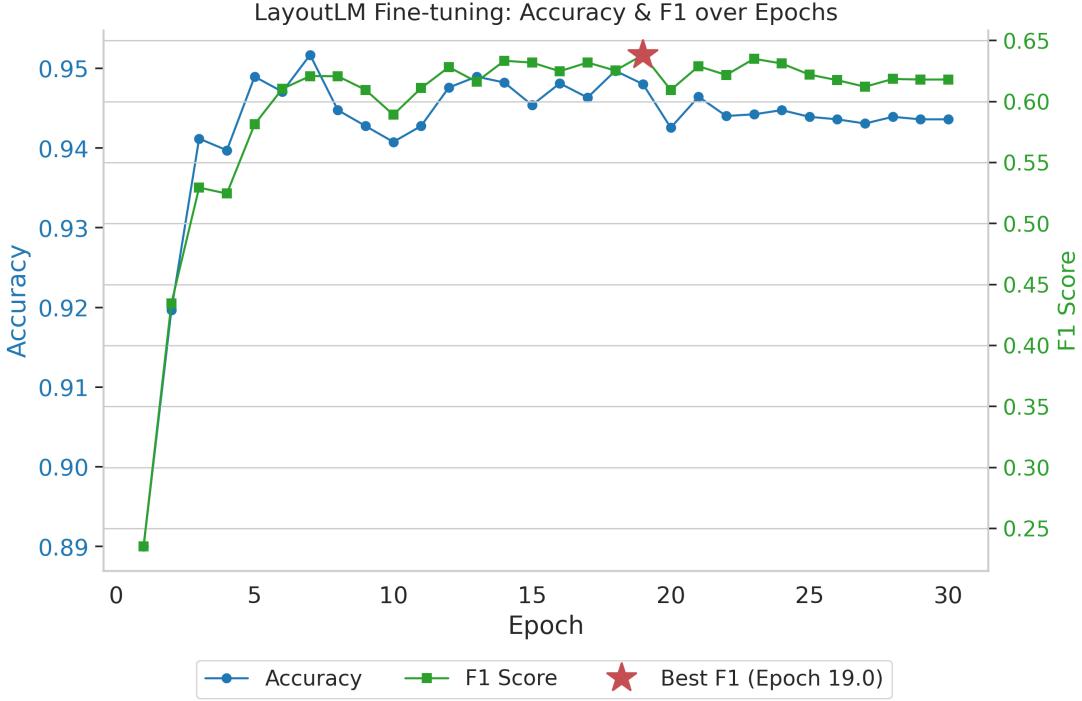


Figure 2: Trajectory of macro-F1 and evaluation accuracy during fine-tuning of the LayoutLM model.

SROIE: Pre-trained model’s inference on the instance of SROIE dataset can be seen in Figure 6, and inference obtained using fine-tuned model can be seen in Figure 7. Pre-trained model classified text such as ‘Pre auth code . . .’, ‘V-Power 97’, etc. as B-Company, which is wrong. Comparing to the inference of the fine-tuned model, there is no text classified to the label ‘B-Company’.

Aadhar Card: The inference of the dummy Aadhar card obtained using pre-trained model can be seen in Figure 8, and that of fine-tuned model can be seen in Figure 9. Pre-train model classifies entities like ‘Name’, as B-HEADER. Compared to inference of the fine-tuned model, the ‘NAME’ is classified as B-QUESTION, enabling a question-answer pair, which is better than the pre-trained inference.

Overall, the fine-tuned model is able to recognize possible question-answer form of text from forms, receipts and aadhar-cards, better than pre-trained model.

7 Future Work

We observe that fine-tuned model still struggles to classify text from Aadhar card, such as ‘Male’, ‘DOB: $\text{\texttt{date}}$ ’ to be different and the Aadhar number as a question-answer, which determines that there’s still uncertainty existing

in the model. We further plan to address these issues by fine-tuning the model on publicly available datasets with annotations. Our last stage will be to make pipeline, which scanned the document and extracts the important key entities based on the type of document, and verify it with the available ground-truth text.

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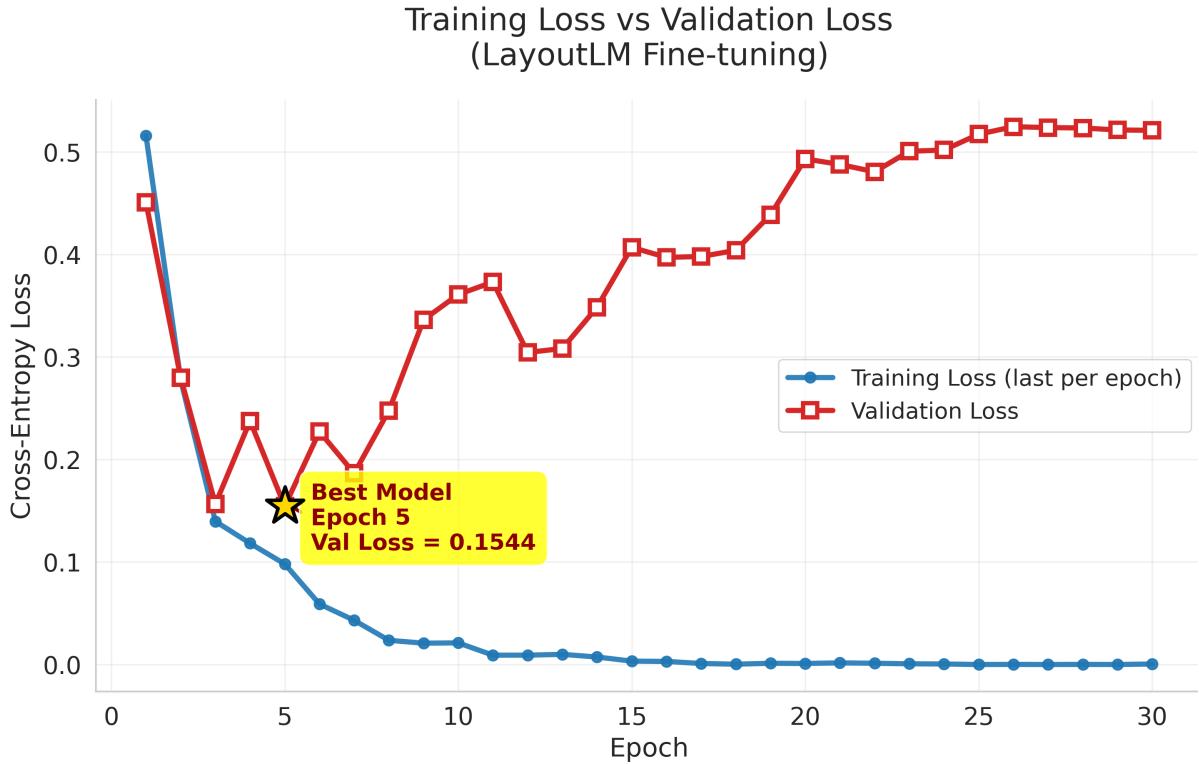


Figure 3: Trajectory of training loss and evaluation loss during the fine-tuning of the LayoutLM model.

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Figure 4: Pre-trained LayoutLM inference on one of the instance of the FUNSD dataset.

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Figure 5: Inference of the fine-tuned LayoutLM model on one of the instance of the FUNSD dataset.

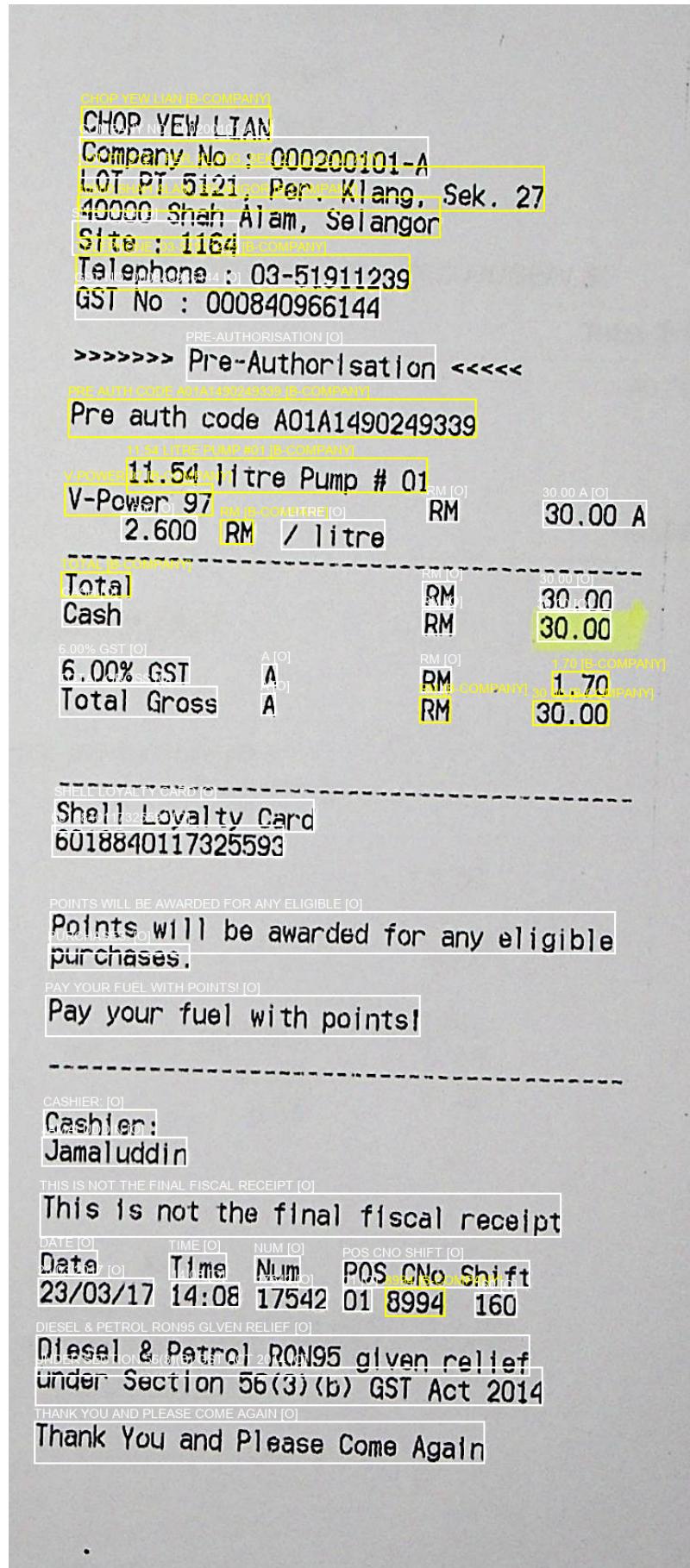


Figure 6: Pre-trained LayoutLM inference on one of the instance of the dataset corpora of SROIE.



Figure 7: Inference of the fine-tuned LayoutLM model on one of the instance of the SROIE dataset.



आधार - आदमी का अधिकार

Figure 8: Pre-trained LayoutLM inference on the dummy Aadhar Card.



Figure 9: Inference of the fine-tuned LayoutLM model on the dummy Aadhar Card.